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Artificial Intelligence (AI) and Augmented Reality (AR) in Preschool Education: Innovative Applications

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ABSTRACT

This study examines how artificial intelligence (AI), Personalization, problem-solving, and augmented reality (AR) technology affect educational outcomes. The rising use of digital technology in education requires understanding how it affects learning to design successful teaching practices. Analyzing student and instructor data using structural equation modelling creates a strong framework for exploring key construct interrelationships. The study focuses on six primary constructs: AI Personalization (AIP), AI Problem Solving (AIPS), Augmented Reality Creativity Enhancement (ARCE), Augmented Reality Engagement (ARE), Augmented Reality Social Interaction (ARSI), and Learning Outcomes (LOS). These three dimensions are positively connected, showing that strategic AI and AR applications in education could transform the experience. These associations were assessed using path analysis on 357 preschool instructors' survey responses. Results show a favourable association between AI personalization, AR engagement, ARCE, and ARSI ($t = 7.947$, $p < 0.001$). AIPS, ARCE, and ARSI have significant beta values ($p < 0.001$): $\beta = 0.331$, $\beta = 0.559$, and $\beta = 0.227$, indicating that LOS directly impacts these variables. Interaction effects show that LOS moderates the connection between AIP, AIPS, are-ARCE, and ARSI, but not ARSI ($\beta = -0.116$, $p <0.001$; $\beta = 0.106$, $p= 0.026$; $\beta = 0.082$, $p = 0.086$. This study has implications for educators, policymakers, and developers who want to learn how to use AI-AR to engage and delight children in learning. These findings feed training and resources to improve early learning with these technologies.

Keywords: Artificial Intelligence, Augmented Reality, Education Technology, Learning Outcomes, Personalization, Problem-Solving, Creativity Enhancement

1. INTRODUCTION

Artificial intelligence (AI) has multiple advantages in personalized learning. Personalized approaches increase student motivation and participation as learners receive tailored feedback and resources that resonate with their interests (Kaswan et al., 2024). AI technologies are particularly beneficial for special education, providing targeted interventions that cater to unique learning challenges (Askarova et al., 2024).

An effective use of AI in education requires significant infrastructure, teacher training, and attention to data privacy concerns (Katiyar et al., 2024; Yılmaz, 2024). Ethical considerations regarding potential biases in AI algorithms must be addressed to ensure fair access to personalized learning opportunities (Kaswan et al., 2024). One of the primary concerns with AI and AR in preschool education is the potential for excessive screen time, which has been linked to adverse effects on young children's health, including impacts on sleep patterns and physical activity levels. Children are frequently exposed to screens as early as 7 to 12 months, with daily usage surpassing recommended limits. Television is the most common screen type, often used during meals or while parents are occupied (Madžar et al., 2024). Excessive screen time is linked to poor sleep quality and duration, exacerbating behavioural and cognitive issues (Merín et al., 2024). Prolonged screen exposure negatively affects attention, language, and motor skills while also increasing risks of obesity and mental health issues (Luiz et al., 2023). Innovative solutions like the Kid Space system have shown promise in alleviating parental concerns about screen time by integrating educational technology with physical activities. Conversely, while excessive screen time poses risks, some studies suggest that when used appropriately, digital tools can enhance learning experiences and engagement in preschool settings, indicating a need for balanced approaches to technology use in early childhood education.

Emerging technologies like artificial intelligence (AI) and augmented reality (AR) are integrated into early childhood education practices outside of the mainstream. New possibilities are being introduced for building individualized, exciting, engaging, and immersive learning experiences designed to meet the varied development needs of young children using these technologies. AI is so flexible that it can create different learning experiences for every child as they move through constantly changing content in real time, which is dictated by performance. More specifically, this Personalization is exceptionally well suited for preschool education, as children in this age group develop their cognitive and social abilities at different speeds (Chen et al., 2020). Likewise, AR transforms abstract ideas into real, interactive experiences to use with their sense-making (Khan et al., 2019).

More than any other application of AI in education, they personalize learning. Given preschool children, this individualized attention is critical as the early problem-solving and critical thinking experiences are the foundation of their learning later (Chen et al., 2020). AI-based platforms consume real-time data on children’s behaviours on educational content, which is then analyzed by the platform, and tasks and the amount of feedback are adjusted, as well as new learning materials being suggested based on the needs of each child’s learner. Beyond this, AI can teach children to understand and learn problem-solving because it allows them to solve tasks at an ability level to feel confident and persistent (Kuchkarova et al., 2024).

Augmented reality (AR) is interactive learning that adds digital information to the physical world. This allows children to understand complex ideas more easily through visualization and interaction with the ideas in a three-dimensional space (Avila-Garzon et al., 2021). AR bridges preschoolers' creative thoughts and real-world applications, which are vivid and highly active. ARs are immersive by nature, so children can create virtual objects, interact with a story, or solve problems in ways that are not possible through traditional learning. On the other hand, the collaborative potential of AR makes it possible to improve social skills by providing the possibility of working together with children who need to work together to achieve a common goal (Iqbal et al., 2022).

AI and AR directly benefit children's development, and broader learning outcomes may enhance or moderate their effectiveness. The cumulative effect of educational experiences on children's cognitive, social, and emotional development is reflected in overall learning outcomes. These outcomes mediate the relationship between AI/AR interventions and the skills they are intended to improve (Kuchkarova et al., 2024).

The present study investigates how AI personalization and AR engagement help children learn problem-solving, creativity, and social skills and how learning outcomes affect them. That is the main objective of the study. The empirically of the study is the uniqueness of the study. Limited existing literature regarding the impact of AI and AR on preschool education underscores the study. The existing research gap is the need for more research on adopting AI and AR, and studies need to examine practitioners' perspectives on utilizing these technologies in preschool education. This gap indicates the necessity for further research to provide insights into the benefits, limitations, and practical implementation of AI and AR in early childhood education. This study presents a novel approach by providing specific insights from a sample of experienced professionals across diverse learning environments, contributing new information to the limited literature on adopting AI and AR in early education.

