THE IMPACT OF AI-EMBEDDED EDUCATION SYSTEMS ON TEACHERS' WORK PERFORMANCE: AN EXTENSION OF THE D&M INFORMATION SYSTEM SUCCESS MODEL*

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Abstract

This study investigates the impact of AI-Embedded Education Systems on the work performance of K-12 teachers in China, as well as the moderating and direct effects of AI anxiety. Using PLS-SEM, the study analysed the responses of 640 valid participants. The results validate the feasibility and effectiveness of adding AI quality as an independent variable to the information system success model. The results show that information quality, system quality, service quality, and AI quality are positively correlated with satisfaction. At the same time, information quality, system quality, and AI quality are positively correlated with usage, but the hypothesis that service quality is positively correlated with usage is rejected. Usage has a significant positive impact on satisfaction. Both usage and satisfaction have a positive impact on work performance. In addition, AI anxiety was found to have a significant negative impact on work performance. However, the results reject the moderating role of AI anxiety. This study integrates

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information system success theory and attention control theory to innovatively develop a new AI-Embedded information system success model. The model extends the application domain of information system success models, and the research results provide new perspectives for education policymakers, promote the orderly advancement of China's smart education projects, and provide a reference and model for other countries' development in the field of smart education.

Keywords: Artificial Intelligence, Information Systems, Work Performance, K-12 Teachers

Introduction

The advent of Industry 4.0, typified by the rapid evolution of information technology, has precipitated the pervasive integration of artificial intelligence (AI) technology across virtually all industry sectors on a global scale. This has given rise to a concerted exploration of AI applications, with the objective of achieving enhanced development and delivering services of a higher calibre. As demonstrated in the survey conducted by the McKinsey Global Institute, China has been identified as a leading nation in the field of AI (Bughin et al., 2017). As early as 2020, the Chinese government allocated over 1 billion USD to the 'Artificial Intelligence Plan' (Agba, Agba, & Obeten, 2023) and explicitly outlined an AI investment strategy, aiming for a total investment of 1 trillion RMB (approximately 147.8 billion USD) by 2030 (He, 2023). AI technology is enabling intelligent actions through software agents (Poole & Mackworth, 2010), continuously innovating and penetrating all aspects of society (Zhang, Zuo, He, Li, & Yu, 2021), and becoming a crucial tool for value re-creation across industries (Analytics, 2020).

In comparison with other nations, China has demonstrated a marked advantage in the strengthening of its professional artificial intelligence talent pool

(Reis, Santo, & Melão, 2019). This advantage can be attributed to the implementation of a forward-thinking educational programme, which has been initiated by the Chinese Ministry of Education. Smart education can be defined as an educational model that uses advanced technology and innovative teaching methods to improve student learning outcomes and teaching efficiency (Lian, 2021). In January 2024, the Ministry of Education of the People's Republic of China published a list of primary and secondary school AI education bases (Ministry of Education of the People's Republic of China, 2024a), establishing 184 primary and secondary school AI education pilot schools nationwide. Concurrently, primary and secondary school teachers (K-12 teachers) are obligated to utilise 'smart education systems' in their quotidian teaching activities (Ministry of Education of the People's Republic of China, 2024c). Smart education systems are defined as artificial intelligence teaching and learning tools for China's smart education programme (Y. Zhao, 2020). The integration of intelligent devices into conventional teaching and learning methodologies has been a subject of considerable interest. The combination of advanced technologies, including artificial intelligence, big data, the Internet of Things and cloud computing, has been demonstrated to facilitate remote interaction, standardised communication and learning methods such as intelligent recording and broadcasting (Cui & Tang, 2019). The objective of this instrument is to enhance pedagogical practices and optimise efficiency (Cui & Tang, 2019). By leveraging advanced technologies and the advantages of the internet, it disrupts the temporal and spatial constraints of traditional education, providing teachers and students with a more flexible and convenient learning and teaching environment (Shoikova, Nikolov, & Kovatcheva, 2017).

The integration of smart education systems into K-12 classrooms in China is an ongoing process, though K-12 teachers have been exposed to information technology-assisted teaching systems for an extended period. Following the publication of the Preliminary Plan for Electrification of Education in 1978, the

People's Republic of China has been engaged in the development of information technology in education. This initiative was initially referred to as the 'electrification of education'. By 1982, the number of schools nationwide that had established educational technology institutions had surpassed 16,000, with secondary schools accounting for 7.5% and primary schools for 0.88% (Huang, 1983). By 2015, the online teaching environment in Chinese primary and secondary schools had undergone significant improvement, with an internet access rate of 83% and a multimedia classroom penetration rate of 73% (Hu, 2019). Digital educational resources were abundant, and information-based teaching was widely promoted. The Ministry of Education of China has recently proposed the implementation of a 'Smart Education System' in primary and secondary schools. This initiative involves the integration of artificial intelligence technology to effect a substantial reform of conventional teaching methodologies (Cui & Tang, 2019). This innovative teaching tool, underpinned by artificial intelligence, aspires to enhance teaching efficiency in a comprehensive manner, thereby assisting primary and secondary school teachers in attaining smart education objectives (Y. Zhao, 2020).

Researchers have found that in the process of using smart education systems to improve teaching efficiency, there are both positive and negative effects on the work performance of K-12 teachers. The impact of smart education systems on teacher work performance is mainly reflected in improving teaching efficiency, optimising evaluation methods, enriching teaching and research activities, and enhancing teachers' information technology application capabilities (Xu, Wang, & Yu, 2018). On the one hand, the use of smart education systems can reduce teachers' paperwork, reduce data entry errors, enrich teaching forms, enhance knowledge-sharing opportunities, and increase student and parent participation in the teaching process (Wang, Li, Tan, Yang, & Lei, 2023). Some teachers have explored new teaching methods, which have been well-received by students and significantly improved teaching effectiveness (Guo, 2024). Teachers with a certain level of AI literacy can use appropriate applications and algorithms to support innovation, enhance satisfaction, and improve work performance (Wang et al., 2023). On the other hand, AI-embedded education systems also bring about the problem of 'technology overload' (J. Zhao, 2021), which increases teachers' workload. In addition to maintaining their existing performance, teachers need to quickly master new technologies to meet the requirements of smart education (Li, Hu, & Gu, 2021). This forces teachers to spend more time learning new technologies, challenging their existing comprehensive qualities and abilities (S.-Y. Kim & Kim, 2013). Faced with job insecurity and technological disruption, teachers' work performance and productivity are negatively affected (Brougham & Haar, 2020), leading to job dissatisfaction, lack of motivation, and even negative work attitudes, absenteeism, and turnover (Zhou, Tang, Lu, Liu, & Chen, 2021).

Despite the consensus among scholars that human teachers possess distinctive qualities, including critical thinking, creativity and emotional intelligence, which render them challenging to substitute with artificial intelligence (Chan & Tsi, 2023), it is imperative to examine the role and impact of artificial intelligence in the educational sector. However, there is currently a significant gap in academic research on how K-12 teachers use AI-embedded education systems to carry out teaching activities (L. Zhao, Zhang, Zhang, & Zhao, 2022). The impact of AI-embedded education systems on teachers' work performance is an area that requires further study.

