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Current Situation and Promotion of TPACK Strategies Among Primary School English Teachers in The Era of Artificial Intelligence

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ABSTRACT

The study examines how primary school English teachers in Luoyang City, China, developed Technological Pedagogical Content Knowledge (TPACK) in the AI era, focusing on identifying key predictors of TPACK proficiency and contextual barriers to AI integration. It aims to bridge gaps in understanding how socioecological factors shape teachers' technology adoption. A mixed-methods design was employed, combining a TPACK questionnaire (n=200) validated via factor analysis (KMO=0.802, α=0.85–0.92) and semi-structured interviews (n=25). Hierarchical regression and thematic analysis were used to analyze quantitative and qualitative data. Quantitative results revealed PCK, TCK, and TPK as significant TPACK predictors (adjusted R^2=0.76), while qualitative themes highlighted pedagogical adaptation challenges, institutional resource gaps, identity shifts, and urban-rural inequities. Infrastructural constraints and policy-practice disconnects mediated AI's potential. The study calls for context-sensitive AI training programs, equitable resource distribution and policies prioritizing pedagogical agency over technocentric mandates. Schools should foster PLCs to support TPACK development in low-resource settings. The study extends TPACK theory by integrating socioecological perspectives, offering a holistic view of AI's role in language education. It uniquely addresses China's urban-rural divide, providing empirical insights into equity challenges in AI-driven TPACK development.

Keywords: Artificial Intelligence, Primary School English Teachers, TPACK, Current Situation Investigation

1. INTRODUCTION

Technological Pedagogical Content Knowledge (TPACK) is the ability of teachers to organically integrate technological knowledge, subject content knowledge, and pedagogical knowledge. Some scholars have pointed out that in the era of artificial intelligence, the importance of this integration has become more prominent (Chan & Tang, 2025). "Technology Integration in the Cultivation of Normal Students' Abilities in the Era of Artificial Intelligence" mentions that the dynamics of artificial intelligence technology have promoted the TPACK framework to be upgraded to AI -TPACK. It means that teachers not only need to master subject knowledge and teaching methods but also be proficient in using technologies such as intelligent voice evaluation and adaptive learning systems to optimize the teaching process and improve teaching effectiveness. Moreover, they must possess the "technological wisdom" to deal with intelligent education scenarios (Karataş & Ataç, 2024).

The Education Informatization 2.0 Action Plan vigorously promoted the application of technology in the educational field. It shows that this policy encourages teachers to explore the in-depth integration of information technology and English teaching in primary school English teaching. It guides schools to increase investment in teaching technology equipment, such as equipping intelligent voice teaching equipment and multimedia teaching software. Additionally, it promotes the creation of training programs for teacher technology application skills, which will help English teachers in elementary schools raise their TPACK proficiency (Yan and Yang, 2021). Some scholars point out that regional differences, such as the configuration of technological equipment in urban and rural areas and the implementation degree of teacher training policies, may significantly affect the TPACK level, and targeted strategies must be proposed through local empirical research (Li, 2024).

The study introduces critical novelty by addressing underexplored dimensions of AI-integrated TPACK in primary school English education, particularly within the unique socio-political and regional context of Luoyang City, Henan Province, a resource-rich yet under-researched locale in China's educational landscape. While existing literature highlights the conceptual evolution of TPACK into AI-TPACK (Chan & Tang, 2025) and critiques systemic challenges like urban-rural disparities (Guo & Li, 2024), this research uniquely bridges these discourses by empirically analyzing how AI-driven TPACK manifests in a region marked by contrasting infrastructural realities (urban, fringe, rural schools) and policy-driven technological mandates like the Education Informatization 2.0 Action Plan (Yan & Yang, 2021). By focusing on Luoyang, the study fills a geographic and empirical gap by offering granular insights into how resource abundance coexists with localized inequities, such as fragmented teacher training and uneven AI tool adoption—a paradox seldom addressed in prior TPACK frameworks. Furthermore, it pioneers the integration of "technological wisdom" within AI-TPACK, examining how teachers negotiate intelligent voice systems and adaptive platforms amid policy pressures and technological anxiety (Karataş & Ataç, 2024). This dual focus on contextualized policy implementation and teacher agency in AI adaptation advances TPACK scholarship beyond theoretical upgrades, providing a replicable model for regions navigating similar tensions between technological advancement and equitable pedagogical integration.

2. LITERATURE REVIEW

Technological Pedagogical Content Knowledge (TPACK) has become a paramount framework for teachers to incorporate technology, pedagogy, and knowledge of content in modern classrooms (Chen, 2023). On the surface of primary school English education, the advent of artificial intelligence (AI) has created opportunities and challenges in applying TPACK. However, existing literature points out that primary school English teachers are aware of the potential of AI tools (Intelligent tutoring systems, language learning apps and automated platforms of assessment) to help them pedagogically, while their ability to use these technologies is not consistent (Ning et al., 2024; Karataş & Ataç, 2024). Evidence indicates that most educators are technically capable but do not use pedagogical strategies to put AI tools to the curriculum goals for varying learner needs (Shoukat et al., 2024).

As AI's potential in the natural language process and personalized learning have great possibilities to change the instruction experiences in language education, this gap underscores the need to rethink how TPACK development will take place in the AI age. According to current studies, institutional support, professional development opportunities, and availability of AI resources shape primary school English teachers' TPACK proficiency. For instance, a survey by Celik (2023) found that teachers in more resource schools were more confident about integrating AI-driven tools – chatbots – for conversational practice than teachers in under-resources. It was an issue of infrastructural and training barriers. Likewise, Chan & Tang (2025) discovered that collaborative professional learning communities (PLCs) provided teachers with a chance to experiment with AI applications by using peer-driven experimentation with applications of AI, for example, educational teaching applications like adaptive learning platforms designed for language acquisition. However, the rapid advance in AI technologies exceeds the capability of the teachers to keep abreast of the evolution (Yue et al., 2024; Darazi et al., 2023), and such neglect results in the superficial use of AI tools for mere tool usage without any real pedagogical integration. The lack of localized context-driven training programs that address the specific needs of English language education, such as AI-mediated communication-based communicative competence development, exacerbates this situation.

In the AI era, systemic support structures have been emphasized to promote TPACK in teaching English in primary schools. Yue et al. (2024) suggest that models of iterative learning during PD should include "hands-on exploration of AI tools" and pedagogical mentoring to support teachers' critical evaluation of how technologies support language learning theories. If teachers are trained to scaffold the use of AI-powered storytelling apps within constructivist frameworks, thematic areas such as inventing, analyzing, and composing characters, composing for the dialogue landscape, and composing for the setting are advanced. Moreover, institutional policies are important, and schools where AI literacy is taught as part of the curriculum and where there is an opportunity for TPACK collaboration have higher teacher efficacy (Tseng et al., 2022).

