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Cultivating innovative behavior through AI awareness: A human resource perspective on early childhood education in Guangdong Province, China

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ABSTRACT

The aim of this study is to examine the effect of artificial intelligence (AI) awareness on innovative practices among early childhood educators in Guangdong, China. Data were collected through online questionnaires from 466 educators across 225 institutions. The study investigates how AI awareness influences intrinsic motivation, creative self-efficacy, learning climate, and innovative behavior. Using SmartPLS-4 and SPSSPRO for analysis, the results indicate that AI awareness significantly affects innovative behavior, with intrinsic motivation (β = 0.505), creative self-efficacy (β = 0.446), and learning climate (β = 0.310) acting as mediating variables. These findings highlight the critical role of AI awareness in promoting innovation among educators and offer practical implications for human resource management in educational institutions. From this perspective, professional development programs that enhance AI literacy can improve teacher motivation, creative self-efficacy, performance, and retention. Future research should also address ethical challenges associated with AI integration in educational contexts.

1. Introduction

Various fields have been transformed by the rapid growth of artificial intelligence (AI), with education being among them, where it increasingly promotes innovative behaviors through personalized learning, adaptive environments, and data-based decision-making. In China, AI adoption in education has expanded rapidly, with the market size for digitalization reaching 407.2 billion yuan in 2018, including 28.7 billion yuan in AI solutions, which are projected to increase to 538.1 billion yuan and 65 billion yuan, respectively, by 2022. China has introduced AI education from kindergarten through 9th grade to improve students' AI literacy (Gong et al., 2020).

China's national guidelines on AI development, published in 2017, address the shortage of qualified teachers who can teach AI (Xia and Zheng, 2020). This study focuses on how AI-related factors influence innovative behavior among early childhood educators in Guangdong Province. From a human resource management perspective, understanding how AI awareness influences educators' innovative behaviors is crucial for designing effective professional development strategies and organizational policies that support sustainable innovation. As educational institutions increasingly function as complex organizations requiring sophisticated HR practices, this study bridges the gap between educational innovation and human resource development.

Guangdong leads China in AI and education integration, making it suitable for this study. Despite progress, research gaps remain concerning the influence of AI on creative activities among early childhood educators. The country's push for AI integration into elementary and high school education is evidenced by AI teaching facilities and Ministry of Education campaigns, but implications for early childhood practice remain largely unexplored.

Current research suggests significant knowledge gaps concerning the effects of AI on innovation among early childhood educators, with most studies focusing on tertiary institutions and high schools. While some research shows that AI encourages playful imagination and creativity in early education

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(Berson et al., 2023) and that digital literacy among preservice teachers is positively related to their self-efficacy in teaching AI (Lim, 2023), little research exists on generative AI applications for younger children (Kanders et al., 2024), and ethical problems remain unresolved (Crescenzi-Lanna, 2023).

This study addresses these gaps by investigating how AI-related factors foster innovation among early childhood educators in Guangdong Province. The research questions include the following:

1) What specific AI-related factors contribute to fostering innovative behaviors among early childhood educators?
2) How do these factors influence the sustainability of such behaviors?
3) What are the implications of these factors for human resource management practices in early childhood education institutions?

The study employs a quantitative approach in which questionnaire surveys are used to gather data on educators' experiences with AI integration. The findings contribute to understanding how AI affects innovative behaviors in early childhood education and provide practical guidance for designing programs that help teachers utilize AI-fostered innovations in their work with young children.

2. Literature review

2.1. AI awareness and innovative behaviors in education

AI emulates human mental processes through machines, particularly computer systems, via mechanisms such as learning (defined as the acquisition of information and associated rules), reasoning (the application of rules to reach conclusions), and self-correction (Jaber, 2022). Beyond potential disruption, AI offers valuable teaching aids that can enhance educational experiences through personalized learning pathways, automated assessment tools, and assistive technologies that allow educators to focus more on nurturing social-emotional development in young children (Ayeni et al., 2024; Kaswan et al., 2024). Important subdivisions include natural language processing, which looks at how computers comprehend human languages, and machine learning, which deals with the analysis of data through the use of pattern-recognition algorithms (Raju et al., 2020; Steinkamp and Cook, 2021). The recognition of the role and applications of AI in educational contexts is termed AI awareness in education. Education is being transformed by AI with implementation strategies aimed at improving learning through adaptive methods. As asserted by Garg et al. (2024), AI has the potential to personalize learning pathways so that students learn according to their capabilities, whereas intelligent tutoring systems offer personalized feedback depending on the level of engagement with the content. The application of AI technologies in preschool education raises ethical issues regarding privacy and data protection in relation to machine learning and learning analytics (Crescenzi-Lanna, 2023). The POWER approach (purposeful optimization, wisdom, ethics, responsibility) ensures that AI is used fairly in education (Chen and Lin, 2024). Addressing privacy concerns along with algorithmic bias is essential for equity in AI-driven educational tools (Garg et al., 2024). Early childhood educators encounter obstacles such as scant educator guidelines surrounding the use of AI technologies and a lack of appropriate educator training (Su et al., 2023). Nevertheless, a lack of AI literacy suffices as a barrier to educational inequalities by hindering equal opportunities to learn. AI technologies, including social robots, act as learning partners to assist children in the foundational stages of understanding AI and allow teachers to monitor developmental progress more efficiently (Su and Zhong, 2022). AI promotes creativity and collaboration while increasing children's understanding of concepts such as machine learning and computational thinking (Su and Yang, 2022). In the preprimary grades, AI technologies drive instructors to develop bespoke methodologies that improve educational standards. As Henriksen et al. (2024) observed, these technologies afford children the opportunity to partake in self-directed experiential play within guided, scaffolded frameworks provided by adults. Furthermore, the integration of AI into education has the potential to support innovative methodologies. A lack of AI knowledge may deter educators from approaching the integration of new technology with creativity, indicating a direct relationship between these factors. In contrast, possessing knowledge of AI improves teachers' digital competencies and their willingness to share AI knowledge, which is a critical factor for innovative activities among educators (Lapsomboonkamol et al., 2022). The integration of AI acts as a catalyst for innovation aimed at resolving technological and social challenges while improving the quality of education (Thurlings et al., 2015).