2. LITERATURE REVIEW

2.1 AI in Education: Personalization and Learning Outcomes

Artificial intelligence enhances education by providing tailored learning experiences for individual students. In this case, Personalization refers to the customization of educational materials to align with the learner's learning mode and pace. AI is utilized to recognize student interactions, and based on their developmental stage, key characteristics are identified to update the content within the dialogue system (Chen et al., 2020). Such an approach to learning is advantageous to preschoolers, as their learning capabilities differ from one child to another.

In the past, we have learned that AI personalization enables students to enhance their problem-solving skills by providing them with problems they can solve based on their understanding. Artificial intelligence in students' learning makes them try various scenarios of tackling issues and improving their decision-making processes (Kuchkarova et al., 2024). Further, AI can give prompt feedback and monitor a student's progress; this way, children can learn with their errors and at their own pace (Chen et al., 2020). Moreover, AI can contribute to the formation of conditions for collective learning. For example, using AI, the systems can run through collaborative problem-solving scenarios where students can be studied from the perspective of communication and teamwork (Khan et al., 2019). These technologies let you mimic social interactions you can engage in when it is safe.

2.2 AR in Education: Engagement and Interactivity

Augmented Reality (AR) opens up the opportunity for a tremendous new way to interact with young learners by integrating the digital and real world. The high interaction provided by AR behind overlapped 3D visual objects in natural spaces increases children's imagination and curiosity (Avila-Garzon et al., 2021). Especially for preschool children, this interactivity is essential since older children have sensory-based experiences and play-based learning, so they help them in cognitive and social development.

As proven, the use of AR enhances creativity very well. This includes AR-based storytelling, where building up virtual characters and environments encourages children to be actively involved in the learning process, and they can provide the ability to explore creatively and help them in problem-solving (Iqbal et al., 2022). Additionally, AR can keep the children focused while immersing them in new learning activities, which means that the knowledge is retained much better than it would be if learning traditionally (Khan et al., 2019).

AR shows excellent promise in social skill development. It is common for AR applications to be collaborative activities where students work together in order to complete a task. However, peer learning is attended by participating in the collaboration, which allows the children to learn how to communicate and submit with their classmates (Iqbal et al., 2022). The ability of AR to create opportunities for children to participate in group activities in a safe context provides a means for children to develop critical social skills vital to success in any academic or personal context.

2.3 The Role of Learning Outcomes in AI and AR Applications

The effectiveness of AI and AR applications in education depends upon how well the learning outcomes can be attained. Although both technologies may help develop some skills, such as problem-solving, creativity, and social interaction, the overall learning outcomes produced by these tools may either magnify these effects or counteract them. The more AI and AR benefit specific educational goals, the more pronounced the benefits of AI and AR are when learning outcomes are improved (Kuchkarova et al., 2024).

Moderation models have been applied in educational research to explore the association between educational treatments and skills and how the learning results affect that association. In this regard, learning outcomes moderate the direct effects of AI personalization and AR engagement on children's solving, creativity and social skills. By understanding the mediating variable of learning outcomes, educators and policymakers can develop better educational interventions for using AI and AR technologies in a way that will yield the highest possible benefits.

After exploring the previous literature, the following research hypothesis regarding the direct and moderated effects of AI and AR on preschoolers' learning outcomes will be tested using quantitative data collected from preschool educators.

H1: Preschool children’s problem-solving abilities are positively associated with AI personalization

H2: Preschool children's creativity enhancement is significant and is positively correlated to AR engagement.

H3: There is a positive correlation between AR engagement and preschool children's social skill level.

H4: Learning outcomes moderates the relationship between problem-solving skills in children and AI Personalization.

H5: Learning outcomes moderates the relationship between creativity enhancement and AR engagement.

H6: Preschool children's general learning outcomes moderate the relationship between AR engagement and social skill development.

2.4 Conceptual Framework of the Study

The conceptual framework, as depicted in Figure 1, explains how AI Personalization and AR Engagement might help kids learn. These technologies encourage problem-solving, creativity, and social skills to improve learning settings and fulfill individual needs. Firstly, AI Personalization adapts education content to learners' abilities, preferences, and rates. AI-delivered educational information and challenging tasks boost students' cognitive and problem-solving skills. The framework requires AI to make learning fun and help kids solve challenges. Personalized instruction challenges and supports students' strengths and weaknesses.

Secondly, AR Engagement immerses students in interactive virtual worlds. This participation stimulates creativity. AR lets students visualize concepts and collaborate with virtual aspects that traditional teaching cannot. AR helps youngsters think creatively, apply concepts in new ways, and think beyond the box. According to the framework, AR helps students understand and use material creatively and realistically to build advanced thinking skills.