The present study proposes an innovative integration of AI quality into the information system success model, with the aim of exploring the new functions brought by AI technology in smart education systems and their impact on the work performance of K-12 teachers in China. The objective of this study is twofold: firstly, to extend the theoretical framework and conceptual model of information system success, and secondly, to enhance the comprehension of AI quality, work performance, and information system success.

Objectives

1. study adds AI quality to the D&M IS Success Model to form an independent variable that is as important as information quality, system quality, and service quality, extends the D&M IS Success Model, constructs an evaluation system applicable to AI information systems, and analyses its direct impact on system use, user satisfaction, and work performance. It is to be noted that this study discusses individual performance and does not involve the study of organisational performance related content.

2. aspect, sample data from China are used to test the impact of intelligent teaching systems on K-12 teachers' work performance. The rationality and feasibility of the D&M IS Success Model with the addition of AI variables are empirically tested.

3. aspect is to analyse the influence mechanism of AI anxiety. Through the research on the current situation of AI anxiety of K12 teachers in China, to detect whether AI anxiety has an impact on teachers' work performance? What are the specific data? And explore the direct and indirect effects of AI anxiety on D&M IS success model.

Methodology

1. Procedure and Participants

This study was conducted between March and May 2025. The research subjects were K-12 teachers in China who used an AI-embedded education system (i.e., the smart education system) for classroom teaching. In February 2024, the Ministry of Education of the People's Republic of China announced the establishment of 184 primary and secondary school AI education bases nationwide (Ministry of Education of the People's Republic of China, 2024a). This study will use this pilot list as the basis for its sample. As the pilot list is already divided into 31 administrative levels according to China's administrative divisions and the number of schools in each level is consistent, a stratified random sampling method will be employed.

According to the national K-12 statistical data published by the Ministry of Education of the People's Republic of China (2024b), there are 211,200 K-12 schools and 12,954,200 full-time teachers nationwide. The 184 schools included in the pilot list account for 0.087% of the total. Based on this proportion, the total sample frame (full-time teachers) for this study is approximately 11,286 individuals. Based on the formula proposed by Cochran (1977), with a 95% confidence level corresponding to a Z-value of 1.96 and a p-value of 0.5 to obtain the maximum sample size and an allowable error margin (e) of 0.05, the minimum required sample size is 384 individuals. After the questionnaire had been collected, the final sample comprised 640 valid responses. All questions were made mandatory to prevent missing values from causing problems.

The majority of respondents were female (55.63%), with most aged between 18 and 29 (50.47%). Almost all of the teachers had received a higher education qualification (73.44% had a bachelor's degree and 24.06% had a master's degree or higher), and the majority had information technology skills certificates or relevant training experience (69.06%). More than 60% of the respondents said that they had been using the Smart Education System for more than one year (39.38% had used it for between one and two years, and 28.13% had used it for more than two years). Descriptive statistics of the population are given in Appendix 1.

2. Construct Operationalizations and Methods

The theoretical model to be validated in this study is presented in Figure 1. The proposed model will be analysed using a partial least squares structural equation model (PLS-SEM), following the data analysis procedure outlined by

Joseph F Hair et al. (2021). As the core endogenous construct of this model is a second-order reflective structure, the analysis will use the two-stage approach proposed by Sarstedt, Hair, Cheah, Becker, and Ringle (2019) and implemented in Smart PLS 4 software.

Information quality, system quality, service quality and usage will be measured using the Information System Success Model Scale (Wibowo et al., 2023) from the employee perspective. Satisfaction will be measured using the satisfaction measurement items in the information system success model developed by Stefanovic et al. (2016). AI quality will be measured using the scale developed by Noor et al. (2022). The teacher work performance scale, developed and validated by Ali and Haider (2017), will be used to measure the work performance of K-12 teachers. These scales will be assessed using a seven-point Likert scale (Peterson, 1997).

3. Multicollinearity and Common Method Bias Assessment

Since this study exclusively employs self-report measures and all scales utilise a uniform response scale, there is a potential risk of common method bias (CMB). Following the questionnaire design guidelines of previous similar studies (Jin, Jin, & Qing, 2023; Mellouli et al., 2020; Peng & Wan, 2023), this study included an unrelated variable-‘attitude towards blue’-in the questionnaire to test for CMB (Miller & Simmering, 2022).

This study uses the difference-in-differences (DID) method to systematically examine the effects of marker variables on model parameters. The results show that, following the introduction of exogenous marker variables, the maximum fluctuation amplitude of the R^2 value for the core path is just 0.002 - well below the 10% sensitivity threshold set by Ahmad, Liu, and Butt (2020). Following the addition of the marker variables, the path coefficients relating to usage (β = 0.045, p = 0.099), satisfaction (β = 0.019, p = 0.531) and work performance (β = 0.115, p = 0.908) were not statistically significant ($p > 0.05$).

Based on the criteria provided by Podsakoff, MacKenzie, Lee, and Podsakoff (2003), the above evidence indicates that common method bias (CMB) does not pose a significant threat in this study.

In the context of multiple regression analysis, statistical collinearity refers to the approximate linear dependence between predictor variables (Kock, 2015). The variance inflation factor (VIF) is commonly used as a diagnostic indicator to investigate the presence of multicollinearity in a model (Joseph F Hair et al., 2021). This rigorous multicollinearity control mechanism effectively ensures the stability of regression coefficient estimates and the reliability of statistical inferences (Mu, Xu, & Chen, 2023). Following testing, all explanatory variables had VIF values below 3.0, with a maximum value of 2.641 (AIQ -> SAT) being observed. This suggests that multicollinearity is not an issue (Joseph F Hair et al., 2021).

Results

1. Measurement Model Analysis

1.1 Measurement Model Assessment of LOCs

This study strictly adhered to the reliability and validity testing standards proposed by Sarstedt, Hair, et al. (2019), conducting empirical tests on the first-order reflective measurement model. The majority of item loadings exceeded the threshold of 0.708 (Joseph F Hair et al., 2021), indicating excellent reliability. A small number of item loadings fell within the acceptable range for exploratory research (between 0.6 and 0.7) (Diamantopoulos, Sarstedt, Fuchs, Wilczynski, & Kaiser, 2012), thereby ensuring reliability. All Cronbach's alpha (α) composite reliability coefficients for the variables were within the ideal range of greater than 0.7 and less than 0.95 (Marcoulides, 1998; Tavakol & Dennick, 2011), indicating reliable internal consistency across structures. All CA (rho_a) scores were above 0.7, and all CR (rho_c) scores were above 0.8, demonstrating the measurement model's high consistency (Dijkstra & Henseler, 2015). All calculated average variance (AVE) values were well above 0.5, indicating that each construct possesses significant convergent validity (Joseph F. Hair, Black, Babin, & Anderson, 2009).