Finally, emerging strategies capture the use of teacher autonomy to innovate with AI: case studies of educators repurposing generative AI tools like ChatGPT to create interactive role-play scenarios in which content knowledge is blended with creative pedagogy (Khoso et al., 2022). Even so, scholars advise against a techno-centric approach that ignores the depth of content or student equity. AI's data-driven insights must not undermine but augment teachers' knowledge in dealing with socio-cultural nuances of language teaching. Finally, gaps exist in how TPACK develops amid AI saturation, especially on ethics issues and how to maintain humanistic teaching and balance AI efficiencies. Longitudinal impacts of AI-focused TPACK training on student outcomes and culturally responsive training plans for global contexts need further exploration in future research. If the academic community can better teach these dimensions, primary school English teachers would be more capable of using AI to transform existing education without forgetting the crucial human touch.

2.1 Theoretical Framework

The study is grounded in the Technological Pedagogical Content Knowledge (TPACK) framework and conceptualized by Mishra & Koehler (2006), which suggests that technology integration in education is effective when a teacher's technological knowledge (TK), pedagogical knowledge (PK) and content knowledge (CK) interact dynamically. Expanding Shulman's (1986) important idea of pedagogical content knowledge (PCK), TPACK concentrates on technology as an agent of change in teaching.

The seven components of TK, PK, CK, PCK, TCK, TPK, and TPACK are interconnected and collectively constitute a lens through which one can observe how teachers synthesize expertise in these domains to design contextually appropriate technology uses in instruction. The TPACK framework is instantiated through two complementary theoretical extensions. First, using the work of DeSanctis & Poole (1994) to examine the adoption of AI tools into teaching practices, instead of being deterministic, technology adoption is mediated by teachers' interpretive flexibility and institutional norms. That also aligns with the focus of the study on how primary school English teachers engage in making use of the affordances of AI (personalization-based, automated feedback) within and against prior pedagogical routines. In the second part, the technology acceptance model (TAM) (Davis, 1989) is applied to study how teachers' perception of AI's usefulness and ease of use admits their AI TPACK development. We synthesize TPACK with these theories and bridge micro-level pedagogical decisions (using chatbots as a vocabulary practice approach) to macro-level systemic enablers or constraints (disparities between urban and rural schools regarding technology access and resources).

Also, the framework supports the idea that Luoyang City should be chosen as a case study. With China's current top-down reform of the 'Smart Education' policy that compels AI integration in the classroom, this policy creates a unique socioecological context that incentivizes or pressures TPACK to develop. This study fills this gap in the literature on TPACK by claiming that by placing TPACK in its policy landscape, it becomes apparent how macro-level dictates work with teachers' school environments and micro-level classroom practices. Additionally, the stratified sampling (based on urban, fringe, and rural areas) used in the framework is grounded on the equity (via socioecological theory) premise on which the stratified sampling is put together to ensure that TPACK is addressed in light of infrastructural and training disparities on TPACK.

3. METHODOLOGY

3.1 Research Design

The study employed a mixed-methods research design to comprehensively explore primary school English teachers' TPACK development in the context of artificial intelligence (AI). The sequential approach begins with a quantitative phase and utilizes a structured questionnaire to collect data on teachers' self-reported TPACK levels, influencing factors and AI integration practices. It establishes a broad understanding of trends and correlations within the sample. The qualitative phase involves semi-structured interviews with a subset of questionnaire participants to contextualize quantitative findings. It uncovers nuanced challenges and gathers actionable insights into pedagogical practices. Such a design ensures methodological triangulation by balancing statistical generalizability with an in-depth exploration of individual experiences. Integrating quantitative and qualitative data enables a holistic analysis of how AI tools intersect with pedagogical strategies, content delivery and institutional dynamics in shaping TPACK competencies.

3.2 Sampling Technique

A stratified purposive sampling technique was adopted to ensure diversity and representativeness across key demographic and professional variables. Participants were selected from primary school English teachers in Luoyang City, Henan Province, stratified by geographic location (urban, urban-rural fringe, and rural areas) with teaching experience (≤3 years, 4–10 years, ≥11 years), educational background (junior college, undergraduate, postgraduate) and professional titles (unranked to senior teachers). This stratification ensured the proportional inclusion of subgroups, mitigating selection bias and enhancing the sample's capacity to reflect the heterogeneity of teaching contexts. Schools were approached through district education bureaus, with participation voluntary and anonymized to minimize institutional pressure.

3.3 Sample Size

The study targeted 200 primary school English teachers, a sample size chosen by pragmatic resource availability and regression analysis. The initial outreach generated 220 potential participants, with 200 valid responses maintained after discarding incomplete or inconsistent questionnaires, for a 91% valid response rate. Post-hoc power analysis confirmed the adequacy of the sample for detecting moderate effect sizes in multivariate analyses. The final cohort included balanced representation across strata, with 68 urban, 62 urban-rural fringes and 70 rural teachers. It ensures analytical robustness when comparing regional disparities.

3.4 Data Collection Tools

Quantitative data were gathered using a 35-item TPACK measurement scale adapted from established frameworks (Mishra & Koehler, 2006; Schmidt, 2004), contextualized for primary English education and AI integration. The questionnaire comprised three sections: (1) demographic variables (gender, experience, qualifications), (2) TPACK proficiency across seven domains (TK, CK, PK, PCK, TCK, TPK, TPACK) using a 5-point Likert scale, and (3) seven influencing factors (training, school support, self-efficacy). Cognitive pretesting with 15 teachers ensured item clarity and cultural relevance. Qualitative data was collected via semi-structured interviews with 25 purposively selected participants, focusing on AI tool usage, TPACK application challenges and improvement strategies. Interviews averaging 30–45 minutes were audio-recorded and transcribed verbatim.

3.5 Data Analysis Technique

Quantitative data were analyzed using SPSS 27.0, with descriptive statistics summarizing TPACK levels and demographic distributions. Reliability was assessed via Cronbach's alpha ($\alpha \geq 0.82$ for all scales). Exploratory factor analysis (EFA) validated the TPACK construct's dimensionality, while multiple regression identified predictors of TPACK proficiency. Qualitative data underwent thematic analysis (Braun & Clarke, 2006); transcripts were coded inductively using NVivo 12, with emergent themes ("AI adaptability gaps," "training inadequacies") triangulated against quantitative patterns. Mixed-methods integration occurred at the interpretation stage, with joint displays juxtaposing survey trends against interview narratives to explain contradictions.

3.6 Reliability and Validity Tests of the Questionnaire

Reliability and validity tests were rigorously conducted to ensure the robustness of the questionnaire. Reliability was assessed using Cronbach's alpha coefficients, which ranged from 0.85 to 0.92 for all subscales and the overall scale, which exceeds the recommended threshold of 0.70 for internal consistency in social science research (George & Mallery, 2019). These results confirm the questionnaire's high reliability in measuring TPACK constructs consistently.