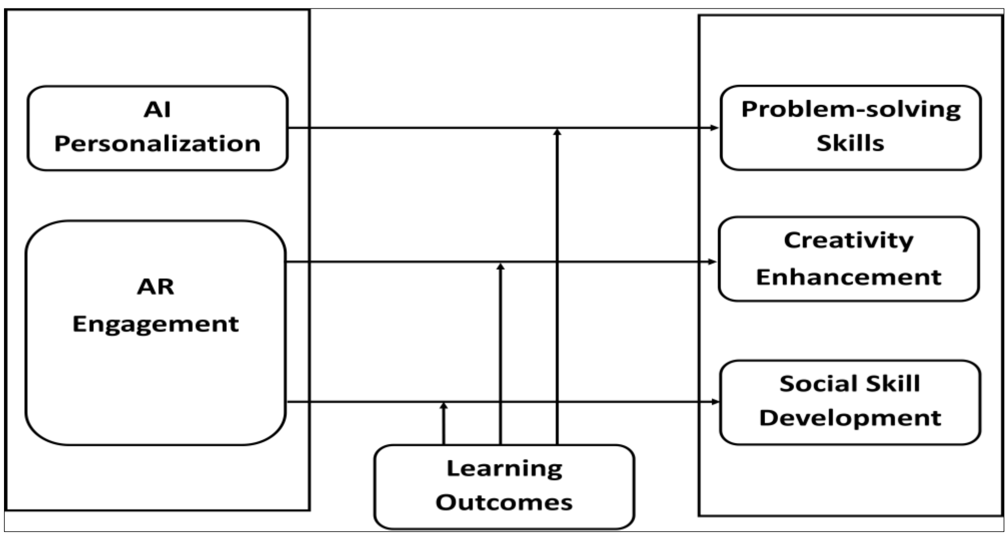

Figure 1: Conceptual Framework

Alternative social skill development methods include AI and AR. The personalized approach of AI may replicate interactive situations where students interact with people (or AI agents) in problem-solving contexts to improve social and communication skills. Teamwork is common in AR group learning and virtual problem-solving. AR promotes teamwork, interaction, and peer learning, which improves students' social skills. This strategy emphasizes learning results that moderate AI personalization and AR engagement. Enhancing knowledge and skill acquisition improves instruction and increases these technologies' impact on students' growth. Thus, better learning outcomes boost creativity, problem-solving, and social skills. Current educational methods like AI and AR turn learning into life skills.

3. METHODOLOGY

3.1 Research Design

This study employed a quantitative research design, and structured questionnaires were administered to preschool teachers. The study aimed to analyze the effect of AI-based Personalization and AR interaction on problem-solving, creativity, social skills, and learning outcomes, which were used as a mediator variable. The analysis of direct and mediated effects on the data was done using Structural Equation Modelling (SEM) with the Partial Least Squares (PLS) estimation method.

3.2 Participants

We recruited 357 preschool educators from various educational institutions across urban and rural Guiyang (the capital of Guizhou province) of the People's Republic of China. Educators were selected from schools that had actively integrated AI and AR tools into their teaching practices, ensuring that the participants were well-suited to provide grounded insights into the effects of these technologies in preschool education. The sampling technique used was purposive sampling, as the selection focused specifically on educators with experience in AI and AR applications in the classroom. This technique ensured that participants had sufficient familiarity with these technologies to contribute valuable, informed perspectives. The sample size of 357 educators was chosen to ensure a robust and diverse representation of views, accommodating the anticipated differences in perspectives between urban and rural educators.

3.3 Data Collection

The questionnaire was designed in two languages: Chinese and English. A Likert scale of 5 was utilized to assess educators' satisfaction with incorporating AI and AR in preschool education, allowing them to select from the following responses: strongly disagree, disagree, neutral, agree, and highly agree. The questionnaire was generated electronically and disseminated via WeChat, email, Google Forms, and other comparable online platforms. The response rate attained in this poll was 75% (i.e., 357 respondents). In actuality, the questionnaire was sent to 476 respondents. The purposive sample strategy was employed to choose individuals with prior experience in AI/AR within teaching practice. A purposive sampling technique was utilized to collect data. The data was collected with a structured questionnaire that included items on AI personalization, AR engagement, problem-solving, creativity, social skills, and learning outcomes. The questions for the questionnaire were derived from validated scales used in prior research (Chen et al., 2020; Khan et al., 2019; Kuchkarova et al., 2024). The items were measured using a five-point Likert scale where one was assigned to 'strongly disagree' and 5 to 'strongly agree'.

3.4 Measurement Scales and Items

The constructs used in the study, along with the measurement scales and items, are given in Table 1.

Table 1: The Constructs Used in the Study

Scale	Dimension	Items	Reference
AI Personalization Scale (AIP)	Personalization	AIP1: AI-assisted in developing learning programmes catering to each student's needs.	(Chen et al., 2020)
		AIP2: The AI platform adapts the content depending on the child's performance in the particular activity.	
		AIP3: Understanding with the help of AI enhances children's learning capacity.	
		AIP4: The AI platform provides feedback on the child's learning style.	
AR Engagement Scale (ARE)	Engagement	ARE1: AR tools are more effective for children to learn than other forms of learning because they are more entertaining.	(Khan et al., 2019)
		ARE2: In the case of AR, students develop an interest in subjects.	
		ARE3: Other approaches could capture children's interest more effectively, and neither does an AR-based lesson.	
		ARE4: AR in teaching is used to encourage active participation.	
AR Social Interaction Scale (ARSI)	Social Interaction	ARSI1: Collaboration among students is encouraged by AR activities.	(Iqbal et al., 2022)
		ARSI2: AR tools help to improve social interaction skills.	
		ARSI3: When using AR applications, children often work together.	
		ARSI4: AR tools help in peer learning in group activities.	
Learning Outcomes Scale (LOS)	Learning Outcomes	LOS1: AI and AR technologies help children solve problems.	(Kuchkarova et al., 2024)
		LOS2: When AI and AR are combined, children have a higher knowledge retention.	
		LOS3: AI and AR technologies help children be creative and curious.	
		LOS4: Using AI and AR applications, students show improved social skills.	
AR Creativity Enhancement Scale (ARCE)	Creativity Enhancement	ARCE1: AR tools make children more creative in their learning tasks.	(Avila-Garzon et al., 2021)
		ARCE2: The AR elements are also active; for example, some three-dimensional models stimulate children's imaginations.	

		ARCE3: AR is applied to enable children to think outside the box to solve various problems.	
		ARCE4: Interactive AR-based storytelling can make a child imagine and be creative.	
AI Problem-Solving Scale (AIPS)	Problem-Solving	AIPS1: Learning activities that have been developed using artificial intelligence assist children to solve problems.	(Luckin et al., 2022)
		AIPS2: The opportunities for learning provided by the AI platform are to encourage children to think.	
		AIPS3: AI-based tools assist children in learning how to solve problems correctly.	
		AIPS4: AI-assisted lessons enable children to use problem-solving strategies in solving problems.	

The above table shows the measurement scales and research items on multiple dimensions of AI and AR in education. The scales focus on the nature of AI personalization, how engaging learners are with AR, the social aspect of interaction with AR, the impact of AR on creative abilities, the effectiveness of learning, and how learners experience problem-solving in educational settings.