The results of the Fornell–Larcker criterion validation show that the square roots of the AVE values (the bold diagonal values) for all latent variables are significantly higher than their respective Pearson correlation coefficients between constructs. This is fully consistent with the framework for testing discriminant validity proposed by Fornell and Larcker (1981). Additionally, most of the heterogeneity-homogeneity factor ratios (HTMT) are below the strict threshold of 0.85 (Clark & Watson, 2016), although some values are greater than 0.85. The highest value is 0.907. For these suboptimal HTMT values, confidence interval tests revealed that the confidence interval values do not include 1. This is consistent with the updated and extended evaluation criteria for PLS-SEM in information systems, as proposed by J. Hair, Hollingsworth, Randolph, and Chong (2016). Therefore, the discriminant validity of the first-order model is ensured.

Table: 1 First-order measurement model summary

LOC	Indicator	Indicator Reliability	Internal Consistency Reliability			Convergent Validity
		loadings	α	CA	CR	AVE
AIQ-AN	AIQ-AN1	0.802	0.751	0.751	0.857	0.667
	AIQ-AN2	0.826				
	AIQ-AN3	0.822				
AIQ-AV	AIQ-AV1	0.758	0.713	0.717	0.840	0.637
	AIQ-AV2	0.777				
	AIQ-AV3	0.856				
AIQ-EF	AIQ-EF1	0.795	0.726	0.726	0.845	0.646
	AIQ-EF2	0.807				
	AIQ-EF3	0.809				

LOC	Indicator	Indicator Reliability	Internal Consistency Reliability			Convergent Validity
		loadings	α	CA	CR	AVE
AIQ-SE	AIQ-SE1	0.832	0.879	0.880	0.917	0.734
	AIQ-SE2	0.881				
	AIQ-SE3	0.862				
	AIQ-SE4	0.853				
IFQ	IFQ1	0.773	0.789	0.790	0.856	0.543
	IFQ2	0.723				
	IFQ3	0.696				
	IFQ4	0.769				
	IFQ5	0.720				
SAT	SAT1	0.825	0.719	0.720	0.842	0.640
	SAT2	0.798				
	SAT3	0.777				
SEQ	SEQ1	0.751	0.829	0.832	0.880	0.594
	SEQ2	0.783				
	SEQ3	0.756				
	SEQ4	0.774				
	SEQ5	0.788				
SYQ	SYQ1	0.753	0.756	0.757	0.837	0.507
	SYQ2	0.709				
	SYQ3	0.678				
	SYQ4	0.729				
	SYQ5	0.689				
TWP	TWP1	0.764	0.912	0.915	0.926	0.533
	TWP2	0.728				
	TWP3	0.761				
	TWP4	0.761				
	TWP5	0.743				
	TWP6	0.751				
	TWP7	0.760				
	TWP8	0.577				
	TWP9	0.683				
	TWP10	0.707				
	TWP11	0.773				

LOC	Indicator	Indicator Reliability	Internal Consistency Reliability			Convergent Validity
		loadings	α	CA	CR	AVE
USE	USE1	0.754	0.700	0.706	0.833	0.625
	USE2	0.808				
	USE3	0.807				

Note: AIQ-AN = AI Quality-Anthropomorphism, AIQ-AV = AI Quality-Availability, AIQ-EF = AI Quality-Efficiency, AIQ-SE = AI Quality-Security, IFQ = Information Quality, SAT = Satisfaction, SEQ = Service Quality, SYQ = System Quality, TWP = K-12 Teachers' Work Performance, USE = Usage.

Table: 2 Fornell-Larcker at first-order

	AIQ-AN	AIQ-AV	AIQ-EF	AIQ-SE	IFQ	SAT	SEQ	SYQ	TWP	USE
AIQ-AN	**0.817**									
AIQ-AV	0.566	**0.798**								
AIQ-EF	0.542	0.569	**0.804**							
AIQ-SE	0.493	0.458	0.404	**0.857**						
IFQ	0.486	0.553	0.605	0.380	**0.737**					
SAT	0.517	0.568	0.601	0.332	0.627	**0.800**				
SEQ	0.530	0.572	0.584	0.383	0.618	0.614	**0.770**			
SYQ	0.519	0.599	0.595	0.339	0.687	0.641	0.663	**0.712**		
TWP	0.292	0.376	0.385	0.086	0.399	0.476	0.380	0.419	**0.730**	
USE	0.536	0.575	0.624	0.334	0.591	0.648	0.555	0.609	0.433	**0.790**

Table: 3 HTMT ratio at first-order

	AIQ-AN	AIQ-AV	AIQ-EF	AIQ-SE	IFQ	SAT	SEQ	SYQ	TWP	USE
AIQ-AN										
AIQ-AV	0.772									
AIQ-EF	0.734	0.788								
AIQ-SE	0.608	0.581	0.506							
IFQ	0.632	0.735	0.800	0.455						
SAT	0.702	0.792	0.831	0.419	0.832					
SEQ	0.668	0.739	0.752	0.450	0.762	0.791				
SYQ	0.690	0.814	0.803	0.416	0.890	0.868	0.837			
TWP	0.365	0.465	0.478	0.128	0.473	0.586	0.436	0.508		
USE	0.740	0.809	0.872	0.428	0.789	0.907	0.721	0.835	0.540	

Table: 4 Heterotrait-monotrait ratio (HTMT) - Confidence intervals at first-order (Selected projects)

	Original sample (O)	**Sample mean (M)**	**2.5%**	**97.5%**
SYQ <-> IFQ	0.890	0.890	0.832	0.944
SYQ <-> SAT	0.868	0.868	0.787	0.942
USE <-> AIQ-EF	0.872	0.872	0.791	0.949
USE <-> SAT	0.907	0.909	0.829	0.985

1.2 Measurement Model Assessment of HOCs

In the context of hierarchical confirmatory factor analysis, the concept of AI quality (AIQ) is distinguished by its unique manifestation of a second-order dimensional structure. The preceding subsection expounded the measurement model parameters of its four first-order dimensions (AIQ-AN, AIQ-AV, AIQ-EF and AIQ-SE). This subsection delineates the process by which LOCs are loaded onto the HOCs of AIQ to execute a second-order CFA.

The results of the analysis indicate that the loadings of all second-order factors range from 0.672 to 0.835. Despite the fact that the loading of AIQ-SE is marginally below the threshold of 0.7, it does not have a detrimental effect on the AVE value of the second-order AIQ (0.627). Consequently, in accordance with the recommendations of Deng, Turner, Gehling, and Prince (2017), the factor structure can be maintained. The reliability and convergent validity of the second-order construct AIQ is ensured by the fact that Cronbach's α coefficient, CA value, and CR value are all greater than 0.8.

Furthermore, the Fornell-Larcker values for the second-order construct were found to be fully consistent with the Fornell-Larcker criteria (Fornell & Larcker, 1981). The HTMT of the second-order construct demonstrated notable similarities with the first-order test, with certain HTMT values exceeding 0.85. However, it is notable that the confidence intervals of these models do not include 1, thereby meeting the evaluation criteria outlined by J. Hair et al. (2016) and ensuring the discriminant validity of the model.

