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EXPLORING THE ROLE OF ARTIFICIAL INTELLIGENCE IN ADAPTIVE LEARNING SYSTEMS: A MIXED METHODS INVESTIGATION OF STUDENT LEARNING EXPERIENCES

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ABSTRACT

This study investigates the impact of artificial intelligence (AI) in adaptive learning systems on student learning experiences through a mixed-methods approach. Qualitative methods included in-depth interviews with seven students and focus group discussions with ten students, identifying key themes: clear expectations, positive reinforcement, effective communication, consistent consequences, and restorative practices. These themes informed the development of a 50-item scale. Quantitative analysis of 200 questionnaire responses using exploratory factor analysis (EFA) revealed five dimensions: adaptive content delivery, real-time feedback and assessment, data-driven insights for educators, personalized learning paths, and lifelong learning and skill development. The 38-item scale demonstrated good internal consistency (Cronbach's Alpha = 0.872), emphasizing AI's critical role in enhancing student learning experiences in adaptive learning systems.

Keywords: *Artificial Intelligence, Adaptive Learning Systems, Exploratory Sequential Design, Factor Analysis, Kidapawan City, Philippines*

INTRODUCTION

Artificial Intelligence (AI) in adaptive learning systems faces significant challenges, particularly biased algorithms and unequal access to educational opportunities. Studies show that many AI algorithms in these systems may inadvertently perpetuate existing inequalities by favoring certain demographics or reinforcing pre-existing biases in training data. UNESCO reports that 60% of adaptive learning systems suffer from biased content or design, disproportionately affecting marginalized groups (UNESCO, 2020). Addressing this issue requires scrutinizing and rectifying biases in AI algorithms, promoting transparency, and using diverse datasets to foster inclusive adaptive learning systems (Diakopoulos, 2021; Mittelstadt et al., 2021).

In the Philippines, the digital divide is a prominent issue, especially in rural and underserved areas. Many Filipinos lack access to the necessary technological infrastructure, hindering participation in AI-driven learning. About 30% of Filipino households do not have internet access (National Telecommunications Commission, 2021). This disparity exacerbates educational inequalities, favoring urban students with better access to AI tools. Bridging this digital gap requires strategic policies and investments to ensure equitable access to AI-enhanced educational resources (Alampay & Warschauer, 2021).

Several studies highlight the multifaceted factors influencing AI effectiveness in adaptive learning systems, such as the quality of training data and human factors like teacher-student interactions and adaptable instructional strategies (Baker, 2021; Viberg et al., 2018). Ethical considerations, including algorithmic bias and fairness, are also crucial in AI system design and deployment (Baker & Yacef, 2019).

Despite extensive research, gaps remain in understanding AI adaptive learning systems, particularly concerning ethical considerations and AI's impact on different student demographics. Addressing these gaps is crucial for developing inclusive and ethical AI applications in education. Studying AI in adaptive learning systems is vital for personalizing learning experiences, enhancing educational effectiveness, and ensuring equitable learning environments.

FRAMEWORK

This study highlights the necessity of examining Artificial Intelligence (AI) in Adaptive Learning Systems due to their transformative impact on education. As AI becomes more prevalent, it is crucial for educators, policymakers, and researchers to understand its implications. The study aims to identify benefits such as personalized learning and improved outcomes while addressing challenges like algorithmic bias and ethical considerations. It emphasizes the importance of research to inform effective implementation strategies, promote inclusivity, and ensure ethical AI deployment to enhance educational quality and accessibility.

Theoretical frameworks are essential for understanding AI in Adaptive Learning Systems. Grounding research in Cognitive Load Theory (CLT) by Sweller (1988) and Connectivism by Siemens (2004) helps analyze AI's impact on cognitive processes and social dynamics. These theories guide hypothesis formulation, experiment design, and result interpretation, leading to deeper insights and informed recommendations for educators and policymakers.

CLT posits that the human cognitive system has limits on processing information. In AI-driven adaptive learning systems, CLT helps understand how AI design impacts cognitive load. Optimizing information presentation and instructional strategies is crucial for effective learning. Researchers can explore how AI affects cognitive load, aiming to reduce extraneous load and enhance learning experiences.

Connectivism emphasizes the importance of networks and connections in knowledge acquisition. In AI adaptive learning systems, learning is seen as distributed across people and technology. AI leverages technology to create personalized learning experiences based on individual needs. Connectivism highlights the significance of digital literacy skills, understanding AI algorithms, and critically engaging with technology-mediated learning environments.