The Personalization using AI Tools for Students (PAI) scale gauges the extent to which AI instruments individualize student learning. The items relate to AI's ability to deliver differentiated instruction, adjust content delivery according to student progress, enhance higher-order thinking skills, and give feedback. They are inspired by Luckin et al. (2022) and describe the growing use of AI in developing responsive learning contexts.

The AR Engagement Scale (ARE) is centred on enhancing engagement and interactivity in learning through augmented reality tools. According to Khan et al. (2019), items in this scale show that the application of AR technology offers a more engaging way to capture the students' attention compared to traditional forms of teaching, enhances the students' interest in subjects, and promotes participation.

The AR Social Interaction Scale (ARSI) assesses AR's role in maintaining social interaction in students. According to the study by Iqbal et al. (2022), the scale items are based on the degree to which AR tools enhance collaborative spirit, interpersonal communication skills, and group learning during group tasks.

The Learning Outcomes Scale (LOS) captures the impact of AI/AR learning on children’s learning outcomes. According to (Kuchkarova et al., 2024), the items reflect changes in problem-solving capability, knowledge enhancement, innovativeness, curiosity and social skills when AI and AR are integrated into the learning process. The AR Creativity Enhancement Scale (ARCE) captures the impact of AR on children’s creativity. As pointed out by (Avila-Garzon et al., 2021), the items derived from AR tools foster creativity by using appealing 3D models and storytelling and enhancing children’s motivation and learning when solving tasks.

The AI Problem Solving Scale (AIPS) is the long overdue measurement of the contribution of AI in the problem-solving aspects of learning. The tools that use AI in learning are described in the study by (Luckin et al., 2022) as posing the challenge that orients learners to think critically, increases the efficiency of problem-solving, and refines strategies of learning activities. The interaction of these scales provides an overview of how AI and AR technologies influence the multiple educational results of Personalization and interest, social interaction, creativity, and problem-solving.

3.5 Pre-PLS Analysis

Before data analysis, multiple assumptions about PLS-SEM data suitability and robustness were evaluated. External validity is predicated on enough sample size, data normality, construct linearity, and no multicollinearity. Following PLS-SEM recommendations, the sample size was sufficient to capture significant effects in the proposed model. A skewness and kurtosis test assessed normalcy and identified variable outliers that could harm the inquiry. Linear construct interactions were also verified for path coefficient estimation. All model predictors' variance inflation factor (VIF) is assessed simultaneously. VIF values below 5 suggest multicollinearity factor independence.

3.6 Data Analysis

The data were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to examine the direct and mediated relationships between the constructs of interest. It was chosen because PLS-SEM is suitable for multiple dependent variables, and the data does not have to be normally distributed. The analysis was conducted in two stages: The first involved assessing the measurement model's psychometric properties, and the second involved examining the structural model to confirm the proposed relationship.

3.7 Validity and Reliability

Both convergent and discriminant validity were examined to assess the validity of the employed constructs. Convergent validity was assessed by examining factor loadings, composite reliability, and average variance extracted for each construct. High factor loadings were defined as those exceeding 0.7, with composite reliability above 0.7 and average variance extracted greater than 0.5. Two diagnostic tests were performed to assess discriminant validity. The Fornell and Larcker (1981) criterion evaluates the ratio of the square root of the Average Variance Extracted (AVE) to the maximum correlation between a construct and other constructs. An HTMT ratio exceeding 0.9 indicates acceptable discriminant validity. Reliability was assessed using Cronbach's alpha, revealing acceptable alpha coefficients exceeding .70, indicating that the measurement instrument is reliable and internally consistent.

3.8 Ethical Consideration

This research upheld participants' rights by adhering to privacy, confidentiality, and self-determination principles. All participants recruited for the study were provided with descriptive information, and written informed consent was obtained from them to participate.

4. RESULTS

4.1 Demographics of the Respondents

This study included a sample of 357 educators, categorized by gender, age, education level, and years of teaching experience. The sample comprised 68% females and 32% males. Of the participants, 56% identified as multi-national. Age distribution revealed that 25% were 20-29, 40% were 30-39, 22% were 40-49, and 13% were 50 or older. Regarding academic qualifications, 45% of individuals possessed at least a Master's degree, 35% held a Bachelor's degree, 10% attained a Doctorate, and 10% received a diploma, certificate, or other related certification. Teaching experience varied as follows: 18% reported less than five years, 30% between five and ten years, 35% between eleven and twenty years, and 17% more than twenty years.

4.2 Convergent Validity of Constructs in the Study

Table 2 shows the convergent validity of AI personalization, AR, and learning findings. Convergent validity requires that two measures of the same construct be connected. This is done using statistical coefficients, including loadings, Cronbach's Alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE). Many elements are used to evaluate each construct with varied loadings. Loadings exceeding 0.7 indicate substantial mapping between items and constructs. AI personalization piece AIP1 strongly connects with the construct with a loading of 0.901. AIP2 (0.854) and AIP3 (0.774) have strong associations, but AIP4 (0.685) is slightly below the acceptable floor, suggesting it may be less beneficial in AI personalization.

Cronbach's Alpha and Composite dependability assess construct reliability. AI Personalization has a Cronbach's Alpha exceeds 0.7, with $\alpha = 0.931$, CR = 0.951, and AVE = 0.829. These findings show well-defined, reliable, and convergent AI personalization. Other constructs (AR Engagement, $\alpha = 0.908$, CR = 0.936, and AVE = 0.785) also show validity and reliability. Although the α value of 0.818 is favorable for Learning Outcomes, the AVE of 0.649 falls below the acceptable threshold of 0.7, indicating limitations in capturing the construct's variance. Measurement of learning outcomes may be improved. Table 2 shows that AI personalization, AR creativity improvement, AR engagement, and AR social interaction have high loadings, Cronbach's Alpha, and Composite Reliability values, indicating convergent validity. Learning Outcomes need improvement to capture the full range of this key statistic, as its AVE illustrates. The data validates the study paradigm by confirming that the construct measurement items work.