Table: 5 Second-order measurement model summary

HOC	Reflective Indicators	Indicator Reliability loadings	Internal Consistency Reliability α	CA	CR	Convergent Validity AVE
AIQ	**AIQ-AN**	0.821	0.804	0.830	0.870	0.627
	AIQ-AV	0.835				

AIQ-EF	0.828
AIQ-SE	0.672

Table: 6 Fornell-Larcker at second-order

	IFQ	AIQ	SAT	SEQ	SYQ	TWP	USE
IFQ	**0.737**						
AIQ	0.652	**0.792**					
SAT	0.627	0.655	**0.800**				
SEQ	0.618	0.665	0.614	**0.770**			
SYQ	0.687	0.666	0.641	0.663	**0.712**		
TWP	0.399	0.386	0.476	0.380	0.419	**0.730**	
USE	0.590	0.673	0.648	0.555	0.609	0.433	**0.790**

Table: 7 HTMT ratio at second-order

	IFQ	AIQ	SAT	SEQ	SYQ	TWP	USE
IFQ							
AIQ	**0.801**						
SAT	**0.832**	**0.837**					
SEQ	**0.762**	**0.798**	**0.791**				
SYQ	0.890	0.830	0.868	0.837			
TWP	0.473	0.432	0.586	0.436	0.508		
USE	0.789	0.869	0.907	0.721	0.835	0.540	

Table: 8 Heterotrait-monotrait ratio (HTMT) - Confidence intervals at second-order (Selected projects)

	Original sample (O)	Sample mean (M)	2.5%	97.5%
SYQ <-> IFQ	0.890	0.890	0.832	0.944
SYQ <-> SAT	0.868	0.868	0.787	0.942
USE <-> AIQ	0.869	0.869	0.806	0.926
USE <-> SAT	0.907	0.909	0.829	0.985

2. Structural Modelling Analysis

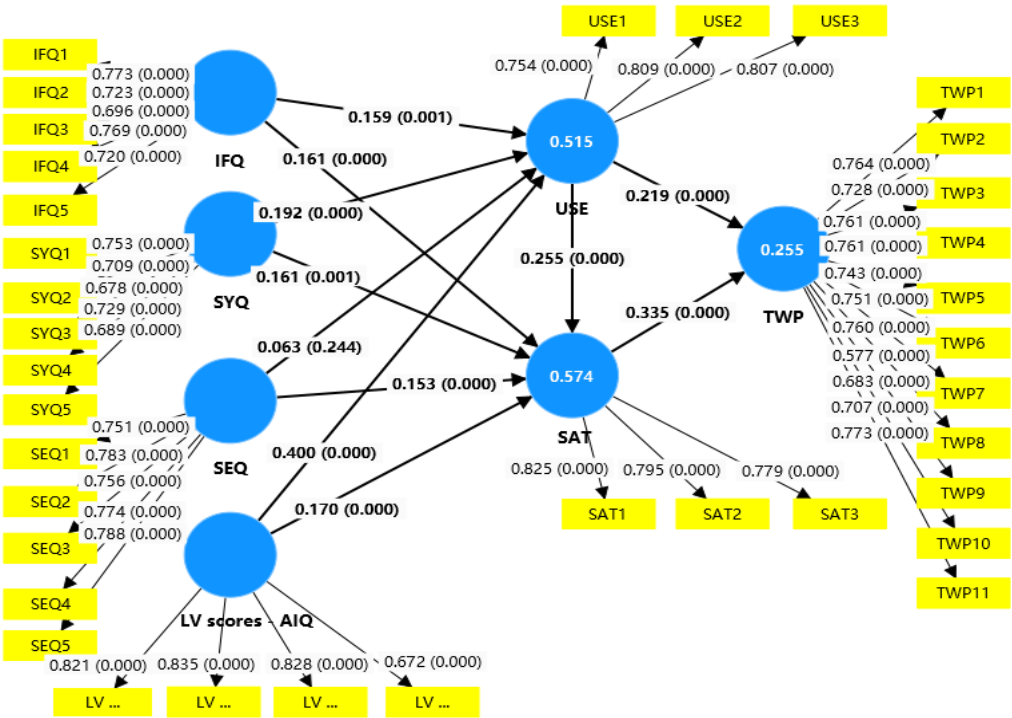
2.1 Path Coefficients and Hypothetical Results

This section employs path coefficient estimation to assess the association and significance of structural relationships. The path coefficients (β values) are generally understood to range from -1 to +1. A coefficient that approximates -1 signifies a robust negative correlation, whilst a coefficient that approximates +1 signifies a robust positive correlation. A coefficient is deemed to be significant when the p-value is less than 0.05, and the 95% confidence interval does not include zero. The findings suggest that, with the exception of Hypothesis 3, all ten hypotheses are substantiated. In particular, information quality (β = 0.159, p = 0.001) and system quality (β = 0.192, $p < 0.001$) both exerted a significant positive influence on utilisation. Therefore, H1 and H2 were accepted. However, service quality did not have a significant effect on usage (β=0.063, p=0.244), and the 95% confidence interval included zero, so H3 was rejected. However, information quality (β = 0.159, $p < 0.001$), system quality (β = 0.152, p = 0.001), and service quality (β = 0.139, $p < 0.001$) all had a significant positive effect on satisfaction. Thus, H4, H5, and H6 were supported. The significant positive influence between usage and satisfaction (β = 0.255, $p < 0.001$) was once again proven, and H7 was supported. In addition, the study established a substantial positive correlation between AI quality and usage (β = 0.400, $p < 0.001$) and satisfaction (β = 0.170, p < 0.001). Consequently, H8 and H9 were substantiated. Finally, it is evident that usage (β = 0.219, p < 0.001) and satisfaction (β = 0.335, p < 0.001) exert a significant positive influence on work performance. And, H10 and H11 were supported.

Table: 9 Structural model results

Hypotheses	Direct paths	Original sample (O) β	P values	CI		f^2	Results
H1	IFQ -> USE	0.159	0.001	0.060	0.252	0.023	Supported
H2	SYQ -> USE	0.192	0.000	0.105	0.282	0.031	Supported
H3	SEQ -> USE	0.063	0.244	-0.043	0.171	0.004	Rejected
H4	IFQ -> SAT	0.161	0.000	0.082	0.237	0.026	Supported
H5	SYQ -> SAT	0.161	0.001	0.064	0.258	0.024	Supported
H6	SEQ -> SAT	0.153	0.000	0.078	0.231	0.025	Supported
H7	USE -> SAT	0.255	0.000	0.174	0.333	0.074	Supported
H8	AIQ -> USE	0.400	0.000	0.310	0.488	0.143	Supported
H9	AIQ -> SAT	0.170	0.000	0.072	0.266	0.026	Supported
H10	USE -> TWP	0.219	0.000	0.129	0.307	0.037	Supported
H11	SAT -> TWP	0.335	0.000	0.243	0.421	0.087	Supported

Figure: 2 Result of the structural model



2.2 Explanatory Power (R^2)

The coefficient of determination (R^2) is a measure of how well a statistical model explains the variability in observed data (Chin, 1998). The closer the R^2 value is to 1, the better the model fits the data, indicating a higher degree of explanation of the dependent variable by the independent variables. The results show that the R^2 values for satisfaction, usage, and work performance are 0.574, 0.255, and 0.515, respectively. The model's predictive validity is supported by the evaluation criteria proposed by Joseph F. Hair, Risher, Sarstedt, and Ringle (2019) and Chin (1998). The model demonstrates adequate explanatory power in predicting satisfaction, usage, and work performance, thereby underscoring its validity and practicality.