Anchoring this study in CLT and Connectivism provides a comprehensive understanding of AI's role in adaptive learning, guiding research and practice toward effective, inclusive, and ethical educational advancements.

METHOD

Research design

This study utilized an Exploratory Research design to comprehensively understand AI's integration in educational settings. This design is chosen to explore the dynamic and relatively unexplored field of AI in adaptive learning, which is characterized by rapid evolution and emerging technologies. Exploratory research allows for flexible exploration of new phenomena, identification of variables, and generation of hypotheses for further investigation. In this study, the exploratory approach will delve into how AI is implemented, its impact on student learning experiences, and the challenges and opportunities in adaptive learning systems.

Exploratory research, as described by Zikmund (2003), involves investigating poorly understood areas to establish foundations for deeper studies. It offers flexibility to gather preliminary data and develop hypotheses for subsequent research. This approach is ideal for understanding complex phenomena like AI integration in adaptive learning, aiming to uncover patterns and relationships that can inform future research and contribute to discussions on AI's role in education.

Respondents

For the qualitative phase, ten students from Kidapawan City underwent in-depth interviews, while seven others participated in focus group discussions. Themes emerging from these interviews led to the development of a questionnaire, utilizing purposive sampling for participant selection using a non-probability method.

In the quantitative phase, 200 students completed a survey designed for exploratory factor analysis and confirmatory analysis. Following this, an additional 30 participants recruited for a reliability test. Only tertiary school students from Kidapawan City included as participants in this study, excluding those not meeting this criterion.

Statistical Tools

This study employs thematic analysis and factor analysis to analyze its data. Thematic analysis, as outlined by Kiger and Varpio (2020), involves identifying patterns in qualitative data through a systematic process: familiarization with the data, initial coding, theme development, review, definition, and reporting. It aims to interpret and describe data, making it suitable for exploring views on artificial intelligence in adaptive learning systems through in-depth interviews.

In the quantitative aspect, factor analysis (FA), following Tavakol and Wetzel's (2020) approach, simplifies complex variables to uncover underlying dimensions explaining relationships between multiple items. This study uses FA to validate construct measures by exploring these underlying dimensions. Prior to FA, the Kaiser-Meyer-Olkin (KMO) test assesses data adequacy. Once data pass the KMO test, principal axis factoring with Promax rotation extracts factors based on item communalities of .40 or higher. Factors with eigenvalues ≥ 1 and confirmed by Cattel's scree plot criterion are retained. Factor loadings indicate correlations between items and factors, elucidating latent dimensions of AI in adaptive learning systems. Reliability testing, specifically Cronbach's alpha, evaluates internal consistency among items, crucial for ensuring the tool's reliability in measuring AI's impact on learning.

RESULTS AND DISCUSSION

Construction of the role of artificial intelligence in adaptive learning systems on student learning experiences Scale

Based from the narratives of the participants, the Table 1 presents the role of artificial intelligence in adaptive learning systems on student learning experiences' scale items which are selected based on their frequency of occurrence from the responses in qualitative interviews. This 50-item questionnaire was subjected to data reduction technique using the exploratory factor analysis (EFA). Hence, the number of factors was fixed to five based on the a priori qualitative analysis dimensions.

Table 1
The role of artificial intelligence in adaptive learning systems on student learning experiences scale

ITEMS	
1	I appreciate tailored learning paths with AI.
2	I believe AI adapts well to me.
3	I consider AI vital for my education.
4	I feel AI understands my learning needs.
5	I find AI's role enhances my learning.
6	I see benefits in personalized learning.
7	I sense AI positively impacts my learning.
8	I think AI improves my learning journey.
9	I trust AI to guide my learning.
10	I value AI for customizing my path.
11	I appreciate AI's real-time feedback mechanism.
12	I appreciate AI's role in quick assessments.
13	I believe AI enhances my learning feedback.
14	I consider AI vital for timely feedback.
15	I feel AI positively impacts my feedback.
16	I find AI's quick feedback highly beneficial.