2.2. Impact of AI-related factors on early childhood educators' innovative behaviors

The perceptions of individual and instruction processes are influential factors that AI awareness, in turn, modifies intrinsic motivation (Liang et al., 2022). Wang et al. (2024) reported that AI anxiety has a negative effect on learning motivation; however, fear of job replacement positively impacts motivation in terms of the value or incentive external to the task. This paradox underscores the simultaneous ways in which artificial intelligence can be anxiety-inducing—and therefore, demotivating—and utilitarian, thus increasing motivation.

Performance across different forms of creative activity increases with intrinsic motivation, especially when the task is perceived as not overly difficult and engaging. Challenge-intrinsic motivation strongly relates to creativity by acting as a mediator between learning goals and creative outputs (Leung et al., 2014), highlighting the extent to which intrinsic motivation amplifies creative thinking in educational contexts.

Creative self-efficacy derives from AI awareness (Liang et al., 2022). Empirical research has shown that teaching with AI increases intention and self-efficacy among preservice teachers and that both intrinsic and extrinsic motivation mediate the relationships between enabling conditions and self-efficacy in AI-instructed teaching frameworks (Xie et al., 2023). Equipped with a clearer grasp of their capabilities, teachers become confident in the creative use of AI tools.

AI awareness has a positive effect on the educational atmosphere by presenting additional approaches for teachers to foster supportive settings (Bucea-Manea-Țoni et al., 2022). It can stimulate innovative behavior either through heightened intrinsic motivation or dampen it via greater emotional exhaustion (Liang et al., 2022), suggesting that AI awareness can have positive or negative impacts on motivating creative learning environments, thus requiring careful management.

Studies have shown that AI use improves early childhood educators' teaching efficacy and classroom management capabilities. Research specifically focused on early education settings has demonstrated that when teachers effectively integrate AI tools, they report higher levels of teaching efficacy and greater ability to individualize instruction (Su and Zhong, 2022; Lim, 2023).

AI-supported smart learning environments improve educational outcomes through learning analytics dashboards that track student actions (Hu, 2022). Bucea-Manea-Țoniş et al. (2022) reported that AI, combined with efforts to address digital gaps, can develop educational environments that prepare students for advancing technology and job market demands.

AI enhances early childhood educators' professional growth (Kitcharoen et al., 2024). Social robots and other AI tools have helped young children understand AI basics while fostering innovative teaching methods (Su and Zhong, 2022). AI literacy programs have positively changed preservice teachers' attitudes toward AI education for young children, highlighting the importance of enhancing digital literacy and self-efficacy in using AI technology in early childhood classrooms (Lim, 2023).

Challenges in implementing AI in early childhood education include data privacy concerns, a lack of knowledge and confidence, inadequate curriculum design, and teaching guidelines specifically tailored to the developmental needs of young children (Crescenzi-Lanna, 2023; Su et al., 2023). Effective AI integration in early childhood settings requires holistic support systems designed for the unique context of early education, ethical frameworks that protect young children's data, and continuous teacher training focused on age-appropriate technology use.

The integration of AI technologies in early childhood education presents unique challenges and opportunities for human resource management. Effective HR practices are essential for supporting educators' adoption of AI tools and fostering innovative teaching approaches. Educational institutions that implement strategic HRM practices focused on technology integration show greater teacher satisfaction and improved organizational performance. HR managers play a crucial role in designing professional development programs that enhance teachers' AI literacy and application skills, whereas performance evaluation systems that recognize innovative teaching approaches significantly influence educators' motivation to adopt AI-enhanced pedagogical methods.

2.3. Conceptual framework and hypothesis development

How teachers perceive AI influences their intrinsic motivation. Fear of being outperformed by AI can undermine motivation, yet it can also highlight areas for professional growth (Wang et al., 2024). Intrinsic motivation—doing things because they are enjoyable—drives creative output and innovation (Leung et al., 2014). Teachers who are intrinsically motivated tend to be more innovative. AI awareness can increase this intrinsic motivation (Liang et al., 2022) and improve decision-making effectiveness (Buçinca, 2024). Thus, we propose the following:

H1: AI awareness positively influences intrinsic motivation.