Table 2: Convergent validity

Constructs	Items	Loadings	Alpha	CR	AVE
AI Personalization	AIP1	0.901	0.931	0.951	0.829
	AIP2	0.854			
	AIP3	0.774			
	AIP4	0.685			
AI Problem-Solving	AIPS1	0.784	0.869	0.911	0.720
	AIPS2	0.834			

	AIPS3	0.921			
	AIPS4	0.849			
AR Creativity Enhancement	ARCE1	0.837	0.868	0.910	0.716
	ARCE2	0.852			
	ARCE3	0.860			
	ARCE4	0.836			
AR Engagement	ARE1	0.890	0.908	0.936	0.785
	ARE2	0.934			
	ARE3	0.923			
	ARE4	0.893			
AR Social Interaction	ARSI1	0.941	0.880	0.919	0.743
	ARSI2	0.859			
	ARSI3	0.912			
	ARSI4	0.716			
Learning Outcomes	LOS1	0.855	0.818	0.880	0.649
	LOS2	0.922			
	LOS3	0.878			
	LOS4	0.888			

4.3 Construct Discriminant Validity: Fornell-Larcker Criterion

Table 3 shows the Fornell-Larcker criterion results for the study's operationalized constructs' discriminant validity. Discriminant validation evaluates whether concepts or measurements should be distinct. This table shows the square root of the Average Variance Extracted for each construct as diagonal values and construct correlations as off-diagonal values. Each construct has a strong relationship with itself, indicating internal consistency, as seen by diagonal values. AI Personalization (AIP) and Learning Outcomes (LOS) have square roots of AVE of 0.808 and 0.886, respectively, indicating that these constructs may represent their underlying concepts.

Discriminant validity requires lower correlations between constructs than their square root AVE values. The link between AI Personalization (AIP) and AI Problem Solving (AIPS) is moderately high (0.487). With a correlation of 0.628, AR Engagement (ARE) and AR Social Interaction (ARSI) are less related than their AVEs (0.910) and (0.861), demonstrating their distinctness. Finally, the table shows this study's notions are unique enough to meet the Fornell-Larcker discriminant validity requirement. This resilience of the measurement approach shows that the constructs can be treated independently without damaging the research's comprehensive picture of AI and AR's influence on education.

Table 3: Fornell Larcker

	AIP	AIPS	ARCE	ARE	ARSI	LOS
AIP	0.808					
AIPS	0.487	0.848				
ARCE	0.454	0.537	0.846			
ARE	0.394	0.554	0.405	0.910		
ARSI	0.470	0.593	0.456	0.628	0.861	
LOS	0.432	0.495	0.624	0.452	0.462	0.886

4.4 Construct Validity: Cross-Loadings Analysis

Table 4 shows that measurement item cross-loadings across constructs indicate the validity of this study's constructs. This analysis compares item loadings to constructions and others. Each item's construct validity is to load highest on its intended construct and lowest on others. The off-diagonal numbers reflect the loadings of items on other constructions, while the diagonal values represent their construct loadings. An item loads 0.901 on AIP1 and 0.444 on AIP, significantly higher than on other constructs, with the second highest on AIPS. AIP elements follow this pattern, which is aligned to their construct but is different.

As with AI Problem Solving (AIPS), they have high loadings on the targeted construct (e.g., AIPS3 has 0.921) and low loadings on other constructs, providing them a distinctive contribution to the measurement model. AR Engagement (ARE) and AR Social Interaction (ARSI) items also show clarity and validity, with loadings of 0.890 for ARE1 and 0.941 for ARSI1. However, Learning Outcomes (LOS) items like LOS2 have a high loading of 0.922, indicating a strong association with the construct and less cross-loading on other items, verifying its distinctiveness. Finally, this table illustrates that each item measures its intended construct and supports the study's construct validity.

Table 4: Cross-loadings

	AIP	AIPS	ARCE	ARE	ARSI	LOS
AIP1	**0.901**	0.444	0.359	0.351	0.413	0.365
AIP2	**0.854**	0.364	0.271	0.297	0.344	0.281
AIP3	**0.774**	0.318	0.361	0.298	0.293	0.384
AIP4	**0.685**	0.419	0.458	0.314	0.437	0.360
AIPS1	0.321	**0.784**	0.473	0.452	0.497	0.391
AIPS2	0.404	**0.834**	0.442	0.503	0.550	0.407
AIPS3	0.481	**0.921**	0.492	0.504	0.512	0.471
AIPS4	0.431	**0.849**	0.420	0.424	0.459	0.405
ARCE1	0.424	0.480	**0.837**	0.393	0.373	0.532
ARCE2	0.400	0.439	**0.852**	0.322	0.345	0.548
ARCE3	0.343	0.455	**0.860**	0.353	0.443	0.533
ARCE4	0.369	0.441	**0.836**	0.300	0.384	0.495
ARE1	0.339	0.528	0.391	**0.890**	0.576	0.426

ARE2	0.328	0.496	0.350	**0.934**	0.519	0.393
ARE3	0.405	0.526	0.398	**0.923**	0.576	0.448
ARE4	0.358	0.465	0.333	**0.893**	0.608	0.375
ARSI1	0.458	0.597	0.433	0.541	**0.941**	0.444
ARSI2	0.399	0.509	0.429	0.443	**0.859**	0.437
ARSI3	0.365	0.513	0.363	0.511	**0.912**	0.383
ARSI4	0.382	0.411	0.340	0.631	**0.716**	0.322
LOS1	0.362	0.450	0.546	0.354	0.384	**0.855**
LOS2	0.325	0.441	0.572	0.370	0.425	**0.922**
LOS3	0.366	0.396	0.501	0.459	0.401	**0.878**
LOS4	0.473	0.462	0.586	0.423	0.426	**0.888**

4.5 Analysis for Construct Validity: Heterotrait-Monotrait Ratio (HTMT)

Table 5 shows the Heterotrait-Monotrait Ratio (HTMT), and it indicates that higher HTMT values weaken discriminant validity, meaning constructs are similar. Off-diagonal numbers are the HTMT ratios between constructs, while diagonal values are correlations between items in the same construct and are not shown. The AI Personalization (AIP) to AI Problem Solving (AIPS) HTMT value is 0.564, indicating that these constructs are generally independent but moderately connected. AI Personalization (AIP), AR Creativity Enhancement (ARCE), and AR Engagement (ARE) have lower HTMT values of 0.534 and 0.447, respectively, indicating more substantial discriminant validity. The HTMT score between AR Engagement (ARE) and AR Social Interaction (ARSI) is 0.683, which is strong and may imply a conceptual overlap. This shows that various constructions may share a common element but offer unique insights worth investigating. The HTMT analysis in Table 5 reveals that most constructs have sufficient discriminant validity, indicating the study framework's robustness. These values must be maintained to ensure study construct dependability and research credibility.