17 I rely on AI for prompt assessments.
18 I see advantages in AI's instant assessments.
19 I trust AI to provide timely assessments.
20 I value AI's immediate performance assessment feature.
21 I appreciate AI's data-driven approach for educators.
22 I appreciate AI's role in guiding educators.
23 I believe AI's insights benefit my education.
24 I consider AI essential for educator insights.
25 I feel AI positively impacts educator insights.
26 I find AI's data-driven feedback beneficial.
84 I rely on AI to support educators.
28 I see advantages in AI's data analysis.
29 I trust AI's data-driven insights for educators.
30 I value AI providing insights to educators.
31 I appreciate AI's role in dynamic content.
32 I appreciate AI's tailored content for me.
33 I believe AI's adaptive delivery benefits learning.
34 I consider AI crucial for tailored content.
35 I feel AI positively impacts my learning.
36 I find AI's adaptive content engaging.
37 I rely on AI for individualized learning.
84 I see advantages in AI's dynamic content.
39 I trust AI for personalized learning paths.
90 I value AI's adaptive content delivery approach.
41 I appreciate AI fostering lifelong learning habits.
42 I appreciate AI's role in continuous learning.
43 I believe AI contributes to lifelong learning.
44 I consider AI crucial for lifelong learning.
45 I feel AI positively influences skill development.
46 I find AI promotes continuous skill development.
47 I rely on AI for ongoing skill development.
48 I see advantages in AI's skill development.
49 I trust AI's impact on lifelong learning.
50 I value AI's role in skill development.

Dimensions of the role of artificial intelligence in adaptive learning systems on student learning experiences Scale

Testing a 50-item the role of artificial intelligence in adaptive learning systems on student learning experiences' scale. To ensure that the construct can be tested for factor analysis, the Kaiser Meyer-Olkin Measure (KMO) of Sampling Adequacy and Bartlett's test of sphericity were performed. It can be gleaned in Table 3 that KMO value is .582 which is above recommended value of .5, which indicates that the sample is meritorious and adequate factor analysis. Kaiser (1974) recommends accepting values greater than .5 are acceptable. Furthermore, values .5 to .7 are mediocre, values between .7 to .8 are good, and the values between .8 to .9 are superb (Kaiser, 1974)

Table 2
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.782
Bartlett's Test of Sphericity	Approx. Chi-Square	7853.226
	Df	1225
	Sig.	.000

As shown in the preliminary analysis, it can be generalized that the 50-item the role of artificial intelligence in adaptive learning systems on student learning experiences is suitable and adequate for extraction of factors, and thus, ready for factor analysis.

Derivation of the Number of Factor Structure. The derivation of factor structure was determined through a priori results of qualitative data analysis wherein there are five dimensions of the role of artificial intelligence in adaptive learning systems on student learning experiences Hence, the five-factor model exhibit clean patterns as shown in Table 3.

The factor loading below .4 are reduce from the model and based on the results only 38 items were accepted and passed the criteria then subjected for rotation and analysis.

After which, the 38 – item construct is then subjected for rotation. The Promax rotation was used since the factors seem to be correlated with a coefficient above .40 which reflects that the data is not assumed as orthogonal.

The Table 3 shows the pattern matrix using Principal Axis factoring with a Promax rotation method of Promax with Kaiser Normalization. It can be observed in the results the loading of items in the five factors are above .4. It can be supported by Filed (2005) that .4 is recommended and necessary to obtain the desired factors. Furthermore, it can be observed that there is no item cross-loading or not loading at all which means that the items best represent their factors. It is emphasized that loadings indicate the degree of correspondence between the variable and the factor, with higher loadings making the variable representative of the factor (Hair et al., 1998).

Table 3
Pattern Matrix Five Factor Model

		Factor 1	2	3	4	5
1	I appreciate tailored learning paths with AI.					.567
2	I believe AI adapts well to me.					.625
3	I consider AI vital for my education.					.618
4	I feel AI understands my learning needs.				.720	
5	I find AI's role enhances my learning.					
6	I see benefits in personalized learning.				.678	
7	I sense AI positively impacts my learning.					.701
8	I think AI improves my learning journey.					.755
9	I trust AI to guide my learning.					.566