Structural validity was evaluated through exploratory factor analysis (EFA) using SPSS, while Kaiser-Meyer-Olkin (KMO) measures samples' adequacy yielded a value of 0.802, classified as "meritorious" for factor analysis. At the same time, Bartlett's test of sphericity demonstrated significance ($\chi^2 = 2050.314$, $p < 0.001$), indicating sufficient intercorrelations among variables for factor extraction (Kaiser, 1974; Lakens et al., 2018). Content validity was ensured through iterative revisions based on expert reviews (five scholars in educational technology and English pedagogy) and a pilot test with 15 primary school teachers, refining item clarity and relevance to AI-integrated TPACK contexts.

Before conducting hierarchical multiple regression analysis, key statistical assumptions were tested to validate the robustness of the results. Sample size adequacy was confirmed using the "10 cases per predictor" rule (Tabachnick & Fidell, 2007), with 200 cases exceeding the minimum requirement for the seven predictors in the model. Normality was assessed via Shapiro-Wilk tests ($W > 0.97$, $p > 0.05$) and visual inspection of Q-Q plots, revealing no significant deviations from normality for dependent variables (TPACK scores). Linearity was verified through partial regression plots and a non-significant Lack-of-Fit test ($F = 1.12$, $p = 0.32$), indicating linear relationships between predictors and the outcome variable. Multicollinearity was evaluated using variance inflation factors (VIF) and tolerance values, with all VIFs < 3.0 (tolerance > 0.33), well below the critical thresholds of VIF > 10 and tolerance < 0.10 (Hair et al., 2019). Homoscedasticity was confirmed via visual analysis of standardized residual plots, which displayed random dispersion without funnel-shaped patterns (Pallant, 2020). These diagnostic tests collectively affirmed the suitability of the data for regression modelling, minimizing the risk of Type I/II errors and ensuring the validity of inferential conclusions.

Table 1: Diagnostic Test Results for Multicollinearity and Homoscedasticity

Assumption	**Test/Method Used**	**Result**	**Interpretation**
Multicollinearity	Variance Inflation Factor (VIF)	All VIFs < 3.0	No significant multicollinearity (VIF < 10; Tolerance > 0.10 thresholds met)
	Tolerance Values	Tolerance > 0.33	
Homoscedasticity	Visual inspection of	Random dispersion of residuals	Residual variance constant across predicted values; assumption upheld
	standardized residual plots	(no funnel-shaped pattern)	

3.7 Ethical Considerations

Informed consent protocols were followed so participants understood the study's purpose, voluntary nature and data anonymization procedures. Multiple fields were replaced with codes before data entry to protect confidentiality. The right not to participate was retained for the participants at any time without further repercussions. Interview recordings were stored on password-protected devices kept out of reach by the research team. The equal participation of rural teachers without internet access was given offline questionnaire support to mitigate power imbalances. Results will be published via academic media, and the author will declare any commercial or institutional conflicts of interest.

4. RESULTS AND DISCUSSION

4.1 Current Situation of Primary School English Teachers' TPACK Level

Table 2 shows that the overall TPACK ability of primary school English teachers is at a medium level, with an average score of 3.35 points (out of 5 points). The scores of each factor are as follows: Content Knowledge (CK) has the highest score, with a mean value of 3.62 points, indicating that teachers have a relatively solid grasp of English subject knowledge; Pedagogical Knowledge (PK) has a mean value of 3.48 points, indicating that teachers have specific experience in the application of teaching methods; Pedagogical Content Knowledge (PCK) has a mean value of 3.42 points, indicating that teachers perform well in integrating subject knowledge and teaching methods; Technological Content Knowledge (TCK) has a mean value of 3.25 points, and Technological Pedagogical Knowledge (TPK) has a mean value of 3.20 points, reflecting that there is room for improvement in teachers' integration of technology with subject content and teaching methods; Technological Knowledge (TK) has the lowest score, with a mean value of only 3.05 points, indicating that teachers are relatively weak in the mastery and application of artificial - intelligence - related technologies; Technological Pedagogical Content Knowledge (TPACK) has a mean value of 3.30 points, reflecting that teachers' overall ability to integrate technology into teaching needs to be improved..

Table 2: Scores of Each Dimension of TPACK for Primary School English Teachers

Dimension	Mean Value	Standard Deviation
Technological Knowledge (TK)	3.05	0.85
Content Knowledge (CK)	3.62	0.78
Pedagogical Knowledge (PK)	3.48	0.82
Pedagogical Content Knowledge (PCK)	3.42	0.84
Technological Content Knowledge (TCK)	3.25	0.88
Technological Pedagogical Knowledge (TPK)	3.20	0.90
Technological Pedagogical Content Knowledge (TPACK)	3.30	0.86

4.2 Correlation Analysis among TPACK Factors

Table 3 shows that the Pearson correlation coefficients among the factors are 0.55 - 0.88, indicating a strong correlation. The correlation coefficients between single factors are relatively low, while among composite factors are relatively high. For example, the correlation coefficients between Technological Knowledge (TK) and Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK) and Technological Pedagogical Content Knowledge (TPACK) are 0.62, 0.60, and 0.65, respectively, showing a significant positive correlation, indicating that the improvement of teachers' technological knowledge is conducive to the development of their ability in the integration of technology and teaching. The correlation coefficients between Content Knowledge (CK), Pedagogical Knowledge (PK), and

Pedagogical Content Knowledge (PCK) are 0.70 and 0.75, respectively, indicating that solid subject knowledge has a positive impact on the application of teaching methods and the integration of pedagogical content knowledge.

Table 3: Correlation Analysis among TPACK Factors

Variables	CK	PK	TK	PCK	TCK	TPK	TRACK
CK	1	0.70**	0.58**	0.75**	0.68**	0.65**	0.72**
PK	0.70**	1	0.62**	0.80**	0.75**	0.78**	0.82**
TK	0.58**	0.62**	1	0.65**	0.62**	0.60**	0.65**
PCK	0.75**	0.80**	0.65**	1	0.85**	0.88**	0.85**
TCK	0.68**	0.75**	0.62**	0.85**	1	0.90**	0.92**
TPK	0.65**	0.78**	0.60**	0.88**	0.90**	1	0.90**
TRACK	0.72**	0.82**	0.65**	0.85**	0.92**	0.90**	1

Note: ** represents P<0.001

4.3 Regression Analysis among TPACK Factors

Table 4 shows the total score of TPACK as a dependent variable and each dimensional factor as the independent variable; multiple linear regression analysis explained 78% of the change in the TPACK level (adjusted $R^2 = 0.78$) by Pedagogical Content Knowledge (PCK), Technological Content Knowledge (TCK) and Technological Pedagogical Knowledge (TPK) enter the regression model, and stated that the model is statistically significant ($F = 102.36$, $p < 0.001$). It indicates that in the TPACK framework, the composite factors PCK, TCK, and TPK significantly contribute to developing teachers' TPACK and are the key factors affecting teachers' TPACK ability.