2.3 Predictive Power ($PLS_{predict}$)

Joseph F Hair et al. (2021) provide evaluation criteria that require the $PLS_{predict}$ method to assess the model's out-of-sample predictive ability. This methodological approach ensures the generalizability of the findings to other datasets. These criteria employ LM as the baseline for the purpose of comparing the prediction errors of PLS-SEM and LM (Joseph F. Hair et al., 2019).

This study utilizes root mean square error (RMSE) and mean absolute error (MAE) as evaluation metrics. Through a thorough analysis of the distribution characteristics of prediction errors, it was determined that they manifest a symmetrical distribution pattern. Consequently, the RMSE was selected as the primary metric for evaluating the efficacy of the visualization. A comparison of the RMSE values of PLS-SEM with the LM benchmark reveals that, with the exception of three indicators, the RMSE values of all other indicators in the PLS-SEM analysis demonstrate reduced prediction errors. Specifically, PLS-SEM exhibited notable advantages in the prediction of most key indicators, including satisfaction, usage, and work performance. This finding not only corroborates the model's medium to high level of predictive ability but also further accentuates its significant advantages in practical application scenarios.

Table: 10 PLSpredict results

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-LM
SAT1	0.398	0.634	0.641	-0.007
SAT2	0.322	0.750	0.760	-0.010
SAT3	0.307	0.835	0.857	-0.022
TWP1	0.095	0.880	0.881	-0.001
TWP2	0.086	0.939	0.949	-0.010
TWP3	0.110	0.923	0.909	0.014
TWP4	0.122	0.955	0.963	-0.008
TWP5	0.083	0.947	0.953	-0.006

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-LM
TWP6	0.126	0.963	0.970	-0.007
TWP7	0.100	0.983	0.996	-0.013
TWP8	0.101	1.105	1.117	-0.012
TWP9	0.118	1.043	1.061	-0.018
TWP10	0.078	1.020	1.021	-0.001
TWP11	0.151	0.946	0.942	0.004
USE1	0.264	0.919	0.929	-0.010
USE2	0.334	0.757	0.753	0.004
USE3	0.339	0.781	0.797	-0.016

2.4 Control Variable Analysis

A multitude of individual factors have been identified as potentially influencing teachers' effectiveness in applying intelligent teaching systems. These factors include gender, age, educational background, duration of system use, and technical training experience, among other key variables. A study on the motivational factors influencing Chinese civil servants' use of e-government systems found that men and women have different attitudes toward using e-government systems. Experienced civil servants have a tendency to be accustomed to traditional workflows and are often reluctant to adopt new technologies, as incorporating new technologies into their work requires additional time and effort (Zhan, Wang, & Xia, 2011).

Gunawan and Sinaga (2018) employed the Unified Theory of Technology Acceptance and Use model to examine the impact of gender on the acceptance of "smart city" technology. Their findings confirmed that men and women exhibit divergent patterns in their acceptance and use of smart city technology. Elgohary and Abdelazyz (2020) found that employee gender, age, educational attainment, job position differences, and work experience all influence the implementation of e-government systems. Therefore, this study analyzed five control variables:

gender, age, education level, years of experience using smart education systems, and whether respondents had certificates in information technology skills such as computers, the internet, or artificial intelligence or whether they had participated in training in information technology skills such as computers, the internet, or artificial intelligence.

The findings of the study indicate that gender exerts a substantial positive influence on usage (**β** = 0.155, p = 0.005, f^2 = 0.012). Given that gender was designated as a dummy variable, with males serving as the reference group, the findings suggest that men exert a considerably more substantial influence on usage compared to women.

Table: 11 Impact of Control Variables on Endogenous Variables

Control Variable	Path	Original sample (O) β	P Values	f^2
Gender	Gender -> USE	0.155	0.005	0.012
	Gender -> SAT	-0.012	0.819	0.000
	Gender -> TWP	-0.002	0.977	0.000
Age	Age -> USE	0.132	0.150	0.007
	Age -> SAT	-0.124	0.184	0.007
	Age -> TWP	0.017	0.894	0.000

Control Variable	**Path**	**Original sample (O) β**	**P Values**	**f^2**
Level of education	Level of education -> USE	0.050	0.725	0.000
	Level of education -> SAT	-0.102	0.588	0.002
	Level of education -> TWP	-0.249	0.343	0.006
Years of use	Years of use -> USE	0.070	0.466	0.002
	Years of use -> SAT	0.008	0.882	0.000
	Years of use -> TWP	-0.073	0.456	0.002
Relevant Technology or Training Experience	Relevant Technology or Training Experience -> USE	0.055	0.384	0.001
	Relevant Technology or Training Experience -> SAT	-0.070	0.250	0.002
	Relevant Technology	-0.081	0.216	0.002

Control Variable	Path	Original sample (O) β	P Values	f²
	or Training Experience -> TWP			

3. Robustness Analysis

In the context of structural model testing, the presence of insignificant indicators may be indicative of two distinct scenarios. Firstly, the indicator may genuinely possess an absence of theoretical significance. Secondly, the data structure may manifest heterogeneity. As Joe F. Hair, Ringle, and Sarstedt (2011) have noted, researchers must pay particular attention to the potential impact of heterogeneity on the coefficients of the measurement model. This process is referred to as robustness analysis. The fundamental value of robustness analysis lies in its ability to assess the sensitivity of model results to data assumptions (Sarstedt, Ringle, et al., 2019). The proposed methodology is designed to assist researchers in validating the reliability and stability of the model, excluding interference from outliers or assumption violations, enhancing the credibility of model results, and improving the scientific and methodological rigor of the research. To this end, this study will systematically conduct three robustness tests: potential heterogeneity analysis (FIMIX-PLS), nonlinear effect analysis, and endogeneity analysis.

3.1 Potential Heterogeneity Analysis (FIMIX-PLS)

In the Smart PLS 4 system, the FIMIX function was enabled, starting with one group, and five groups were tested sequentially (Table 12). Based on the data output results, although the sample size distribution within each group was not significantly different ($<$ 3 times) regardless of whether the data were divided into 2, 3, 4, or 5 groups, the EN values for each subgroup were all less than 0.5, indicating that grouping was not necessary (Ringle, 2006). Therefore, the integration results of this study's model are not influenced by potential heterogeneity in the structural model.