Moreover, AI awareness has a positive effect on self-perception of creativity or creative self-efficacy (Xie et al., 2023). Teaching through AI technology positively impacts intentions and self-efficacy, meaning that teachers become more confident in employing these tools. Puente-Díaz and Cavazos-Arroyo (2017) reported that encouragement for creativity plays a substantial role in determining one's creative self-efficacy. Thus, we propose the following:

H2: AI awareness positively influences creative self-efficacy.

AI integration contributes to a more supportive educational environment by providing resources, interactive tools, and adaptive platforms. A positive learning climate emerges when educators perceive institutional readiness and support for AI adoption (Bucea-Manea-Țoniş et al., 2022). Thus, educators' AI awareness is expected to foster a stronger learning climate that encourages collaboration and innovation.

H3: AI awareness has a positive effect on the learning climate.

There is a strong relationship between intrinsic motivation and innovative behavior. This relationship is positively impacted by organizational support for innovation (Venketsamy and Lew, 2024). Moreover, motivated employees tend to hold more central positions in organizational advice networks, which enhances their innovative capabilities (Carnabuci et al., 2023). Thus, we propose the following:

H4: Intrinsic motivation has a positive effect on innovative behavior.

It has been established that creative self-efficacy predicts innovative behavior, and this relationship is intensified by situational job autonomy and work engagement (Orth and Volmer, 2017). In addition, creative self-efficacy reportedly positively mediates the relationship between knowledge sharing and innovation among employees (Hu and Zhao, 2016). Therefore, we propose the following:

H5: Creative self-efficacy positively influences innovative behavior.

Finally, the learning climate has an impact on innovative behavior. In unfamiliar settings, the adaptation of one's learning increases a person's drive to perform, which in turn stimulates Boulamatsi et al.'s (2021) innovative behaviors. Additionally, organizational learning, along with the work atmosphere, has a considerable effect on innovative work behavior. Thus, we suggest the following:

H6: The learning climate positively influences innovative behavior.

On the basis of all the above hypotheses, we also assume that intrinsic motivation, creative self-efficacy, and the learning climate mediate the relationship between AI awareness and innovative behavior. By influencing these psychological and contextual factors, AI awareness indirectly shapes educators' innovative practices.

H7: Intrinsic motivation mediates the relationship between AI awareness and innovative behavior.
H8: Creative self-efficacy mediates the relationship between AI awareness and innovative behavior.
H9: Learning climate mediates the relationship between AI awareness and innovative behavior.

From the literature review, we created the research model presented in Fig. 1, which assumes that AI awareness affects innovative behavior through intrinsic motivation, creative self-efficacy, and the learning climate.

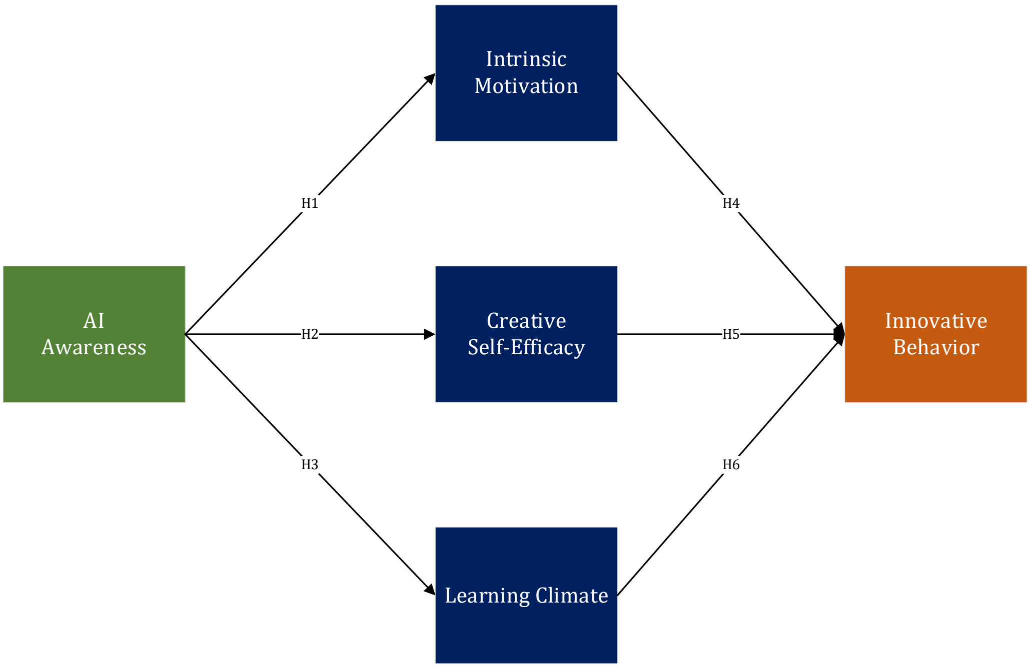

Fig. 1: Research framework

3. Methodology

3.1. Research design

This study adopted a positivist research philosophy grounded in the belief that reality is objective and measurable through empirical data. Positivism in social research seeks to understand phenomena by collecting and analyzing quantifiable evidence, using statistical techniques to identify patterns and relationships.