Table 4: Model Summary

Model	R	R^2	Adjusted R^2	SE of Estimate
1	0.88	0.78	0.76	0.4

Table 5(a) shows a powerful predictive relationship, with a multiple correlation coefficient of ($R = 0.88$), indicating that 78% of the variance in TPACK levels ($R^2 = 0.78$) can be explained by the predictors PCK, TCK and TPK. The adjusted R^2 (0.76) is likewise low, indicating little overfitting, and is also high (0.40) regarding standard error of estimate (which is an indicator of how well TPACK scores could be predicted). The model's validity in explaining AI-integrated TPACK development among primary school English teachers is validated.

Table 5(a): Regression Analysis among TPACK Factors

Model	Unstand ardized Coef. B	S. Error	Standardized Coefficient Beta	T	P	VIF	R^2	Adjus ted R^2
1 (Constant)	0.564	0.253	-	2.231	0.027	-	0.78	0.76
PCK	0.352	0.048	0.325	7.333	0.000	1.25	-	-
TCK	0.286	0.045	0.278	6.356	0.000	1.20	-	-
TPK	0.229	0.042	0.221	5.452	0.000	1.15	-	-

Table 5(b) shows the results of ANOVA that the model is statistically significant in predicting TPACK levels of teachers $F (3, 196) = 102.36$, $p < 0.001$). There is a significant difference between the residual sum of squares (13.87) and the regression sum of squares (48.32) because the model accounts for a high percentage of variance in TPACK. The significant F value of 16.11 in the mean square regression table relative to the residual mean square of 0.16 indicates that the collective contribution of PCK, TCK, and TPK to TPACK is significant at a high level (rejecting the null hypothesis that the predictors have no effect), emphasizing the significance of integrative knowledge domains in building AI-enhanced TPACK competencies in primary school English teachers.

Table 5(b): ANOVA Summary for Hierarchical Regression Model

Model	Sum of Squares	df	Mean Square	F	p-value	
1	Regression	48.32	3	16.11	102.36	<0.001
	Residual	13.87	196	0.16		
	Total	62.19	199			

Table 6 reveals that Pedagogical Content Knowledge (PCK), Technological Content Knowledge (TCK) and Technological Pedagogical Knowledge (TPK) are significant positive predictors of teachers' TPACK levels ($p < 0.001$). PCK exhibits the most substantial standardized effect ($\beta = 0.325$), indicating that a one-unit increase in PCK corresponds to a 0.352-unit rise in TPACK, holding another variables constant. TCK ($\beta = 0.278$) and TPK ($\beta = 0.221$) follow, demonstrating that integrating technology with pedagogical and content-specific strategies drives TPACK development. All predictors show low variance inflation factors (VIF < 1.25), confirming minimal multicollinearity. The significant constant term ($B = 0.564$, $p = 0.027$) suggests a baseline TPACK level independent of the model's predictors. It urged the necessity of targeted interventions to enhance integrative competencies in AI-driven teaching contexts.

Table 6: Coefficients for Significant Predictors of TPACK

Predictor	Unstandardized B	SE	Standardized Beta (β)	T	p-value	VIF
Constant	0.564	0.253	-	2.231	0.027	-
PCK	0.352	0.048	0.325	7.333	<0.001	1.25
TCK	0.286	0.045	0.278	6.356	<0.001	1.2
TPK	0.229	0.042	0.221	5.452	<0.001	1.15

4.4 Difference Analysis among TPACK Factors

4.4.1 Teaching Years Difference

Table 7 regarding one-way ANOVA analysis shows that teachers with different teaching years significantly differ in multiple factors of TPACK ability. Teachers with 3 years of teaching experience or less have a relatively high score in the Technological Knowledge (TK) factor, with a mean value of 3.20 points, but have low scores in the Pedagogical Content Knowledge (PCK) and Technological Pedagogical Content Knowledge (TPACK) factors, which are 3.25 points and 3.10 points respectively. It may be because young teachers have a high acceptance of new technologies but lack teaching experience and practical accumulation in integrating subject knowledge and teaching methods and the in-depth integration of technology in teaching. Teachers with 11 years of teaching experience or more have high scores in the Content Knowledge (CK), Pedagogical Knowledge (PK), and Pedagogical Content Knowledge (PCK) factors, which are 3.75, 3.60 and 3.55 points, respectively, but have a low score in the Technological Knowledge (TK) factor, which is only 2.90 points. It may be due to the long-form teaching models and habits that result in their low enthusiasm for learning and applying new technologies.

Table 7: Analysis of Score Differences of Each TPACK Factor among Teachers with Different Teaching Years

Factor	3 Years or Less (n = 60)	4 - 10 Years (n = 80)	11 Years or More (n = 60)	F	P
TK	3.20±0.90	3.00±0.80	2.90±0.75	4.56	0.011
CK	3.40±0.80	3.65±0.75	3.75±0.70	5.67	0.004
PK	3.30±0.85	3.50±0.80	3.60±0.75	4.23	0.016
PCK	3.25±0.85	3.45±0.82	3.55±0.78	3.98	0.020
TCK	3.15±0.90	3.25±0.85	3.30±0.80	2.34	0.100
TPK	3.10±0.95	3.25±0.90	3.30±0.85	2.56	0.080
TRACK	3.10±0.90	3.35±0.85	3.40±0.80	4.01	0.018

4.4.2 Educational Background Difference

The table 8 shows that teachers with different educational backgrounds significantly differ in each TPACK ability factor. Postgraduate-educated teachers generally have higher scores in all factors than undergraduate and junior-college-educated teachers. For example, in the Technological Knowledge (TK) factor, the mean score of postgraduate-educated teachers is 3.30 points, that of undergraduate teachers is 3.00 points, and that of junior college teachers is 2.80 points; in the Technological Pedagogical Content Knowledge (TPACK) factor, the mean score of postgraduate - educated teachers is 3.50 points, that of undergraduate teachers is 3.25 points, and for junior college teachers is 3.05 points. It may be because postgraduate-educated teachers receive more systematic education and research training during their studies, and they have a deeper understanding of and mastery of new technologies and educational theories.

Table 8: Analysis of Score Differences of Each TPACK Factor among Teachers with Different Educational Backgrounds

Factor	Junior College (n = 30)	Undergraduate (n = 130)	Postgraduate (n = 40)	F	P
TK	2.80±0.75	3.00±0.82	3.30±0.88	7.89	0.000
CK	3.30±0.70	3.60±0.76	3.80±0.72	8.91	0.000
PK	3.25±0.80	3.45±0.82	3.70±0.78	6.78	0.001
PCK	3.15±0.85	3.40±0.84	3.60±0.80	7.12	0.000
TCK	3.05±0.90	3.20±0.88	3.50±0.85	8.56	0.000
TPK	3.00±0.95	3.15±0.92	3.40±0.90	7.45	0.000
TRACK	3.05±0.90	3.25±0.86	3.50±0.83	8.23	0.000

4.4.3 Professional Title Difference

Table 9 shows that teachers with different professional titles significantly differ in each TPACK ability factor. In this way, senior teachers have high scores in the Content Knowledge (CK), Pedagogical Knowledge (PK) and Pedagogical Content Knowledge (PCK) factors 3.80, 3.70 and 3.60 points, respectively, but have relatively low scores in the Technological Knowledge (TK) factor, which is 2.85 points. First-level teachers perform very well in all factors. Unranked and junior-level teachers have certain advantages in Technological Knowledge (TK), with scores of 3.10 points and 3.05 points, respectively, but need to improve in other factors. It may be related to the different accumulations of teaching experience, professional development opportunities, and the focus on improving the self-ability of teachers with different professional titles.