Table 5: Heterotrait Monotrait ratio

	AIP	**AIPS**	**ARCE**	**ARE**	**ARSI**	**LOS**
AIP						
AIPS	0.564					
ARCE	0.534	0.620				
ARE	0.447	0.616	0.448			
ARSI	0.542	0.680	0.522	0.683		
LOS	0.500	0.554	0.700	0.492	0.517	

4.6 A Structural Equation Model

Figure 2 represents a structural equation modeling (SEM) analysis using Partial Least Squares (PLS) path modeling. The figure displays relationships between latent variables (represented by blue circles) and their corresponding observed indicators (denoted in yellow), along with the standardized factor loadings and path coefficients. In the figure, AIP (Artificial Intelligence Personalization) and ARE (Augmented Reality Engagement) are exogenous latent variables with their respective indicators (AIP1, AIP2, AIP3, AIP4, and ARE1, ARE2, ARE3, ARE4). The loadings indicate the strength of each observed variable's relationship with its latent construct. For instance, the indicator AIP1 has a loading of 0.901, indicating a strong relationship with the latent variable AIP.

The latent variable LOS (Learning Outcome Satisfaction) is connected to the indicators LOS1, LOS2, LOS3, and LOS4, with similarly strong factor loadings ranging from 0.855 to 0.922. The endogenous latent variables AIPS (AI-Personalization Satisfaction), ARCE (Augmented Reality Creativity Enhancement), and ARSI (Augmented Reality Social Interaction) are the outcomes of interest, connected to their respective indicators with high loadings as well. The figure shows the path coefficients between the latent variables. For example, the path from AIP to AIPS has a coefficient of 0.308, indicating a moderate positive relationship. Additionally, the path from ARE to ARSI has a higher coefficient of 0.534, suggesting a stronger relationship. The dashed lines between latent variables such as LOS and AIPS show there are also mediating effects in the model.

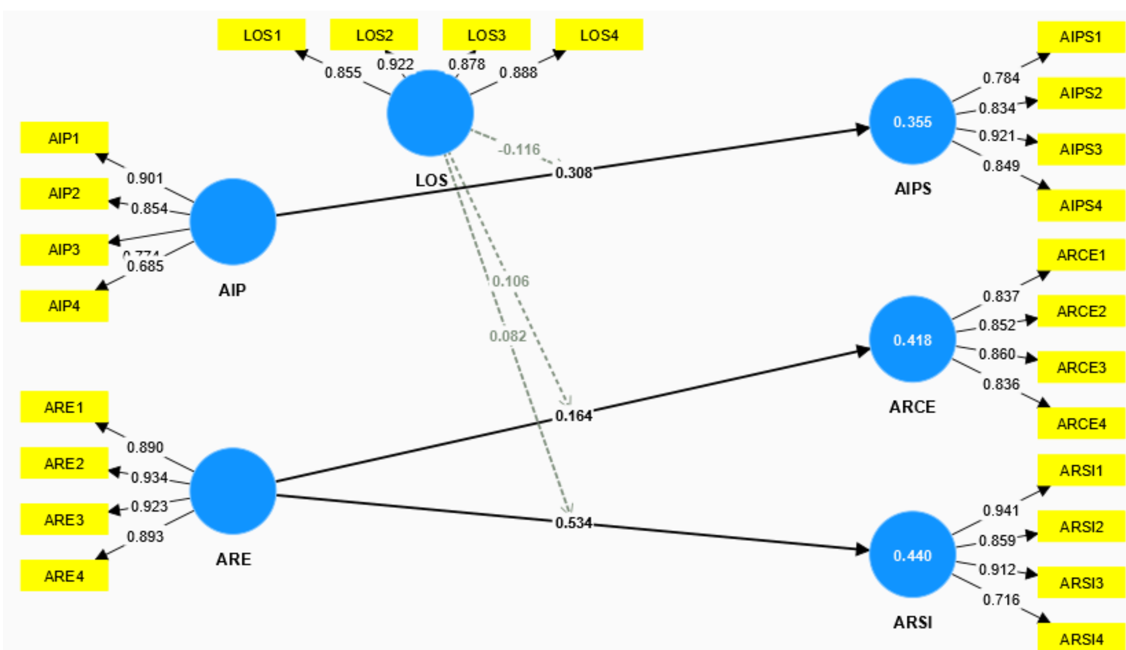

Figure 2: Structure Equation Model

4.7 Structural Relationships Among Constructs: Path Analysis Results

Table 6 shows the path analysis results for the study model's constructs, coefficients, standard deviations, t statistics, and P values.

The beta coefficients indicate the strength and direction of these routes, and the t statistics and P values demonstrate their significance. The analysis demonstrates a significant effect between AI Personalization (AIP) and AI Problem Solving (AIPS) with a Beta of 0.308, t statistic of 6.724, and p-value of 0.000. As with AR Engagement (ARE), AR Creativity Enhancement (ARCE) (Beta = 0.164, t = 3.432, P = 0.001) and AR Social Interaction (ARSI) (Beta = 0.534, t = 8.957, P = 0.000) are also significantly affected by AR Engagement, indicating that higher engagement increases creativity and social interaction. The Learning Outcomes (LOS) construct shows significant positive pathways to AIPS (Beta = 0.331, t = 7.273, P = 0.000) and ARCE (Beta = 0.559, t = 10.478, P = 0.000), demonstrating that more excellent learning outcomes promote problem-solving and creativity (Dodridge, 1999; Kinta, 2013). The results also confirm that the Learning Outcomes (LOS) significantly affect ARSI, meaning that LOS improve the ARSI level.