We used a questionnaire to conduct this study. This device is popular in positivist studies because it helps collect measurable information. The objective of the survey was to obtain detailed information about how teachers in early childhood education feel when they include AI in their teaching process. Constructs such as AI awareness, intrinsic motivation, creative self-efficacy, learning climate, and innovative behavior are measured by structured items on the questionnaire.

The study design involves several steps. First, researchers have reviewed some of the literature to determine what factors affect innovative behaviors in education. It then creates some hypotheses about how AI awareness is associated with intrinsic motivation, creative self-efficacy, the learning climate, and innovative behavior, such that these can be tested against one another via data that would be collected later through questionnaires based on validated scales used in other similar research to ensure accuracy and credibility when the results from this particular study are analyzed.

The target population for this study comprises early childhood educators in Guangdong, China. A purposive sampling technique ensured the inclusion of relevant participants; the results should be generalized with caution beyond similar contexts. Data collection is conducted through online channels. Moreover, the collected data are analyzed via statistical techniques such as descriptive statistics, correlation analysis, and regression analysis. These methods test hypotheses and identify significant predictors of innovative behavior.

3.2. Sample size

To ascertain the sample size needed for this study, Cochran's formula for sample size in surveys was employed (Cochran, 1977). Cochran's formula is expressed as $N_0 = \frac{Z^2 \times p \times (1-p)}{E^2}$, where, Z = 1.96 (95% confidence level), p = 0.5 (maximum variance), and E = 0.05 (5% margin of error). The calculation yielded a minimum required sample of 384 respondents (Abdulraheem and Imouokhome, 2021; Makinde and Abati, 2024).

3.3. Questionnaire design

The questionnaire incorporated validated scales measuring AI awareness, intrinsic motivation, creative self-efficacy, innovative behavior, and learning climate via a 5-point Likert scale (1 = "strongly disagree," 5 = "strongly agree"). The learning climate variable combines three dimensions from Nikolova et al. (2014): Facilitation, appreciation, and error avoidance. Other variable items were adapted from Liang et al. (2022), Yin et al. (2024), and Verma and Singh (2022), with wording modified to fit the educational context while maintaining the original meaning. Table 1 outlines the variables, original literature items, current study items, and sources of the literature.

3.4. Data collection

The questionnaires were distributed online via the Wenjuanxing platform (www.wjx.cn) to early childhood educators from 225 institutions on the member list of the Infant Care and Early Development Industry Association of Guangdong Province in 2023 (www.gdeea.org.cn). The participants received information about the study's purpose, confidentiality measures, and their right to withdraw. The responses were anonymized and securely stored.

3.5. Data analysis

The analysis employed SmartPLS-4 for partial least squares structural equation modelling (PLS-SEM). Indicator reliability was assessed with loadings above 0.70, whereas internal consistency reliability was confirmed through composite reliability and Cronbach's alpha (> 0.70). Convergent validity was tested via average variance extracted (threshold of 0.50), and discriminant validity was verified via the Fornell–Larcker criterion. Path coefficients were tested by bootstrapping (5,000 resamples), generating t values and p values. Model fit was assessed via the standardized root mean square residual (SRMR). Demographic information was analyzed via the online analytical tool SPSSPRO.

4. Results

The demographic profile (Table 2) revealed that the largest age group was 34–44 years (41.8%, predominantly 62.8% female), followed by 24–34 years (32.3%). Junior college diploma holders constituted 41.3% of the respondents, with 37.7% having a bachelor's degree. Most respondents had 3–6 years of professional experience (38.5%).

Table 3 confirms good measurement reliability and validity. Cronbach's alpha values exceed 0.7 for all the constructs: AI awareness (0.841), creative self-efficacy (0.823), innovative behavior (0.788), intrinsic motivation (0.889), and learning climate (0.893). The composite reliability values (rho_c) range from 0.876–0.916, whereas the AVE values demonstrate good convergent validity (0.540–0.739). Table 4 confirms discriminant validity, with square roots of the AVE values (diagonal) exceeding the correlations between the constructs. AI awareness is correlated with creative self-efficacy (0.446), innovative behavior (0.382), intrinsic motivation (0.505), and the learning climate (0.310).

Path analysis (Table 5) reveals that AI awareness significantly influences creative self-efficacy (β = 0.446, $p < 0.001$), intrinsic motivation (β = 0.505, $p < 0.001$), and the learning climate (β = 0.310, $p < 0.001$). Creative self-efficacy strongly influences innovative behavior (β = 0.331, $p < 0.001$), as do the learning climate (β = 0.210, $p < 0.001$) and intrinsic motivation (β = 0.182, p = 0.001). Fig. 2 illustrates these relationships with path coefficients.

Table 6 presents the outer loadings of the measurement indicators for all the constructs in the model. All the indicators demonstrated strong loadings on their respective constructs, with values ranging from 0.697 to 0.869.