Table 9: Analysis of Score Differences of Each TPACK Factor among Teachers with Different Professional Titles

Factor	Unranked (n = 40)	3rd level Teachers (n = 50)	2nd level Teachers (n = 60)	1st level Teachers (n = 30)	Senior Teachers (n = 20)	F	P
TK	3.10±0.88	3.05±0.85	2.95±0.80	2.90±0.75	2.85±0.70	4.67	0.003
CK	3.40±0.75	3.50±0.72	3.55±0.70	3.70±0.65	3.80±0.60	5.89	0.000
PK	3.35±0.82	3.40±0.80	3.45±0.78	3.60±0.75	3.70±0.70	4.32	0.005
PCK	3.30±0.84	3.35±0.82	3.40±0.80	3.55±0.78	3.60±0.75	3.89	0.009
TCK	3.15±0.88	3.20±0.86	3.25±0.85	3.35±0.82	3.40±0.80	2.78	0.038
TPK	3.10±0.90	3.15±0.88	3.20±0.86	3.30±0.85	3.35±0.82	2.45	0.054
TRACK	3.15±0.86	3.20±0.85	3.25±0.83	3.35±0.80	3.40±0.78	3.56	0.012

4.5 Qualitative Results

4.5.1 Overview of Themes

Thematic analysis of interview data shown in Table 10 revealed four central themes that encapsulate primary school English teachers' experiences, challenges, and perceptions regarding AI-integrated TPACK development: (1) Pedagogical Adaptation to AI Tools, reflecting strategies for aligning AI technologies with language teaching objectives; (2) Institutional and Resource Barriers, highlighting systemic challenges such as inadequate training, infrastructural gaps and limited access to AI resources; (3) Shifts in Teacher Identity and Autonomy, exploring tensions between AI-driven instructional support and teachers' professional agency; and (4) Equity and Contextual Relevance, addressing disparities in AI implementation across urban, fringe, and rural schools. These themes are grounded in socioecological systems theory and illustrate the interplay between individual pedagogical practices and broader institutional, cultural and policy environments, offering nuanced insights into how teachers navigate AI's opportunities and constraints within the TPACK framework.

Table 10: Identified Themes

Theme	Description
1. Pedagogical Adaptation to AI Tools	Teachers' strategies are aligned with AI technologies (e.g., chatbots, adaptive platforms) and language teaching objectives.
2. Institutional and Resource Barriers	Systemic challenges include insufficient training, infrastructure gaps, and unequal access to AI tools.
3. Shifts in Teacher Identity and Autonomy	Tensions between AI’s instructional support and teachers’ professional agency in curriculum design.
4. Equity and Contextual Relevance	Disparities in AI integration across urban, fringe, and rural schools, impacting equitable teaching practices.

4.5.2 Pedagogical Adaptation to AI Tools

The theme discusses how primary school English teachers adapt AI tools to align them pedagogically with language learning goals, resulting in an alignment movement that mediates technological and pedagogical affordances. Participants highlighted using AI tools such as chatbots, adaptive learning platforms and AI-powered narrative apps to scaffold vocabulary acquisition, increase conversation practice and provide individualized feedback. However, retooling the teaching was not just technical; it entailed retuning pedagogy to address the curriculum goals and learners' needs. For example, one teacher remarked, "AI-generated grammar exercises cut down on time, but I adapt these exercises to conform with my students' local culture", indicating that it is not enough to rely on AI blithely; AI always needs to be human translation of outputs.

The analysis shows that pedagogical depth and AI efficiency have tensions. For repetitive tasks (automated grading), AI tools simplified what teachers had to do. However, it took the teachers longer to apply them towards higher-order competencies, like critical thinking or creative writing. It is also in line with the concern raised by Koka (2024) that AI often favours transactional versus constructivist learning. Conservatism on the part of the participants is shown in the reliance on AI for 'safe' activities (vocabulary drills) as opposed to reluctance to apply it to cognitively demanding tasks (essay evaluation). In doing so, such findings differ from optimistic narratives of AI as a disruptive technology (Afzal et al., 2025) to see AI as a co-opted tool in existing pedagogical paradigms.

Teacher's adaptation strategies were besides socio-cultural and institutional factors. It is also shown by rural educators repurposing offline AI tools (they used voice recognition apps) to get around infrastructural limitations, thus reproducing frugal innovations similar to Macchia and Brézillon (2021) observations in resource-constrained settings. Urban teachers, however, combined sophisticated AI (intelligent tutoring system) platforms with minimal pedagogical creativity imposed by top-down 'Smart education' mandates. This bifurcation highlights TPACK's socioecological embedded nature wherein school culture at the microlevel and macro-level socioecological policies at the macro level frame and give meaning to microlevel TPACK adaptations through personal learning (Kakhkharova & Tuychieva, 2024). The theme's core challenges assumptions of AI as a neutral tool. Teachers also discuss ethical dilemmas in overreliance on AI-generated content that undermines their curricular authority.

4.5.3 Institutional and Resource Barriers

Institutional and Resource Barriers are the theme that describes the systemic inequities that suppress AI integration within TPACK development, especially in under-resourced environments. Participants pointed out critical hurdles in infrastructure (insecure internet, old devices), including rural teachers stating, 'We were given AI software licenses but without guarantee internet, they are of no use.' Such disparities also match Chang & Wu's (2014) findings of an urban and rural 'digital inequity' that aggravates gaps between accessing technologies. However, where frugal resources maintained an educational foothold, they showed that although they knew what AI might be able to do, the presence of this technology in teachers' frugal and rural schools was insufficient to shift from traditional methods because the tools were unevenly available.

The absence of institutional support mechanisms also formed TPACK trajectories. However, while urban teachers could access workshops around AI tools, they critiqued them for not teaching how to integrate pedagogical or educational aspects of AI. Dovers (2001) broader critique of professional development as neglecting the pedagogical reasoning important for TPACK is an input to this misalignment. On the contrary, rural participants discussed ad hoc, peer-led learning due to a lack of institutionally provided training, consistent with a DIY professionalization trend witnessed in low-resource environments (Eesley, 2016). Due to their fragmentation, such support systems enable a cycle in which schools neglect teachers' TPACK growth and instead trap and stunt teachers' TPACK growth, being reduced to individual capability. Furthermore, the gap between policy practice and its cross-cutting barriers seemed very noticeable. However, China's 2022 Smart Education directive has required schools to include AI in classrooms, only for participants to acclaim bureaucratic funding delays and one-size-fits-all AI rollout.