Table: 12 Segment Size (segment size) in percent

	Segment1	**Segment2**	**Segment3**	**Segment4**	**Segment5**
%	0.610	0.390			
%	0.500	0.320	0.181		
%	0.293	0.278	0.266	0.162	
%	0.278	0.215	0.201	0.191	0.115

Table: 13 Model selection criteria (FIMIX-PLS)

	Group 1	**Group 2**	**Group 3**	**Group 4**	**Group 5**
AIC (Akaike's information criterion)	4279.048	4100.996	4056.562	4025.486	3987.548
AIC3 (modified AIC with Factor 3)	4293.048	4129.996	4100.562	4084.486	4061.548
AIC4 (modified AIC with Factor 4)	4307.048	4158.996	4144.562	4143.486	4135.548
BIC (Bayesian information criterion)	4341.509	4230.378	4252.867	4288.712	4317.696
CAIC (consistent AIC)	4355.509	4259.378	4296.867	4347.712	4391.696
HQ (Hannan-Quinn criterion)	4303.292	4151.215	4132.758	4127.657	4115.694
MDL5 (minimum description length with factor 5)	4703.351	4979.909	5390.085	5813.619	6230.291
LnL (LogLikelihood)	-2125.524	-2021.498	-1984.281	-1953.743	-1919.774

	Group 1	Group 2	Group 3	Group 4	Group 5
EN (normed entropy statistic)	0.000	0.418	0.416	0.428	0.462
NFI (non-fuzzy index)	0.000	0.487	0.436	0.409	0.418
NEC (normalized entropy criterion)	0.000	372.377	373.474	366.189	344.271

3.2 Nonlinear Effect Analysis

In conventional statistical analysis, researchers generally operate under the assumption that latent variables are linearly related. Nonetheless, this fundamental assumption is frequently not subjected to rigorous testing. In instances where there is an authentic nonlinear association between exogenous and endogenous variables, this unidentified nonlinear effect has the potential to result in biased parameter estimates, consequently affecting the magnitude of the effect and its statistical significance. In addressing this methodological challenge, Joe F. Hair et al. (2011) proposed a systematic method for testing quadratic relationships and established evaluation criteria in their seminal study. This study provided researchers with an operational framework for identifying and validating nonlinear effects. The ensuing analysis yielded results that are delineated in Table 14. With the exception of a single item with a p-value less than 0.05, all other p-values are greater than 0.05. Consequently, the quadratic effect is deemed non-significant, and the relationship between the variables in this study conforms to a linear distribution.

Table: 14 The results of nonlinear effects analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
QE (IFQ) -> SAT	-0.019	-0.027	0.025	0.775	0.438
QE (IFQ) -> USE	-0.061	-0.072	0.033	1.815	0.070

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
QE (SYQ) -> SAT	0.033	0.035	0.028	1.192	0.233
QE (SYQ) -> USE	-0.021	-0.016	0.032	0.643	0.520
QE (SEQ) -> SAT	0.039	0.039	0.023	1.738	0.082
QE (SEQ) -> USE	0.019	0.018	0.037	0.508	0.612
QE (AIQ) -> SAT	-0.083	-0.078	0.030	2.788	0.005
QE (AIQ) -> USE	0.039	0.048	0.031	1.271	0.204
QE (USE) -> SAT	-0.001	0.003	0.026	0.035	0.972
QE (USE) -> TWP	-0.006	-0.001	0.027	0.220	0.826
QE (SAT) -> TWP	-0.001	-0.003	0.027	0.038	0.970

3.3 Endogeneity Analysis

The presence of a statistical correlation between the error terms of exogenous and endogenous variables gives rise to the endogeneity problem (J. Hair, Joe F, Sarstedt, Matthews, & Ringle, 2016). This issue generally originates from errors in model specification, specifically the exclusion of critical explanatory variables. To effectively address this endogeneity bias, the utilization of the Gaussian copula approach is recommended. This method constructs a copula variable to capture the potential correlation between the endogenous variable and the error term, thereby achieving statistical correction for the endogeneity problem (Cheah, Magno, & Cassia, 2023). As illustrated in Table 15, the overwhelming majority of p-values are greater than 0.05, with a mere two p-values falling below 0.05, specifically 0.006 and 0.036. Among them, the p-value of GC (AIQ) -> SAT is 0.036. However, in this study, because the smart education system is mandatory, "loyalty" was not considered, resulting in a p-value less than 0.05. Consequently, it can be concluded that the model under study is free of endogeneity.

Table: 15 The results of endogenous analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
GC (USE) -> SAT	0.019	0.038	0.144	0.129	0.897
GC (USE) -> TWP	0.060	0.068	0.176	0.343	0.731
GC (SAT) -> TWP	0.008	-0.004	0.159	0.051	0.960
GC (IFQ) -> SAT	-0.154	-0.168	0.168	0.917	0.359
GC (IFQ) -> USE	-0.499	-0.504	0.181	2.761	0.006
GC (SYQ) -> SAT	0.221	0.195	0.175	1.262	0.207
GC (SYQ) -> USE	0.031	0.028	0.184	0.169	0.866
GC (AIQ) -> SAT	-0.537	-0.472	0.256	2.098	0.036
GC (AIQ) -> USE	0.357	0.341	0.215	1.664	0.096
GC (SEQ) -> SAT	0.143	0.136	0.129	1.107	0.268
GC (SEQ) -> USE	-0.095	-0.064	0.192	0.496	0.620

Discussion

This study uses a research paradigm that combines theoretical construction and empirical testing to explore the theoretical basis and operational feasibility of integrating AI quality dimensions into information system success models. Subsequently, the extended model is used to empirically analyze the impact of smart education systems in Chinese primary and secondary schools on the work performance of K-12 teachers. The empirical analysis results partially verify almost all of the core propositions of information system success theory. The study finds that AI quality has a significant positive impact on system usage and satisfaction. This finding not only validates the rationality of the theoretical integration but also confirms from an empirical perspective the possibility of adding AI quality as a new independent variable to information system success models. The extended information system success model will be more applicable to the study of AI-embedded information systems.

1. Theoretical Implications

The advent and propagation of AI technology have precipitated a paradigm shift in the manner in which individuals engage in their professional and personal activities. The 2003 update of the information system success models included only the following independent variables: information quality, system quality, and service quality (Delone & Mclean, 2003). Evidently, this information system success theory is no longer adequate to meet the research needs of rapidly iterating AI. The present study is an exploration of this theoretical gap. This study proposes the incorporation of AI quality as a novel independent variable into the information system success model, a development that is particularly pertinent in the current era of rapid advancements in AI technology. The expanded AI-Embedded Information System Model (Figure 1) provides a solid theoretical basis for this research project.

The integration of artificial intelligence technology has significantly contributed to the transformation of the education ecosystem. The technological capabilities of AI have been instrumental in facilitating the development of new products, technologies, business models, and operational methodologies, thereby generating novel prospects for the digital transformation of education (People's Daily - PRC newspaper, 2022). In Chinese primary and secondary schools, an AI-embedded education system known as the "Smart Education System" is currently being implemented. This study utilizes a research paradigm focused on the users of the system in question, specifically Chinese K-12 teachers. The findings of this study illuminate the nuanced relationships that emerge when AI quality factors are integrated into models of information system success. The study's design entailed the formulation of 11 research hypotheses, of which 10 were subsequently validated. One research result does not align with the original information system success theory (Delone & Mclean, 2003). Specifically, the data results reject the hypothesis (H3) that service quality is positively correlated with usage. This finding is consistent with the conclusions of Stefanovic et al. (2016) and Veeramootoo, Nunkoo, and Dwivedi (2018), suggesting that factors related to service quality may not be a primary influence on user behavior in the context of educational information systems.