Table 1: Comparison of original and current study items for variables

Variable	Original literature items	Current study items	Source
AI awareness (AA)	1. Given that AI is being widely used workplace, I will concern about my future in this industry.	AA-1. Given that AI is being widely used in education, I will concern about my future in this profession.	Liang et al. (2022)
	2. Given that AI is being widely used workplace, I will concern about my future in the organization.	AA-2. Given that AI is being widely used in education, I will concern about my future in the institution.	
	3. I think there is a possibility that my current job will be replaced by AI.	AA-3. I think there is a possibility that my current teaching role will be replaced by AI.	
	4. I think AI might replace our jobs.	AA-4. I think AI might replace our teaching roles.	
Intrinsic motivation (IM)	1. To overcome the uncertainty brought about by AI, I hope that my work will provide me with the opportunity to increase my knowledge and abilities.	IM-1. To overcome the uncertainty brought about by AI, I hope that teaching will provide me with the opportunity to increase my knowledge and abilities.	Liang et al. (2022)
	2. To overcome the uncertainty of AI, I wanted to know how well I could do the job.	IM-2. To overcome the uncertainty of AI, I want to know how well I could teach.	
	3. Overcoming the uncertainty of AI brings me joy.	IM-3. Overcoming the uncertainty of AI brings me joy.	
	4. Overcoming the uncertainty brought about by AI helps with self-expression.	IM-4. Overcoming the uncertainty brought about by AI helps with self-expression.	
	5. Regardless of the outcome of overcoming the uncertainty that AI brings, I am content with gaining new experiences.	IM-5. Regardless of the outcome of overcoming the uncertainty that AI brings, I am content with gaining new experiences.	
	6. I'm happier when I can set goals for myself to overcome the uncertainty that AI brings.	IM-6. I'm happier when I can set teaching goals for myself to overcome the uncertainty that AI brings.	
Creative self-efficacy (CS)	I have confidence in my ability to solve problems creatively when working with AI assistance.	CS-1. I have confidence in my ability to solve problems creatively when teaching with AI assistance.	Yin et al. (2024)
	2. I feel that I am good at generating novel ideas when working with AI assistance.	CS-2. I feel that I am good at generating novel ideas when teaching with AI assistance.	
	3. I have a knack for further developing the ideals of others when working with AI assistance.	CS-3. I have a knack for further developing the ideas of others when teaching with AI assistance.	
Innovative behavior (IB)	I create new ideas for improvement.	IB-1. I create new teaching ideas for improvement.	Verma and Singh (2022)
	2. I often search out new working methods, techniques, or instruments.	IB-2. I often search out new teaching methods, techniques, or instruments.	
	3. My ideas generate original solutions to problems.	IB-3. My teaching ideas generate original solutions to educational problems.	
Learning climate (LC)	1. My organization provides appealing educational facilities (resources).	LC-1. My school provides appealing educational facilities (resources).	Nikolova et al. (2014)
	2. My organization provides sufficient resources to develop my competencies.	LC-2. My school provides sufficient resources to develop my competencies.	
	3. In my organization, one receives the training they need.	LC-3. In my school, one receives the training they need.	
	4. In my organization, employees who continuously develop themselves professionally are being rewarded.	LC-4. In my institution, educators who continuously develop themselves professionally are being rewarded.	
	5. Employees get quickly promoted here if they engage in continuous professional development.	LC-5. Educators get quickly promoted here if they engage in continuous professional development.	
	6. In my organization, employees who make an effort to learn new things earn appreciation and respect.	LC-6. In my institution, educators who make an effort to learn new things earn appreciation and respect.	
	7. In my organization, one is afraid to admit mistakes.	LC-7. In my institution, one is afraid to admit mistakes.	
	8. In my organization, employees do not dare to discuss mistakes.	LC-8. In my institution, educators do not dare to discuss mistakes.	
	9. In my organization, employees are anxious to openly discuss work-related problems.	LC-9. In my institution, educators are anxious to openly discuss work-related problems.	

Table 2: Demographic information summary

Category	Options	Gender		Total
		Female	Male	
Age	18-24 years old	21(41.2%)	30(58.8%)	51
	24-34 years old	77(48.1%)	83(51.9%)	160
	34-44 years old	130(62.8%)	77(37.2%)	207
	44-54 years old	16(57.1%)	12(42.9%)	28
	54 years old and above	11(55.0%)	9(45.0%)	20
Academic qualification	Junior college diploma	119(58.0%)	86(42.0%)	205
	Bachelor's degree	100(53.5%)	87(46.5%)	187
	Master's degree	27(54.0%)	23(46.0%)	50
	Doctoral degree	2(22.2%)	7(77.8%)	9
	Other	7(46.7%)	8(53.3%)	15
Years of professional experience	1-3 years	73(51.8%)	68(48.2%)	141
	3-6 years	108(56.5%)	83(43.5%)	191
	6-10 years	55(57.9%)	40(42.1%)	95
	More than 10 years	19(48.7%)	20(51.3%)	39

The AI Awareness construct showed robust indicator loadings between 0.804 and 0.847, with AA3 having the highest loading (0.847). The creative self-efficacy indicators displayed particularly strong loadings (0.841–0.869), with CS2 and CS3 showing the highest values (0.868 and 0.869, respectively). The innovative behavior indicators ranged from 0.818 to 0.848, whereas the intrinsic motivation indicators showed consistent loadings between 0.795 and 0.810. The learning climate indicators had slightly lower but still acceptable loadings ranging from 0.697 to 0.760, with LC7 demonstrating the highest loading (0.760).