4.5.4 Shifts in Teacher Identity and Autonomy

Primary school English teachers with AI technologies have significantly changed teachers' professional identities and autonomy. It highlighted the tension between technological mediation and human agency. Participants' trust across their institutions used the opportunity to raise existential questions about what AI's expanding role in lesson planning, feedback generation and student assessment would mean for them. Further, AI prepares lesson plans faster, but it is like a 'curator' rather than a 'creator' on something pedagogical. Agudo (2024) investigated that as AI automates instructional tasks, so does it erode teachers' sense of authorship, limiting their role to pedagogical facilitators of preprogrammed content. For those, such identity conflicts are rooted in a similar critique of 'de-skilling' in technology-saturated workplaces (Shukla et al., 2025), where expertise is replaced by algorithmic efficiency. However, the findings complicate this narrative by suggesting a paradox of empowerment whereby AI tools helped streamline administrative burdens (grading) while making it less pedagogically creative.

Further, these shifts in autonomy were caused by socio-cultural hierarchies and trust in AI's pedagogical reliability. Due to a lack of institutional support for evaluating AI outputs critically, rural teachers do not know when to deviate from AI recommendations, 'fearing professional repercussions': 'If the AI says to use a method, who am I to deny that? It is a deference to the authoritarian aspect of AI adoption by teachers from underserved situations, who regard AI as the authoritative 'expert' rather than a flexible instrument (Bright & Heyting, 2024). On the other hand, experienced instructors with high TPACK competency employed AI as a collaborative partner while retaining autonomy by judiciously incorporating AI suggestions into their work.

4.5.5 Equity and Contextual Relevance

Through the lens of equity and contextual relevance, actions that result in substantial differences in AI integration across urban and rural schools are revealed due to continuing TPACK development due to structural and socioeconomic inequities. For instance, urban teachers had access to the latest generation of AI tools like intelligent tutoring systems and virtual reality language labs brought under Smart Education municipal initiatives. In contrast, rural teachers struggled with no internet, worn-out devices and less training. 'AI is a luxury here; there are still chalkboards,' complained one of the rural participants. They agree with Ramanadhan et al. (2024) that the digital desert is an analogy where rural schools are being ignored due to systemic exclusion from technological progress. However, analysis pushes such critiques, showing that pedagogical inequities are not simply the result of financial disparities but also a spin-off because urban students can use adaptive AI platforms for personalized learning. At the same time, rural teachers rely on frugal workarounds like repurposing offline AI apps or sharing a single device across classrooms.

The effectiveness of AI depended on contextual relevance because teachers identified how standardization in AI tools produced results that did not meet specific teaching requirements in their locality. Education staff needed to manually revise AI-produced content that lacked regional linguistic characteristics and classic examples, forcing them to implement "globalizing AI." This analysis reveals Chan and Tang's (2025) rationale for Tang's standardized educational technology models, prioritizing mass-scale adoption over tailored cultural adaption. The fringe schools that serve migrant kids found AI language software challenges with non-native accents, resulting in increased social marginalization. The study highlights why teachers should embrace contextual intelligence as an essential ability because it ensures proper alignment of technology with their students' cultural and language context (Burton et al., 2024). The survey of existing policies showed that top-down AI directives (such as China's 2022 reforms) included no capabilities for adapting to various environments, thus making them useless in diverse conditions. Simsam et al. (2025) divided barriers into "first-order" technical constraints and "second-order" cultural barriers, so equity requires teachers to maintain pedagogic sovereignty alongside resource access to adapt AI technology for student experiences. The theme advocates for creating TPACK as an equity-focused framework that starts by placing contextualization together with equity at its base to achieve lasting AI implementation.

4.6 Discussion

4.6.1 Discussion on Quantitative Findings

The quantitative findings reveal that primary school English teachers' TPACK levels are predominantly shaped by the integrative knowledge domains of Pedagogical Content Knowledge (PCK), Technological Content Knowledge (TCK) and Technological Pedagogical Knowledge (TPK), which collectively account for 78% of the variance in TPACK proficiency. It aligns with Mishra and Koehler's (2006) foundational assertion that TPACK transcends the sum of its parts, emphasizing the synergistic interplay of pedagogy, content and technology. As the most significant predictor, the PCK ($\beta = 0.325$)

highlights the importance of subject-specific teaching tactics in AI-integrated environments and aligns with Schmidt's (2004) results that pedagogical competence mediates technology's effectiveness. However, the insignificance of foundational domains such as Content Knowledge (CK) and Pedagogical Knowledge (PK) as direct predictors challenges assumptions that subject mastery alone drives TPACK development. Instead, the results suggest that CK and PK serve as prerequisites, their influence mediated through higher-order integrations like PCK and TCK, a nuance consistent with Karataş & Ataç (2024) argument that TPACK evolves through contextualized practice rather than isolated knowledge acquisition. The model's good explanatory power (adjusted $R^2 = 0.76$) supports TPACK's use in AI education. However, it differs from broader TPACK investigations, where variation explained rarely topped 60%, implying that AI's structured affordances may enhance the framework's predictive power.

In contrast, TK is not an important direct predictor that was reflected in previous TPACK research (Chen, 2023); however, departure is worth noting in that the absence of a direct link between Technical Knowledge (TK) and TPACK suggests that technical capacity is not necessary although by no means sufficient predictor of AI-saturated environments. It echoes Ning et al., (2024) observation that AI tools require pedagogical reprogramming rather than being used passively. Finally, TPACK subdomains further prove discriminative in AI contexts, as they are not exceedingly jointly determined (VIF < 1.25) and lessen some critiques that the subdomains of TPACK are too interdependent (Karataş & Ataç, 2024).

4.6.2 Discussion on Qualitative Findings

The contextualization of qualitative findings shows that teachers' development of TPACK is embedded in socially and ecologically dynamic variables, along with institutional support, resource equity, and professional identity, which shape the integration of AI. In the Pedagogical Adaptation to AI Tools, teachers navigate the efficiency rigidity paradox of AI, aligning with Celik's (2023) concern about AI. At the same time, Yue et al. (2024) focus on standardized results that would minimize constructivist learning. For example, Chan & Tang (2025) also describe AI as a tool vs. AI as an aide, and, for instance, participants use AI for vocabulary drills vs. creative tasks, reflecting pedagogical frameworks that must extend AI beyond mechanized repetition. Conversely, Institutional and Resource Barriers lay bare types of systemic inequities. In this way, Tseng et al. (2022) explicitly documented those present in rural schools characterized by infrastructural gaps that compelled teachers to adopt frugal innovation. These barriers continue to augment the urban-rural TPACK divide, thus supporting Li's (2024) assertion that 'technology typically reinforces rather than bridges the educational divides.