Furthermore, the integration of AI quality into the information system success models proposed by Delone and Mclean (2003) was nearly optimal. The findings indicated that AI quality had a significant positive impact on usage, surpassing the impact of information quality and system quality. Concurrently, the data outcomes further demonstrated that the positive correlation between AI quality and satisfaction exhibited considerably greater strength in comparison to the remaining three factors. That is to say, AI quality emerged as the predominant factor influencing teacher satisfaction within the context of smart education systems, with information quality, system quality, and service quality following in succession. These findings contribute to the existing body of knowledge surrounding the theory of information system success. Moreover, they underscore the pivotal role of AI quality in the utilization of smart education systems. This research breakthrough offers a more profound comprehension of the present development status and management needs of AI-embedded education systems.

2. Practical Implications

The results of this study will reveal the impact of introducing AI into daily teaching on the work performance of K-12 teachers in China. This initiative aligns with the call to action issued by the United Nations Educational, Social and Cultural Organization (UNESCO): "We are currently operating under a state of significant ignorance regarding the manner in which the implementation of AI technologies impacts the professional performance of educators" (Pedro, Subosa, Rivas, & Valverde, 2019). The expanded AI-Embedded Information System model has been validated in AI-Embedded Education Systems in developing countries, thereby confirming the positive impact of such systems on work performance.

The sample characteristics of this study demonstrate that the interviewed teachers possess high levels of professional qualifications, with 97.5% holding a bachelor's degree or higher qualification and 69.06% possessing qualifications or practical experience in artificial intelligence or information technology. While smart education systems in primary and secondary schools remain in the pilot application stage, data indicates that 71.88% of teachers in pilot schools nationwide have been utilizing the system continuously for over a year. This empirical finding further validates the conclusions of Du, Sun, Jiang, Islam, and Gu (2024), highlighting the critical role of artificial intelligence literacy in K-12 teachers' technology acceptance and continued use behavior. In other words, AI-embedded education systems need to improve AI quality, but at the same time, education administrators should consider providing teachers with more supporting resources and educational training opportunities (Hong, 2022) to ensure the effective use of data and information and familiarity with system operation processes. The research data also indicates that 11.25% of the surveyed teachers are aged 40 or older. Wardat, Tashtoush, Alali, and Saleh (2024) have noted that in the face of educational informatisation transformation, senior teachers often need to invest more time and effort into learning to adapt to new intelligent teaching systems. Given this practical challenge, this study recommends that age factors be fully considered when developing artificial intelligence-based educational systems with age-friendly design enhancements to improve user experience. Examples of such interfaces include high-contrast, large-font display interfaces, options to switch to simplified operation workflows, step-by-step guidance prompts, intelligent batch processing, and one-click operation functions. Drawing upon the findings of this real-world challenge, the study puts forward the recommendation that age factors be given full consideration during the development of AI education systems.

Furthermore, it calls for the enhancement of user experience through the implementation of age-friendly design principles. Examples of such interfaces include high-contrast displays, large fonts, simplified operation process switching, step-by-step operation guidance prompts, intelligent batch processing, and one-click operation functions. Moreover, the study revealed significant gender differences, namely that male teachers use smart education systems significantly more than their female counterparts. Therefore, in promoting intelligent education, it is necessary to establish a gender-sensitive technical support system, which is not only a matter of technical promotion efficiency but also an important manifestation of educational equity.

3. Limitations and Future Studies

This study established that, despite the advancement observed, there are also certain limitations that require consideration. The study utilized published pilot schools as a sample framework; however, these pilot schools are predominantly located in urban areas, resulting in a paucity of data from rural, mountainous or remote regions. The collection of data was dependent on self-reporting methods, which have been shown to be subject to bias due to individual differences in social expectations or self-awareness among respondents (Contzen, De Pasquale, & Mosler, 2015). It is possible that certain respondents may have exaggerated their work performance or attempted to conceal their feelings of anxiety, which may have had a distorting effect on the survey results.

Recommendation

Recommendations from the Research

1. AI System Development

Emphasis should be placed on system quality and information quality, particularly the accuracy, transparency, and explainability of AI systems. These qualities build trust and satisfaction among teachers who use the system.

1. User Support (Service Quality) Educational institutions and system developers should provide continuous technical and professional support, such as user manuals, helpdesk platforms, and advisory teams to ensure that teachers can utilize the system effectively.

2. Impact on Teachers' Work Performance AI-embedded education systems should primarily aim to reduce repetitive tasks—such as grading and performance analysis—so that teachers can devote more time to designing creative learning experiences and enhancing instructional innovation.

3. Policy and Management School administrators and policymakers should promote AI adoption in ways that preserve teachers' professional autonomy while ensuring fairness, safety, and data ethics through responsible AI policies.

Recommendations for Future Research

1. Expanding Variables and Conceptual Frameworks Future studies should include psychological and behavioral factors such as *technostress*, *digital self-efficacy*, and *trust in AI* to provide a more comprehensive explanation of the relationship between AI usage and teachers' work performance.

2. Adopting Mixed Methods Future research should employ both quantitative methods (e.g., surveys, system log data) and qualitative methods (e.g., in-depth interviews, classroom observations) to capture the multifaceted mechanisms of AI use in education.

3. Comparative Studies across Educational Levels and Disciplines Further research should involve teachers from different educational levels (primary, secondary, higher education) and across various disciplines (STEM, humanities, social sciences) to compare potential variations in AI’s impact on work performance.

4. Experimental and Longitudinal Designs Future studies should consider experimental designs or long-term follow-up studies to assess the sustainability and continuity of AI’s effects on teachers’ efficiency, satisfaction, and instructional quality.

References

Agba, M. S., Agba, G. E. M., & Obeten, A. W. (2023). Artificial Intelligence and Public Management and Governance in Developed and Developing Market Economies. Journal of Public Administration, Policy and Governance Research, 1(2), 1-14.

Ali, A., & Haider, S. Z. (2017). Developing a Validated Instrument to Measure Teachers' Job Performance: Analyzing the Role of Background Variables. Journal of Educational Research, 20(1), 21.

Analytics, M. (2020). Global survey: The state of AI in 2020. Image.

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., Trench, M. (2017). Artificial intelligence – the next digital frontier. Retrieved from

Chan, C. K. Y., & Tsi, L. H. Y. (2023). The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. ArXiv, abs/2305.01185.

Cheah, J.-H., Magno, F., & Cassia, F. (2023). Reviewing the SmartPLS 4 software: the latest features and enhancements. Journal of Marketing Analytics, 12(1), 97-107.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. Modern methods for business research, 295(2), 295-336.

Clark, L. A., & Watson, D. (2016). Constructing validity: Basic issues in objective scale development.

Cochran, W. G. (1977). Sampling Techniques, 3rd Edition: Sampling Techniques, 3rd Edition.

Contzen, N., De Pasquale, S., & Mosler, H.-J. (2015). Over-reporting in handwashing self-reports: potential explanatory factors and alternative measurements. PloS one, 10(8), e0136445.

Cui, Y., & Tang, Z. (2019). Practical Analysis of Classroom Application of Intelligent Teaching System. China Information Technology Education Magazine(22), 100-101.