All indicator loadings were statistically significant ($p < 0.001$), with t-statistics ranging from 23.313–75.254, confirming the reliability of individual indicators in measuring their respective constructs.

Table 3: Reliability and validity metrics for the constructs

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI awareness	0.841	0.845	0.893	0.677
Creative self-efficacy	0.823	0.826	0.895	0.739
Innovative behavior	0.788	0.788	0.876	0.703
Intrinsic motivation	0.889	0.890	0.916	0.644
Learning climate	0.893	0.895	0.913	0.540

Table 4: Fornell–Larcker criterion

Variables	AI awareness	Creative self-efficacy	Innovative behavior	Intrinsic motivation	Learning climate
AI awareness	0.823				
Creative self-efficacy	0.446	0.859			
Innovative behavior	0.382	0.517	0.838		
Intrinsic motivation	0.505	0.543	0.433	0.802	
Learning climate	0.310	0.418	0.410	0.341	0.735

Table 5: Structural model results (direct path coefficients)

Variables	Original sample	Sample mean	Standard deviation	T-statistics	P-values
AI awareness > creative self-efficacy	0.446	0.448	0.038	11.598	0.000
AI awareness > intrinsic motivation	0.505	0.507	0.042	11.881	0.000
AI awareness > learning climate	0.310	0.314	0.043	7.283	0.000
Creative self-efficacy > innovative behavior	0.331	0.331	0.056	5.906	0.000
Intrinsic motivation > innovative behavior	0.182	0.183	0.054	3.389	0.001
Learning climate > innovative behavior	0.210	0.213	0.052	4.022	0.000

Table 6: Measurement model: Outer loadings

Variables	Original sample	Sample mean	Standard deviation	T-statistics	P-values
AA1 < AI awareness	0.804	0.804	0.020	39.714	0.000
AA2 < AI awareness	0.821	0.820	0.018	45.611	0.000
AA3 < AI awareness	0.847	0.847	0.015	54.720	0.000
AA4 < AI awareness	0.819	0.818	0.018	46.476	0.000
CS1 < creative self-efficacy	0.841	0.840	0.015	54.870	0.000
CS2 < creative self-efficacy	0.868	0.868	0.012	75.254	0.000
CS3 < creative self-efficacy	0.869	0.869	0.012	71.425	0.000
IB1 < innovative behavior	0.818	0.817	0.019	44.121	0.000
IB2 < innovative behavior	0.848	0.847	0.015	56.374	0.000
IB3 < innovative behavior	0.848	0.848	0.015	55.395	0.000
IM1 < intrinsic motivation	0.806	0.806	0.018	44.749	0.000
IM2 < Intrinsic motivation	0.810	0.810	0.018	45.175	0.000
IM3 < intrinsic motivation	0.803	0.803	0.019	43.294	0.000
IM4 < intrinsic motivation	0.801	0.801	0.018	43.525	0.000
IM5 < intrinsic motivation	0.798	0.797	0.017	45.771	0.000
IM6 < intrinsic motivation	0.795	0.795	0.021	38.028	0.000
LC1 < learning climate	0.738	0.737	0.027	27.090	0.000
LC2 < learning climate	0.741	0.740	0.027	27.806	0.000
LC3 < learning climate	0.697	0.695	0.030	23.313	0.000
LC4 < learning climate	0.718	0.717	0.028	25.287	0.000
LC5 < learning climate	0.743	0.741	0.026	28.733	0.000
LC6 < learning climate	0.731	0.728	0.028	26.121	0.000
LC7 < learning climate	0.760	0.759	0.023	33.339	0.000
LC8 < learning climate	0.743	0.741	0.027	27.652	0.000
LC9 < learning climate	0.738	0.736	0.028	26.138	0.000

As shown in Table 7, all three mediators significantly transmitted the effects of AI awareness on innovative behavior. The strongest mediation effect occurred through creative self-efficacy (β = 0.147), followed by intrinsic motivation (β = 0.092) and the learning climate (β = 0.065). These results confirm that AI awareness not only directly enhances innovative behavior but also indirectly fosters innovation by improving teachers' psychological resources and perceptions of their organizational environment. In addition, Fig. 2 illustrates these relationships with all path coefficients.

As shown in Table 8, although the estimated model's SRMR (0.102) is above the conventional 0.08 threshold, the saturated model's SRMR (0.044) and NFI (0.892/0.879) generally indicate acceptable fit; therefore, we interpret the model with appropriate caution.

Table 7: Indirect effects

Variables	Specific indirect effects
AI awareness -> creative self-efficacy -> innovative behavior	0.147
AI awareness -> learning climate -> innovative behavior	0.065
AI awareness -> intrinsic motivation -> innovative behavior	0.092

5. Discussion

The results of this study provide important insights into the effects of AI awareness on early childhood educators' innovative behaviors. AI awareness strongly correlates with intrinsic motivation (β = 0.505), confirming Liang et al.'s (2022) findings that AI awareness triggers motivation through projected benefits and functionality. This strong relationship suggests that

HR managers in educational institutions should prioritize AI literacy training in professional development strategies. By enhancing educators' understanding of AI capabilities, educational leaders can improve teaching innovation, job satisfaction, and retention rates.