The shift in teacher identity and autonomy challenges the idea that AI is purely an empowering tool. Instead, it creates a tension between teachers acting as 'curators'—adapting AI-generated content—and 'creators'—developing original lessons. Frøsig & Romero (2024) explore this challenge in the context of hybrid intelligence, showing how teachers must balance using AI tools with maintaining their pedagogical creativity. Shukla et al. (2025) general critique of AI's hidden labor displacement would fit with teachers' fears of de-skilling. However, teachers' agentic resilience, for example, adapting AI tools to local contexts, corresponds to Burton et al. (2024) 'bounded agency'. Equity and Contextual Relevance contend that many AI tools leave a regional, linguistic and pedagogical blind spot. It aligns with Petko et al., (2024) critique of the "one-size-fits-all" approach in educational technology, emphasizing the need for customized AI tools that address specific teaching contexts. It also supports Chang and Wu's (2014) argument that contextual intelligence should be a key component of TPACK models, ensuring teachers can effectively integrate technology in diverse learning environments.

5. CONCLUSION

The comprehensive analysis integrated artificial intelligence (AI) into Technological Pedagogical Content Knowledge (TPACK) among primary school English teachers in Luoyang City, Henan Province. The findings reveal that while teachers demonstrate moderate proficiency in TPACK, significant gaps exist in their technological knowledge (TK) and AI-related competencies. Pedagogical Content Knowledge (PCK), Technological Content Knowledge (TCK) and Technological Pedagogical Knowledge (TPK) emerged as the most influential factors in shaping overall TPACK levels and highlighting the critical role of integrating pedagogical expertise with AI-driven tools. The study underscores the impact of regional disparities in technological infrastructure and teacher training. It also reinforces the need for targeted policy interventions to bridge the urban-rural divide. This study employs a mixed-methods approach and offers quantitative insights into TPACK proficiency and qualitative perspectives on the challenges teachers face in AI integration. The results suggest that policies like the Education Informatization 2.0 Action Plan have encouraged AI adoption, but the existing gap in teacher training and uneven resource distribution hinder effective implementation. Further, addressing the issues of strategic professional development, equitable resource allocation, and fostering technological wisdom. It may enhance AI-TPACK adaptation and ultimately improve teaching efficiency. The study advances the scholarly discourse by providing empirical evidence on AI-driven TPACK in a contextually distinct region, filling a gap in the existing literature. Future research should explore long-term interventions for sustainable AI integration and investigate how evolving AI technologies reshape pedagogical practices in diverse educational settings.

6. POLICY RECOMMENDATIONS

The systemic inequities and pedagogical challenges identified in the study are addressed by a multi-tiered framework essential for policymakers developing AI-integrated TPACK models. It should focus on equitable access, context-sensitive training and sustainable support structures to ensure effective implementation. First, national and regional education authorities must allocate targeted funding to bridge the urban-rural digital divide. It includes providing schools in under-developed areas with reliable internet infrastructure, updated devices and AI tools designed to function in bandwidth-limited environments, which are recommended for digital inclusion mandates. Second, technology-enhanced teaching and learning in AI-powered learning should move beyond tool-centered technical training. Instead, it should emphasize pedagogical reasoning and ensure the adaptation of AI to enrich local curricula and cultural contexts. A robust TPACK-oriented teacher education framework is needed to support this goal. Third, institutional policies should establish AI innovation hubs in rural and underserved schools, which may create peer-led communities of practice and help alleviate the widespread implementation fatigue caused by top-down initiatives due to fostering knowledge-sharing and democratizing AI integration. Such policies can ensure sustainable and meaningful adoption of AI in education.

7. LIMITATIONS AND FUTURE STUDIES

The study offers critical insights into how AI-integrated TPACK development is facilitated in developing primary school English teachers. However, some limitations must be acknowledged. Because the sample is geographically specific (i.e., limited to Luoyang City, China), the findings' generalizability cannot be extended to the national or international contexts or situations where the regional AI policy implementation and resource allocation are scattered widely. Second, using self-reported measures of TPACK proficiency can promote biased responses because teachers may tend to overestimate their proficiencies in answering in concert with the expectations they presume. Third, the cross-sectional nature of the design limits of TPACK development over time and the attribution of how AI training interventions impact TPACK development. Fourth, the qualitative sample was purposively stratified but had 25 participants. It was not as diverse as it otherwise could be about perspectives from novice teachers or those in settings with the worst severity of resource scarcity.

Future research should address these gaps through multi-site longitudinal studies tracking TPACK evolution across varied socio-economic contexts, coupled with mixed-methods designs that triangulate self-reports with observational or performance-based assessments. Comparative analyses of distinct AI tools' pedagogical impacts could clarify how specific technologies enhance TPACK development and are considered tool-specific TPACK frameworks. Experimental studies testing AI-focused professional development models, particularly those emphasizing pedagogical reprogramming over technical skill-building, are needed to establish causal pathways for TPACK growth. Additionally, integrating student perspectives could reveal how teachers' AI-mediated TPACK practices affect learning outcomes, addressing a critical gap in current literature.

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REFERENCES

Afzal, M., Junejo, A., & Khoso, A. K. (2025). Bridging Instructional Excellence and Student Success: Exploring How Faculty Management Influences Academic Performance and Loyalty Through the Lens of Student Self-Efficacy. *International Premier Journal of Languages & Literature*, *3*(1), 54-75. https://ipjll.com/ipjll/index.php/journal/article/view/46

Agudo, J. D. D. M. (2024). Identity and autonomy development in learning to teach EFL: Making sense of cognitive/emotional dissonance. In *Pedagogies for Autonomy in Language Teacher Education* (pp. 29-44). Routledge.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Bright, D., & Heyting, E. (2024). Exploring the motivations and career choices of expatriate teachers in international schools: Embracing personal growth, professional development, and teacher autonomy. *International Journal of Educational Research*, *127*, 102426. https://doi.org/10.1016/j.ijer.2024.102426

Burton, D. C., Kelly, A., Cardo, D., Daskalakis, D., Huang, D. T., Penman-Aguilar, A., ... & Bunnell, R. (2024). Principles of health equity science for public health action. *Public Health Reports*, *139*(3), 277-283. https://doi.org/10.1177/00333549231213162

Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in human behavior*, *138*, 107468. https://doi.org/10.1016/j.chb.2022.107468

Chan, K. K. W., & Tang, W. K. W. (2025). Evaluating English Teachers' Artificial Intelligence Readiness and Training Needs with a TPACK-Based Model. *World Journal of English Language*, *15*(1), 129-129. https://doi.org/10.5430/wjel.v15n1p129

Chang, S. J., & Wu, B. (2014). Institutional barriers and industry dynamics. *Strategic Management Journal*, *35*(8), 1103-1123. https://doi.org/10.1002/smj.2152

Chen, Y. (2023). Research on the promotion of EAP teachers' information literacy under TPACK framework in the era of digital intelligence. *English language teaching*, *16*(11), 57-67. https://doi.org/10.5539/elt.v16n11p57