As LOS and AIP decrease AIPS (Beta = -0.116, t = 3.494, P = 0.000), learning outcomes may mitigate the effect of AI personalization on problem-solving. Engagement boosts the impact of learning outcomes on creativity (Beta = 0.106, t = 2.223, P = 0.026). However, the path from LOS x ARE to ARSI is marginally significant (Beta = 0.082, t = 1.720, P = 0.086), suggesting further research may be needed to validate the link. The route analysis reveals how these constructs interact and how learning results boost AI-driven engagement and creativity.

Table 6: Path analysis

Relationships	Beta	Standard deviation	t statistics	P values
AIP -> AIPS	0.308	0.046	6.724	0.000
ARE -> ARCE	0.164	0.048	3.432	0.001
ARE -> ARSI	0.534	0.060	8.957	0.000
LOS -> AIPS	0.331	0.046	7.273	0.000
LOS -> ARCE	0.559	0.053	10.478	0.000
LOS -> ARSI	0.227	0.058	3.907	0.000
LOS x AIP -> AIPS	-0.116	0.033	3.494	0.000
LOS x ARE -> ARCE	0.106	0.048	2.223	0.026
LOS x ARE -> ARSI	0.082	0.048	1.720	0.086

4.8 A Partial Least Squares Structural Equation Model

Figure 3 shows Partial Least Squares (PLS) Structural Equation Model examines latent variable-indicator relationships. Interpret construct relationships using variables, trajectories, regression coefficients, factor loadings, and p-values. AIP and ARE are exogenous latent variables measured by four indices. The indicators' loadings (AIP1 = 66.262, AIP2 = 26.543) show their high connection with latent constructs. These values illustrate how well each variable explains its construct. Learning outcome satisfaction (LOS) mediates LOS1, LOS2, LOS3, and LOS4. The indicators' high loadings (LOS2 = 103.581) imply they accurately measure learning outcome satisfaction.

AIP predicts learning outcomes and ARE utilizing endogenous latent variables AIPS, ARCE, and ARSI. From AIP to AIPS, the coefficient is 0.355, indicating a positive and significant effect (p-value = 0.000). ARCE and ARSI are highly influenced by ARE at 0.418 and 0.440. LOS mediates its connections with AIPS (0.106), ARCE (0.082), and ARSI (-0.116). Structural routes reveal LOS's indirect effects, even if some are small (p = 0.086 for LOS-ARSI).

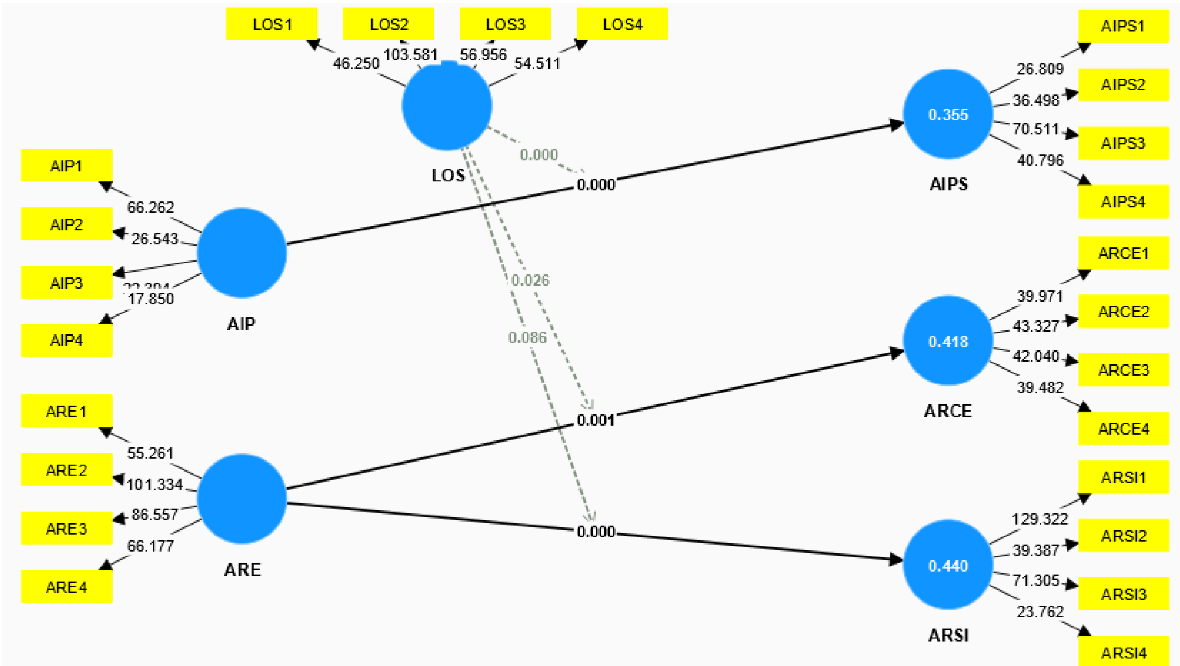

Figure 3: Structural assessment model

5. DISCUSSION

The findings of this study reveal several important insights into the relationships between AI Personalization, AI Problem-Solving, Augmented Reality (AR) Engagement, AR Creativity Enhancement, AR Social Interaction, and Learning Outcomes. The strong positive correlations among these constructs indicate that as the effectiveness of AI and AR increases, so do the learning outcomes, suggesting that well-implemented technologies can significantly enhance educational experiences. Results indicated a strong positive relationship between AI Personalization (AIP) and AI Problem Solving (AIPS). This suggests that personalized AI systems adapted to individual learning needs and preferences or improve learners' problem-solving ability. It aligns with the existing literature regarding the need for tailor-made educational interventions (Alexandre & Enslin, 2017; Chiyoun et al., 2024; Maghsudi et al., 2021; Myhre et al., 2020). This is done with the help of data analytics and AI, leveraging data analytics to adapt instructional methods and improve problem-solving skills (Papadopoulos & Hossain, 2023).