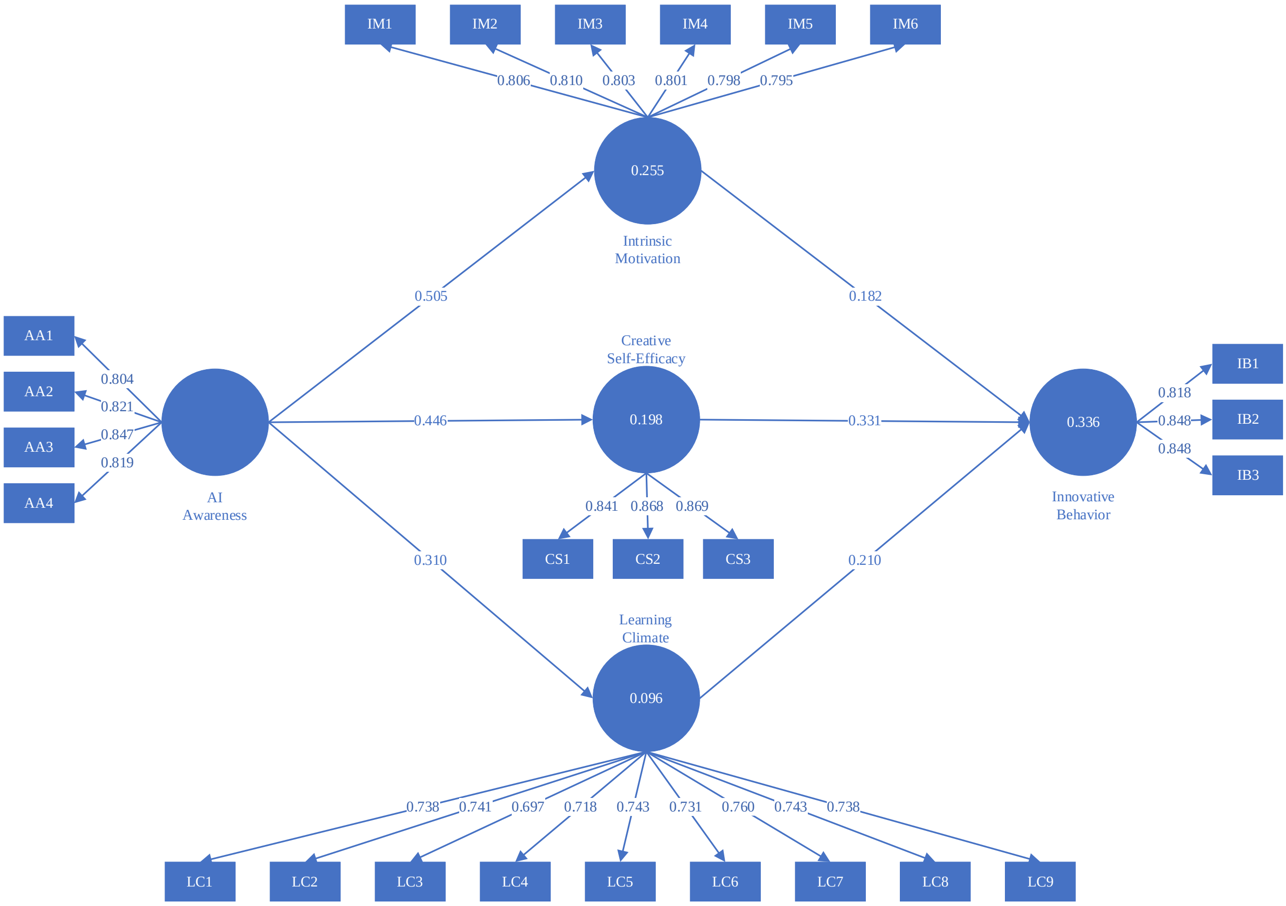

Fig. 2: Structural equation model of AI awareness and its impact on innovative behavior

Table 8: Model fit

Indicators	Saturated model	Estimated model
SRMR	0.044	0.102
d_ULS	0.642	3.362
d_G	0.220	0.264
Chi-square	605.807	674.618
NFI	0.892	0.879

SRMR: Standardized root mean square residual; d_ULS: Squared Euclidean distance discrepancy; d_G: Geodesic distance discrepancy

AI awareness positively influences creative self-efficacy (β = 0.446). This finding aligns with research showing that AI awareness strengthens confidence in creative abilities (Puente-Díaz and Cavazos-Arroyo, 2017). This relationship is important because creative self-efficacy strongly predicts innovation. In a similar study, preservice teachers showed improved self-efficacy when AI-integrated instruction was used, which changed how they perceived their ability to use AI creatively (Xie et al., 2023). HR departments should design performance management systems that recognize and reward teachers who creatively apply AI tools, reinforcing these positive, innovative behaviors.

The analysis revealed that AI awareness positively affects the learning climate (β = 0.310), supporting Bucea-Manea-Ţoniş et al.'s (2022) finding that AI positively influences educational environments through AI-powered technologies that create more supportive learning atmospheres. By building engaging climates that encourage teacher and student participation, Hu (2022) noted that AI-supported learning environments yield better educational results.

