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AI-technological Pedagogical Content Knowledge Framework through Structural Equation Modeling and Wearable Sensor Indicators for English Language Educators

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We investigated the AI-related technological pedagogical content knowledge (AI-TPACK) of 232 primary and secondary school English teachers in China to understand the effects of AI integration into education on the teachers' professional competencies. In a mixed method, a questionnaire survey was conducted with biometric data collected from wearable sensors from a subset of ten participants who simulated teaching tasks. Descriptive statistics indicate that while teachers possessed robust traditional knowledge, they reported lower proficiency in AI-specific integration knowledge. Structural equation modeling results validated the effectiveness of the AI-TPACK framework to enhance pedagogical knowledge and its effect on AI-TPACK competency, mediated through AI-integrated knowledge. The results provide a reference for the development of sensor technology for objective, real-time physiological monitoring to enhance instructional design. Teachers with higher AI-TPACK proficiency exhibited significantly lower physiological stress, characterized by reduced heart rate variability and skin conductance levels due to lower cognitive load. These results underscore the role of pedagogical AI technology literacy and demonstrate the necessity of wearable sensors for effectively assessing teacher self-efficacy and technological readiness in the age of intelligent education.

1. Introduction

With the rapid advancement of AI, its applications have permeated every aspect of social life, and education is no exception. From personalized learning path recommendations and intelligent tutoring systems to automated assessment feedback, AI is reshaping teaching and learning models, enabling education to be equipped with intelligence, personalization, and efficiency.(1,2) In this transformation, teachers' capabilities remain critical, and they need to master and integrate AI technologies to apply them to teaching practices, which determines the quality of future education.(3,4)

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Technological pedagogical content knowledge (TPACK) provides a basis for understanding how teachers integrate technology, pedagogy, and subject content knowledge.[5] It comprises seven dimensions, including technical knowledge, content knowledge, pedagogical knowledge, and their intersections, including pedagogical content knowledge, technological content knowledge, and technological pedagogical knowledge.[6–9] However, the technology for TPACK does not fully capture the disruptive nature of AI in education. Therefore, an AI-specific framework, the AI-TPACK model, is proposed to integrate AI knowledge into teaching strategies and content.[10]

In the AI-TPACK framework, the integration of AI into education necessitates the use of sensors and wearable technologies to enable real-time data collection and personalized learning. Sensors embedded in wearable devices capture physiological, behavioral, and contextual information, providing AI systems with essential inputs for adaptive feedback, intelligent assessment, and context-aware learning environments.[11,12] For instance, wearable sensors can monitor student engagement, stress levels, and language practice behaviors, enriching AI-driven education and supporting AI-TPACK. Without sensor technologies, the capacity of AI to personalize and optimize teaching practices remains limited, as real-time data streams are indispensable for effective AI integration in education.

Since its introduction, the TPACK framework has significantly advanced teachers' ability to integrate technology and has guided professional development initiatives. Since the introduction of AI to TPACK, it increasingly functions as a partner or agent in teaching.[13] Teachers must understand AI principles to evaluate the applicability and ethical implications of related tools and integrate them into subject-specific teaching strategies.[14,15] The AI-TPACK framework adopts AI knowledge, which emphasizes AI integration at the intersections of content and pedagogy. Although AI-TPACK is widely adopted, its effect on teachers' competency has not yet been extensively researched.[16,17]

To address such a gap in the related research, we investigated the influencing factors of AI-TPACK on English education in primary and secondary schools, assuming that AI has considerable potential to enhance language proficiency and cross-cultural communication. We examined whether basic knowledge, including content knowledge, pedagogical knowledge, and AI knowledge, impacts integrated knowledge, and whether any combined knowledge influences the use of AI-TPACK. We then evaluated the extent of content knowledge required for the effective application of AI-TPACK. The results of this study contribute to the validation of the AI-TPACK framework and underscore the necessity of sensor technologies and wearable devices in enabling AI-driven pedagogical innovation.

2. Methodology

We conducted questionnaire surveys and wearable sensor data collection in this study. By the questionnaire survey method, self-assessment data on AI-TPACK were obtained from 232 primary and secondary school English teachers. The data collected were analyzed for descriptive statistics using a structural equation model. Teachers selected randomly from the participants wore wearable devices in simulated or real teaching scenarios to collect physiological and behavioral data. The research process is presented in Fig. 1.

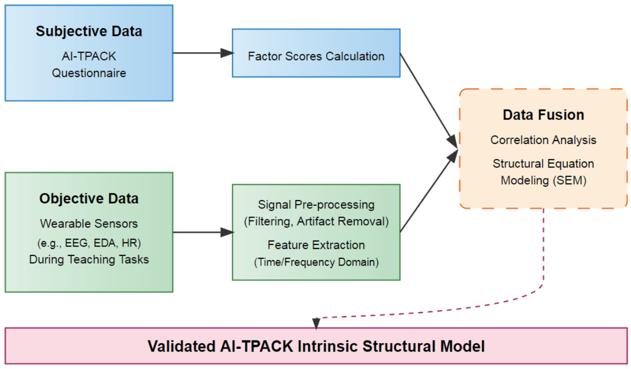

Fig. 1. (Color online) Research process of this study.