This study found that AR Engagement (ARE) has a strong positive effect on AR Creativity Enhancement (ARCE) and AR Social Interaction (ARSI). The power of AR technologies is then reiterated for creating immersive and interactive learning environments. Therefore, AR raises the affinity of creativity by providing a rich context in which to interact (Chandrasekera & Yoon, 2018; Persefoni & Tsinakos, 2015), consequently sparking social interactions among learners (Godoy Jr, 2021; Wannapiroon et al., 2021). AR provides honest life feedback and collaborative opportunities, which improve learning compared to conventional computer-aided learning, thus affirming that engagement plays a vital role in educational technology (Tlili et al., 2023; Weerasinghe et al., 2022). The effectiveness of both AI and AR interventions was influenced by a significant construct, Learning Outcomes (LOS). The results confirmed that LOS positively affects AIPS, ARCE, and ARSI, which implies that better learning outcomes boost problem-solving, creativity and social interactions and vice versa.

This finding underscores the robust relationship between educational technology effectiveness and learning outcomes (Kim & Shim, 2022; Salas-Pilco, 2020). With improved outcomes, learners become more interested in working with AI and AR tools, improving their educational experiences (Behera, 2023).

Interaction effects were investigated and found to moderate the relationships between AI Personalization and AI Problem-Solving and between AR Engagement and Creativity Enhancement. This indicates that the quality of learning outcomes can drive the effective use of these technologies in fostering problem-solving and creativity. This finding underlines the need for creating educational interventions focused on improving the use of technology and improving the assessment and promotion of learning outcomes (Ossiannilsson & Ioannides, 2017).

The results of this study have practical implications for educators and instructional designers. This research highlights the positive relationships that emerged as AI and AR technologies can be effectively integrated into educational settings. AI should be personalized and implemented in institutions as these types of AI enhance the learners' interactions (Papadopoulos & Hossain, 2023). Moreover, any learning application employing these technologies should include a formative evaluation of learning outcomes concerning the intended educational outcomes (Tlili et al., 2023).

Lastly, this work provides fresh perspectives on applying AI and AR technologies in learning environments. In general, there is a positive correlation between the constructs. Therefore, they demonstrate that meaningful and individualized learning can positively impact learning outcomes by enhancing problem-solving skills and creativity. Since there is a constant advancement in educational technology, it will be essential to educate as the technology advances to offer and develop dynamic learning environments that will produce successful students. Longitudinal studies should be the future of research that explores the impact of AI and AR technologies on learning outcomes in different learning environments.

6. CONCLUSION

This paper examines the relationship between AI Personalization, AI Problem Solving, AR engagement, creativity boost, and social interaction in influencing Learning Outcomes. This work implies that differentiated AI interactions and effective utilization of engagement time can boost the learners' problem-solving skills and creativity. All these positive correlations between these constructs imply that effective AI systems and AR environments can create meaningful learning and enhanced learning results. The study's findings reveal a relationship between the use of AI personalization and problem-solving ability, and therefore, AI interventions are required in a learning environment. Furthermore, the level of engagement in AR enhances innovative ability and communication skills, which means that integrating AR technologies in learning facilities will enhance learning as it becomes more collaborative. Analyzing the interaction effects, it has been found that Learning Outcomes are active in changing other constructs and moderating the relationships between them, thus pointing out the complexity of the interactions. Understanding the moderating role of Learning Outcomes, educators and instructional designers can evaluate the potential of leveraging AI and AR technologies with well-designed strategies to increase learning effectiveness. The study provides critical points for designing and utilizing AI and AR in education, with significant implications for educationists, policymakers, and technology developers.

This should be followed up by future research to explore these relationships further in different educational contexts and populations to understand better how these technologies can be used to get the best learning out of them.

7. POLICY SUGGESTIONS AND PRACTICAL IMPLICATIONS

Several policy suggestions could be made to improve the integration of AI and AR technologies in education. The second central area for investment lies in creating individualized AI systems that learn and adapt to each student's learning needs so that they can tailor the problem-solving experience. Second, schools and universities should promote AR technologies to enrich creativity and social interaction among students and provide them with more immersive learning environments. Furthermore, intense focus on regular evaluation and course correction of the learning outcomes are expected to be exercised till these technologies accomplish the planned educational outcomes. Finally, government and educational policymakers should spend dollars to fund teacher training in AI for educators so they can effectively implement these superior technologies in the classroom. The outcome of these initiatives will create an engaging student success environment. The study offers insights into users' needs and challenges in interacting with new technology, aiding developers to create user-friendly, easily implementable, and educationally effective AI and assistive technologies tailored for young children.

9. STUDY’S LIMITATIONS

The sample was limited to educators who reported prior use of AI or AR in their teaching practices, potentially rendering it unrepresentative of the broader population of preschool educators, particularly those with minimal or no experience with these technologies. Secondly, data collection occurred online, resulting in a sample that consisted solely of educators who utilize the internet and are proficient with online tools, thereby introducing potential bias in the sample. Third, this research utilized self-reported data, which may lead participants to offer their own or perceived stereotype responses.

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Author contributions: The author solely contributes to this study.
Ethical Statement: The study procedures were approved by the Faculty of Educational Studies, Urban Vocational College of Sichuan, Chengdu, China. In this case, the study proposal was subjected to the

University Ethical Committee to ensure that all the procedures followed were ethical and met the University's Ethical Standards.

Consent to Participate: Approved

Competing Interests: The author declares that this work has no competing interests.

Data Availability Statement: The associated data is available upon request from the corresponding author.

Declaration Statement of Generative AI: This study's author(s) declared that no AI content has been used in the paper preparation.

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