Delone, W. H., & Mclean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. Journal of Management Information Systems, 19(4), 9-30.

Deng, L., Turner, D. E., Gehling, R., & Prince, B. (2017). User experience, satisfaction, and continual usage intention of IT. European Journal of Information Systems, 19(1), 60-75.

Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: a predictive validity perspective. Journal of the Academy of Marketing Science, 40(3), 434-449.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. MIS Quarterly, 39(2), 297-316.

Du, H., Sun, Y., Jiang, H., Islam, A. Y. M. A., & Gu, X. (2024). Exploring the effects of AI literacy in teacher learning: an empirical study. Humanities and Social Sciences Communications, 11(1).

Elgohary, E., & Abdelazyz, R. (2020). The impact of employees' resistance to change on implementing e-government systems: An empirical study in Egypt. The Electronic Journal of Information Systems in Developing Countries, 86(6).Fornell & Larcker, 1981

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Gunawan, H., & Sinaga, B. L. (2018). Analisis Pengaruh Gender Dalam Penerimaan Teknologi "Smart City" Dengan Model Unified Theory of Acceptance and Use of Technology (UTAUT). 349-354.

Guo, c. (2024). Gathering momentum and empowering precision education with "intelligent education system". Political Work Journal, (01), 44-45.

He, C. (2023). Research on the Current Situation and Development of Local Digital Governance in China—Taking the Hunan Provincial Government Service Hall as an Example. Sustainable Development, 13(03), 990-996.

Hong, J.-W. (2022). I was born to love AI: The influence of social status on AI self-efficacy and intentions to use AI. International Journal of Communication, 16, 20.

Hu, Q. (2019). Review and Prospect: History and Future of Education Informatization Development in China. E-education Research, 40(12), 5-13.

Huang, X. (1983). Adapting to the needs of the development of education and endeavouring to create a new situation for e-learning work. E-education Research(04), 1-8.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2016). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management & Data Systems, 117(3), 442-458.

Zhao, J. (2021). Teachers' Workload in the Digital Era: A New Perspective of Understanding the Digital Transformation of Education. Journal of Educational Research, 42(11), 151-159. Jin, Jin, & Qing, 2023;

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. Journal of Marketing Theory and Practice, 19(2), 139-152.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook: Springer Nature.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). Multivariate Data Analysis. Prentice Hall.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration (ijec), 11(4), 1-10.

Zhao, L., Zhang, L., Zhang, L., & Zhao, K. (2022). Artificial Intelligence Anxiety of Primary and Secondary School Teachers: Current Situation Analysis and Elimination Direction. Journal of Modern Educational Technology, 32(03), 81-91.

Li, S., Hu, Y., & Gu, X. (2021). How to Get Out of the Dilemma of Artificial Intelligence Education Risk: Phenomenon,Causes and Countermeasures. Journal of Electrochemical Education Research, 42(07), 19-25.

Lian, Y. (2021). Smart Education: Education Reform in the Age of Intelligence. Paper presented at the 2021 5th International Conference on Education and E-Learning.

Mellouli, M., Bouaziz, F., & Bentahar, O. (2020). E-government success assessment from a public value perspective. International Review of Public Administration, 25(3), 153-174.

Miller, B. K., & Simmering, M. J. (2022). Attitude Toward the Color Blue: An Ideal Marker Variable. Organizational Research Methods, 26(3), 409-440.

Ministry of Education of the People's Republic of China. (2024a). Artificial Intelligence in Primary and Secondary Schools List of Education Bases. Retrieved from http://www.moe.gov.cn/srcsite/A06/s3321/202402/t20240223_1116386.html

Mu, H.-L., Xu, J., & Chen, S. (2023). The impact of corporate social responsibility types on happiness management: a stakeholder theory perspective. Management Decision, 62(2), 591-613.

Noor, N., Rao Hill, S., & Troshani, I. (2021). Recasting Service Quality for AI-Based Service. Australasian Marketing Journal, 30(4), 297-312.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development.

Peng, Z., & Wan, Y. (2023). Human vs. AI: Exploring students' preferences between human and AI TA and the effect of social anxiety and problem complexity. Education and Information Technologies, 29(1), 1217-1246.

People's Daily - PRC newspaper. (2022). Artificial Intelligence for Transformative Innovation in Education. Retrieved from http://www.moe.gov.cn/jyb_xwfb/s5148/202212/t20221222_1035689.html

Peterson, R. (1997). A quantitative analysis of rating-scale response variability. Marketing Letters, 8, 9-21.

R is, J., Santo, P. E., & Melão, N. F. (2019). Impacts of Artificial Intelligence on Public Administration: A Systematic Literature Review. 2019 14th Iberian Conference on Information Systems and Technologies (CISTI), 1-7.

Kim, S.-Y., & Kim, M.-R. (2013). Comparison of Perception toward the Adoption and Intention to Use Smart Education between Elementary and Secondary School Teachers. Turkish Online Journal of Educational Technology-TOJET, 12(2), 63-76.

Sarstedt, M., Ringle, C. M., Cheah, J.-H., Ting, H., Moisescu, O. I., & Radomir, L. (2019). Structural model robustness checks in PLS-SEM. Tourism Economics, 26(4), 531-554.

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM. Australasian Marketing Journal, 27(3), 197-211.

Shoikova, E., Nikolov, R., & Kovatcheva, E. (2017). Conceptualising of smart education. Electrotechnica & Electronica (E+ E), 52.

Stefanovic, D., Marjanovic, U., Delić, M., Culibrk, D., & Lalic, B. (2016). Assessing the success of e-government systems: An employee perspective. Information & Management, 53(6), 717-726.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53-55.

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an e-government service? Validation of an integrative model of e-filing continuance usage. Government Information Quarterly, 35(2), 161-174.

Wang, X., Li, L., Tan, S. C., Yang, L., & Lei, J. (2023). Preparing for AI-enhanced education: Conceptualizing and empirically examining teachers’ AI readiness. Computers in Human Behavior, 146.

Wardat, Y., Tashtoush, M., Alali, R., & Saleh, S. (2024). Artificial Intelligence in Education: Mathematics Teachers’ Perspectives, Practices and Challenges. Iraqi Journal For Computer Science and Mathematics, 5(1), 60-77.

Wibowo, W. S., Fadhil, A., Sensuse, D. I., Lusa, S., Putro, P. A. W., & Yulfitri, A. (2023). Pinpointing Factors in the Success of Integrated Information System Toward Open Government Data Initiative: A Perspective from Employees. International Journal of Advanced Computer Science and Applications, 14(1).

Xu, X., Wang, Y., & Yu, S. (2018). Teaching Performance Evaluation in Smart Campus. IEEE Access, 6, 77754-77766.

Zhao, Y. (2020). Research on the Smart Teaching Mode of College English Based on Super Star Pan-Asia Smart Teaching System. Science and Technology Perspectives Magazine(35), 61-63.

Zhan, Y., Wang, P., & Xia, S. (2011). Exploring the Drivers for ICT Adoption in Government Organization in China. Paper presented at the 2011 Fourth International Conference on Business Intelligence and Financial Engineering.