10	I value AI for customizing my path.			.784	
11	I appreciate AI's real-time feedback mechanism.				
12	I appreciate AI's role in quick assessments.			.750	
13	I believe AI enhances my learning feedback.			.730	
14	I consider AI vital for timely feedback.		.721		
15	I feel AI positively impacts my feedback.		.652		
16	I find AI's quick feedback highly beneficial.		.570		
17	I rely on AI for prompt assessments.				
18	I see advantages in AI's instant assessments.				
19	I trust AI to provide timely assessments.		.746		
20	I value AI's immediate performance assessment feature.		.701		
21	I appreciate AI's data-driven approach for educators.		.669		
22	I appreciate AI's role in guiding educators.				
23	I believe AI's insights benefit my education.				
24	I consider AI essential for educator insights.				.687
25	I feel AI positively impacts educator insights.				.528
26	I find AI's data-driven feedback beneficial.				
27	I rely on AI to support educators.				
28	I see advantages in AI's data analysis.				
29	I trust AI's data-driven insights for educators.				
30	I value AI providing insights to educators.			.619	
31	I appreciate AI's role in dynamic content.				
32	I appreciate AI's tailored content for me.			.834	
33	I believe AI's adaptive delivery benefits learning.			.826	
34	I consider AI crucial for tailored content.	.572			
35	I feel AI positively impacts my learning.	.668			
36	I find AI's adaptive content engaging.	.602			
37	I rely on AI for individualized learning.	.596			
38	I see advantages in AI's dynamic content.	.723			
39	I trust AI for personalized learning paths.	.738			
40	I value AI's adaptive content delivery approach.	.822			
41	I appreciate AI fostering lifelong learning habits.	.724			
42	I appreciate AI's role in continuous learning.	.637			
43	I believe AI contributes to lifelong learning.	.703			
44	I consider AI crucial for lifelong learning.	.803			
45	I feel AI positively influences skill development.	.814			
46	I find AI promotes continuous skill development.	.726			
47	I rely on AI for ongoing skill development.	.796			
48	I see advantages in AI's skill development.	.735			
49	I trust AI's impact on lifelong learning.				
50	I value AI's role in skill development.	.602			

The item loadings of each item to their factor indicate sufficient correlation between factors and variables, and thus, can be considered as component of the factor. By using the EFA, the five-factor model of the role of artificial intelligence in adaptive learning systems on student learning experiences with 38 items was developed as shown in Table 4, Data-driven insights for educators, Real-time feedback and assessment, Personalized learning paths, Adaptive content delivery, and Lifelong learning and skill development.

Reliability Result

The reliability test results presented in Table 4 indicate the internal consistency and stability of the factors comprising the "Role of Artificial Intelligence in Adaptive Learning Systems on Student Learning Experiences" scale. Cronbach's Alpha, a measure of reliability, is utilized to assess the consistency of responses within each factor. The findings reveal that all factors demonstrate acceptable reliability, with Adaptive Content Delivery and Real-time Feedback and Assessment scoring particularly high at 0.921 and 0.927, respectively, indicating very good internal consistency. The Data-driven Insights for Educators, Personalized Learning Paths, and Lifelong Learning and Skill Development factors exhibit good reliability with Cronbach's Alpha values of 0.822, 0.878, and 0.811, respectively. These results suggest that the items within each factor are consistently measuring the same underlying construct.

The overall Cronbach's Alpha for the entire scale is 0.872, indicating good reliability across the 38 items. Researchers and practitioners can rely on the scale to consistently measure the specified factors related to artificial intelligence in adaptive learning systems and their impact on student learning experiences.

Table 4. Reliability of the five factors of the role of artificial intelligence in adaptive learning systems on student learning experiences scale

Factor	Cronbach's Alpha	Interpretation	No. of Items
Adaptive content delivery	0.921	Very Good	16
Real-time feedback and assessment	0.927	Very Good	6
Data-driven insights for educators	0.822	Good	6
Personalized learning paths	0.878	Good	4
Lifelong learning and skill development	0.811	Good	6
Overall Cronbach's Alpha	**0.872**	**Good**	**38 No. of Items**

Final Version of the role of artificial intelligence in adaptive learning systems on student learning experiences. The final version of the instrument, which is the output of this study, is represented in the form provided in Table 4. From 38 items, the analysis suggests several issues on face validity based on factor loadings on the items. Items that have small coefficient less than .40 are removed. This is supported by Hair et al. (2010)

that those items having no sense and not reflective with the factor can be removed in the model. Also, loading coefficient can be set by the researcher to select only those items that best represents the factor, and those low coefficients may not be included in the factor structure.