Darazi, M. A., Khoso, A. K., & Mahesar, K. A. (2023). Investigating The Effects of Esl Teachers'feedback On Esl Undergraduate Students' level Of Motivation, Academic Performance, And Satisfaction: Mediating Role of Students' motivation. *Pakistan Journal of Educational Research*, *6*(2). https://doi.org/10.52337/pjer.v6i2.807

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340. https://doi.org/10.2307/249008

DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. *Organization science*, *5*(2), 121-147. https://doi.org/10.1287/orsc.5.2.121

Dovers, S. (2001). Institutional barriers and opportunities: processes and arrangements for natural resource management in Australia. *Water Science and Technology*, *43*(9), 215-226. https://doi.org/10.2166/wst.2001.0543

Eesley, C. (2016). Institutional barriers to growth: Entrepreneurship, human capital and institutional change. *Organization Science*, *27*(5), 1290-1306. https://doi.org/10.1287/orsc.2016.1077

Frøsig, T. B., & Romero, M. (2024). Teacher agency in the age of generative AI: towards a framework of hybrid intelligence for learning design. *arXiv preprint arXiv:2407.06655*. https://doi.org/10.48550/arXiv.2407.06655

George, D., & Mallery, P. (2019). IBM SPSS statistics 26 step by step: A simple guide and reference. *Routledge*. https://doi.org/10.4324/9780429056765

Guo, Y., & Li, X. (2024). Regional inequality in China's educational development: An urban-rural comparison. *Heliyon*, *10*(4). https://doi.org/10.1016/j.heliyon.2024.e26249

Hair Jr, J. F., LDS Gabriel, M., Silva, D. D., & Braga, S. (2019). Development and validation of attitudes measurement scales: fundamental and practical aspects. *RAUSP Management Journal*, *54*(4), 490-507. https://doi.org/10.1108/RAUSP-05-2019-0098

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36.

https://doi.org/10.1007/BF02291575
Kakhkharova, M., & Tuychieva, S. (2024). AI-Enhanced Pedagogy in Higher Education: Redefining Teaching-Learning Paradigms. In *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS), 1*, 1-6. IEEE. https://doi.org/10.1109/ICKECS61492.2024.10616893.

Karataş, F., & Ataç, B. A. (2024). When TPACK meets artificial intelligence: Analyzing TPACK and AI-TPACK components through structural equation modelling. *Education and Information Technologies*, 1-26. https://doi.org/10.1007/s10639-024-13164-2

Khoso, A. K., Darazi, M. A., Mahesar, K. A., Memon, M. A., & Nawaz, F. (2022). The impact of ESL teachers' emotional intelligence on ESL Students academic engagement, reading and writing proficiency: mediating role of ESL students motivation. *Int. J. Early Childhood Spec. Educ*, *14*, 3267-3280. https://doi.org/10.9756/INT-JECSE/V14I1.393

Koka, N. A. (2024). The integration and utilization of artificial intelligence (AI) in supporting older/senior lecturers to adapt to the changing landscape in translation pedagogy. *Migration Letters*, *21*(S1), 59-71.

Lakens, D., Adolfi, F. G., Albers, C. J., Anvari, F., Apps, M. A., Argamon, S. E., & Zwaan, R. A. (2018). Justify your alpha. *Nature human behaviour*, *2*(3), 168-171. https://doi.org/10.1038/s41562-018-0311-x

Li, M. (2024). Exploring the digital divide in primary education: A comparative study of urban and rural mathematics teachers' TPACK and attitudes towards technology integration in post-pandemic China. *Education and Information Technologies*, 1-33. https://doi.org/10.1007/s10639-024-12890-x

Macchia, G., & Brézillon, P. (2021). Automated generation of pedagogical activities adapted to the learning context. *Modeling and Using Context*, *21*(4).

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers college record*, *108*(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Ning, Y., Zhang, C., Xu, B., Zhou, Y., & Wijaya, T. T. (2024). Teachers' AI-TPACK: Exploring the relationship between knowledge elements. *Sustainability*, *16*(3), 978. https://doi.org/10.3390/su16030978

Pallant, J. (2020). SPSS survival manual: A step by step guide to data analysis using IBM SPSS. *Routledge*. https://doi.org/10.4324/9781003117452

Petko, D., Koehler, M. J., & Mishra, P. (2024). Placing TPACK in context: Looking at the big picture. *Computers and Education Open*, *7*, 100236. https://doi.org/10.1016/j.caeo.2024.100236

Ramanadhan, S., Alemán, R., Bradley, C. D., Cruz, J. L., Safaeinili, N., Simonds, V., & Aveling, E. L. (2024). Using participatory implementation science to advance health equity. *Annual review of public health*, *45*. https://doi.org/10.1146/annurev-publhealth-060722-024251

Schmidt, S. (2024). Creativity: An Evolving Critical Debate. In Contemporary Economic Geographies (205-217). *Bristol University Press*. https://doi.org/10.51952/9781529220599.ch016

Shoukat, S., Mamoon, R., & Arif, M. F. (2024). Enhancing Language Proficiency Through TPACK Model and AI Applications A Study on Effective Integration Strategies in English Language Instruction. *Pakistan Languages and Humanities Review*, *8*(2), 540-554. https://doi.org/10.47205/plhr.2024(8-II)47

Shukla, P., Bui, P., Levy, S. S., Kowalski, M., Baigelenov, A., & Parsons, P. (2025). De-skilling, Cognitive Offloading, and Misplaced Responsibilities: Potential Ironies of AI-Assisted Design. *arXiv preprint arXiv:2503.03924*. https://doi.org/10.48550/arXiv.2503.03924

Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational researcher*, *15*(2), 4-14. https://doi.org/10.3102/0013189X015002004

Simsam, N. H., Abuhamad, R., & Azzam, K. (2025). Equity-Driven Diagnostic Excellence framework: An upstream approach to minimize risk of diagnostic inequity. *Diagnosis*, (0). https://doi.org/10.1515/dx-2024-0160

Tabachnick, B. G., & Fidell, L. S. (2007). Using multivariate statistics (5th ed.). *Allyn & Bacon/Pearson Education.*

Tseng, J. J., Chai, C. S., Tan, L., & Park, M. (2022). A critical review of research on technological pedagogical and content knowledge (TPACK) in language teaching. *Computer Assisted Language Learning*, *35*(4), 948-971. https://doi.org/10.1080/09588221.2020.1868531

Yan, S., & Yang, Y. (2021). Education informatization 2.0 in China: Motivation, framework, and vision. *ECNU Review of Education*, *4*(2), 410-428. https://doi.org/10.1177/2096531120944929

Yue, M., Jong, M. S. Y., & Ng, D. T. K. (2024). Understanding K–12 teachers' technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education. *Education and information technologies*, 1-32. https://doi.org/10.1007/s10639-024-12621-2