The study confirms intrinsic motivation's effect on innovative behavior (β = 0.182), which is consistent with Venketsamy and Lew (2024), who noted its positive moderating effect on innovative behavior. di Domenico and Ryan (2017) highlighted intrinsic motivation in enhancing creative performance and innovation. Intrinsically motivated educators are more likely to implement practices that foster creativity in teaching.

The strong association between innovative behavior and creative self-efficacy supports Orth and Volmer's (2017) finding that creative self-efficacy strongly predicts innovative behavior. Hu and Zhao (2016) demonstrated that creative self-efficacy mediates the relationship between knowledge sharing and innovation, confirming that educators with greater confidence in their creativity provide more innovative solutions to educational challenges.

Furthermore, the mediation analysis confirmed that AI awareness influences innovative behavior indirectly through intrinsic motivation, creative self-efficacy, and the learning climate. Specifically, intrinsic motivation served as a mediator with an indirect effect of 0.092, indicating that teachers' inner drive partially explains how AI awareness fosters innovative practices. Creative self-efficacy emerged as the strongest mediator, with an indirect effect of 0.147, highlighting that teachers' confidence in their creative abilities is the most powerful channel linking AI awareness to innovation. The learning climate also mediated this relationship, with an indirect effect of 0.065, suggesting that organizational support plays a complementary role in enabling educators to apply AI-driven innovation.

In addition to the statistical relationships identified in this study, our findings highlight important ethical implications for early childhood educators implementing AI. Given young children's limited agency in technology-mediated environments, educators face unique challenges regarding consent, privacy, and developmental appropriateness. Three critical ethical domains emerge from our results: First, the strong relationship between AI awareness and creative self-efficacy ($\beta = 0.446$) necessitates frameworks for maintaining child-centered approaches while experimenting with AI tools; second, the positive effect on the learning climate ($\beta = 0.310$) must be balanced with robust data protection protocols and educator training in data literacy; and third, the connection between intrinsic motivation and innovative behavior ($\beta = 0.182$) should be channeled toward addressing algorithmic bias and equity concerns in AI applications. HR departments must view these ethical considerations not as constraints but as essential components of responsible AI integration aligned with early childhood education values.

Despite its contributions, this study has several limitations. The cross-sectional design limits causal inferences about the relationships between variables. The reliance on self-reported measures may introduce common method bias. Additionally, while the sample from Guangdong Province provides valuable insights, caution should be exercised when generalizing findings to other cultural or educational contexts with different AI implementation approaches.

6. Conclusion

This research explored the impact of AI awareness on the innovative actions of early childhood educators in Guangdong, China, with a focus on the effects of AI awareness on motivation, creative self-efficacy, and the prevailing learning climate. Analytics reveal the positive impacts of AI awareness on intrinsic motivation ($\beta = 0.505$), creative self-efficacy ($\beta = 0.446$), and the learning climate ($\beta = 0.310$) to be synergistic, forming an innovation system among educators.

The results support the notion that awareness of AI not only motivates educators to adopt innovative practices but also helps maintain sustained innovation through the integration of AI tools taught in class. The development of a positive learning climate further supports innovation by assisting in resource provision, appreciation, and motivational feedback toward educators who use technologies in their practices. In addition, the mediation analysis confirmed that intrinsic motivation (indirect effect = 0.092), creative self-efficacy (indirect effect = 0.147), and learning culture (indirect effect = 0.065) significantly mediate the relationship between AI awareness and innovative behavior. Among these factors, creative self-efficacy emerged as the strongest mediator, underscoring the pivotal role of teachers' creative confidence in translating AI awareness into innovative practices.

The strategic recommendations from this study focus on building awareness of AI through structured professional development programs to equip teachers with skills that foster creativity and innovation. For human resource leaders in early childhood education, we propose concrete strategies on the basis of our findings. First, HR departments should implement tiered AI literacy training programs that progress from a foundational understanding of AI in early childhood settings to more advanced applications in curriculum development. Second, performance appraisal systems should be redesigned to include specific dimensions for technology-enhanced teaching innovation, with clear metrics for evaluating creative applications of AI tools and regular review cycles to provide constructive feedback. Third, institutions should establish recognition and reward mechanisms to encourage AI-driven innovation, such as innovation awards, peer recognition, or small-scale project support. Finally, HR policies should support the improvement of the learning climate by allocating dedicated time for professional experimentation with AI tools, facilitating cross-institutional learning communities, and organizing regular showcases of successful practices.

List of abbreviations

AA	AI awareness
AI	Artificial intelligence
AVE	Average variance extracted
β	Standardized path coefficient
rho_c	Composite reliability
CS	Creative self-efficacy
d_G	Geodesic distance discrepancy
d_ULS	Squared Euclidean distance discrepancy
IB	Innovative behavior
IM	Intrinsic motivation
LC	Learning climate
PLS-SEM	Partial least squares structural equation modeling
SPSSPRO	Statistical Package for the Social Sciences – PRO version
SmartPLS-4	Smart Partial Least Squares, version 4
SRMR	Standardized root mean square residual

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Compliance with ethical standards

Ethical considerations

All participants provided informed consent, and data were collected anonymously with appropriate ethical safeguards in place.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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