By using EFA, the role of artificial intelligence in adaptive learning systems on student learning experiences' questionnaire were developed. This tool consists of 38 items which consists of five themes. These five themes were obtained from the qualitative results. A total of five themes were developed which are adaptive content delivery with a total of 16 items, real-time feedback and assessment with a total of 6 items, data-driven insights for educators with a total of 6 items, personalized learning paths with a total of 4 items, and lifelong learning and skill development with a total of 6 items**.** The 5-point Likert-scale from 5-stronly agree to 1-stronly disagree is shown below.

Table 5
The role of artificial intelligence in adaptive learning systems on student learning experiences Questionnaire

	ITEMS
	Adaptive content delivery
1	I consider AI crucial for tailored content.
2	I feel AI positively impacts my learning.
3	I find AI's adaptive content engaging.
4	I rely on AI for individualized learning.
5	I see advantages in AI's dynamic content.
6	I trust AI for personalized learning paths.
7	I value AI's adaptive content delivery approach.
8	I appreciate AI fostering lifelong learning habits.
9	I appreciate AI's role in continuous learning.
10	I believe AI contributes to lifelong learning.
11	I consider AI crucial for lifelong learning.
12	I feel AI positively influences skill development.
13	I find AI promotes continuous skill development.
14	I rely on AI for ongoing skill development.
15	I see advantages in AI's skill development.
16	I value AI's role in skill development.
	Real-time feedback and assessment
17	I consider AI vital for timely feedback.
18	I feel AI positively impacts my feedback.
19	I find AI's quick feedback highly beneficial.
20	I trust AI to provide timely assessments.
21	I value AI's immediate performance assessment feature.
22	I appreciate AI's data-driven approach for educators.
	Data-driven insights for educators
23	I value AI for customizing my path.

24 I appreciate AI's role in quick assessments.
25 I believe AI enhances my learning feedback.
26 I value AI providing insights to educators.
27 I appreciate AI's tailored content for me.
28 I believe AI's adaptive delivery benefits learning.

Personalized learning paths

29 I feel AI understands my learning needs.
30 I see benefits in personalized learning.
31 I consider AI essential for educator insights.
32 I feel AI positively impacts educator insights.

Lifelong learning and skill development

33 I appreciate tailored learning paths with AI.
34 I believe AI adapts well to me.
35 I consider AI vital for my education.
36 I sense AI positively impacts my learning.
37 I think AI improves my learning journey.
38 I trust AI to guide my learning.

Legend:

5 – Strongly Agree
4 – Agree
3 – Moderately Agree
2 – Disagree
1 – Strongly Disagree

This study recommended that future research endeavors in the realm of artificial intelligence (AI) in adaptive learning systems on student learning experiences should delve deeper into the nuanced interactions among the identified factors. While the reliability test results of the scale demonstrated good to very good internal consistency across Adaptive Content Delivery, Real-time Feedback and Assessment, Data-driven Insights for Educators, Personalized Learning Paths, and Lifelong Learning and Skill Development, a more comprehensive understanding of the interplay between these factors could offer valuable insights. Additionally, exploring the moderating effects of various contextual factors, such as cultural differences and diverse educational settings, would contribute to the generalizability of the findings. Furthermore, the study recommended longitudinal investigations to observe the sustained impact of AI in adaptive learning systems over time, offering a more holistic view of its influence on evolving student learning experiences. Finally, considering the dynamic nature of technology, continuous updates and refinements to the scale and its underlying constructs are encouraged to ensure its relevance and applicability in the ever-evolving landscape of AI in education.

CONCLUSION

In the light of the study, the following conclusions were drawn:

1. The emerging themes highlight the the role of artificial intelligence in adaptive learning systems on student learning experiences which put emphasis on personalized learning paths, real-time feedback and assessment, data-driven insights for educators, adaptive content delivery, and lifelong learning and skill development.
2. The result derived from factor analysis indicates that the the role of artificial intelligence in adaptive learning systems on student learning experiences has five factors that includes personalized learning paths, real-time feedback and assessment, data-driven insights for educators, adaptive content delivery, and lifelong learning and skill development.
3. The reliability test, employing Cronbach's Alpha, confirms the internal consistency and stability of the scale assessing the "Role of Artificial Intelligence in Adaptive Learning Systems on Student Learning Experiences," indicating acceptable reliability across all factors and a good overall Cronbach's Alpha of 0.872, ensuring consistent measurement of AI-related factors impacting student learning experiences through 38 items.
4. The role of artificial intelligence in adaptive learning systems on student learning experiences of teaching with 38 items was developed to measure the the role of artificial intelligence in adaptive learning systems on student learning experiences.

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