2.1 Questionnaire survey

The respondents of the questionnaire survey were in-service English teachers from primary and secondary schools in China. Questionnaires were distributed to 232 randomly selected in-service English teachers in primary and secondary schools in Ningxia Hui Autonomous Region, China, through the online survey platform, Wenjuanxing. From the 232 respondents, 10 teachers were randomly invited for interview to collect physiological data through wearable sensors. Despite the small sample size, the analysis revealed a statistically significant correlation between physiological indicators and questionnaire scores, providing preliminary evidence of the feasibility of the methodology (Table 1).

Among the 232 respondents, 68 (29.3%) were male, while 164 (70.7%) were female, indicating that the majority of participants were women. Regarding teaching experience, 120 respondents (51.7%) had between one and five years of experience, 75 (32.3%) had six to ten years of experience, and 37 (15.9%) had more than ten years of experience. With respect to educational attainment, most respondents held a bachelor’s degree (201 teachers, 86.6%), while a smaller proportion had a master’s or higher degree (31 teachers, 13.4%). Fifty-five teachers (23.7%) were at the junior level, 130 teachers (56.0%) held intermediate titles, and 47 teachers (20.3%) were senior or above. Ninety-eight teachers (42.2%) taught in elementary schools, 95 teachers (40.9%) taught in middle schools, and 39 teachers (16.8%) taught in high schools. The majority of the teachers (155, 66.8%) who participated in the survey were employed in urban schools, 62 teachers (26.7%) worked in suburban schools, and only 15 teachers (6.5%) taught in rural schools.

In accordance with the AITPACK theoretical model, we remapped and combined the items of the original questionnaire into seven latent variables in four dimensions (Table 2). Items of each variable were scored by the respondents to evaluate the effectiveness of the AI-TPACK framework.

We employed a structured framework consisting of the variables and their items. Each item was scored by the respondents on a Lickert five-point scale.

- AIK1: I can use basic computer software effectively.
- AIK2: I am able to solve technical problems encountered when using information technology on my own.

Table 1
Description of respondents.

Variable	Category	N	Percentage (%)
Gender	Male	68	29.3
	Female	164	70.7
Teaching experience	1–5 years	120	51.7
	6–10 years	75	32.3
	Over 10 years	37	15.9
Educational level	Bachelor's degree	201	86.6
	Master's or higher	31	13.4
Title	Junior	55	23.7
	Intermediate	130	56.0
	Senior or above	47	20.3
Teaching grade	Elementary school	98	42.2
	Middle school	95	40.9
	High school	39	16.8
School location	Urban area	155	66.8
	Suburban area	62	26.7
	Rural area	15	6.5

Table 2
Variables of AI-TPACK and their descriptions for questionnaire survey.

Dimension	Variable	Number of items
Basic knowledge	AI knowledge (AIK)	4
	Content knowledge (CK)	4
	Pedagogical knowledge (PK)	4
Integrated knowledge	Pedagogical content knowledge (PCK)	3
	Technology-content knowledge with AI (TCK)	7
	Technology-pedagogy knowledge with AI (TPK)	4
Core competency	AI-TPACK	4

- AIK3: I can keep myself up-to-date with the latest technologies.
- AIK4: I can effectively use subject-specific technologies, such as GIS software.
- CK1: I have a sufficient command of professional subject knowledge.
- CK2: I possess strong subject-specific thinking skills.
- CK3: I have mastered all the required content outlined in the curriculum standards.
- CK4: I have mastered all the elective content outlined in the curriculum standards.
- PK1: I can adjust my teaching based on students' classroom performance.
- PK2: I can use multiple methods to evaluate student learning.
- PK3: I can provide students with effective learning strategies.
- PK4: I am familiar with the abilities and common mistakes of most students.
- PCK1: I can effectively complete lesson preparation without relying on technology.
- PCK2: I can select appropriate teaching methods without using technology.
- PCK3: I can help students solve real-world problems without using technology.
- TCK1: I can use information technology to present teaching content.
- TCK2: I can follow and understand cutting-edge information technologies in my subject and know their uses.

- TCK3: I can use technology tools to collect data.
- TCK4: I believe that the information technology I use is both an important tool and a form of learning content.
- TCK5: I can choose appropriate technologies to present concepts that help students understand knowledge.
- TCK6: I can modify and adjust existing digital resources as needed.
- TCK7: I can critically reflect on whether the use of technology in the classroom is appropriate.
- TPK1: I can proficiently use information technology for instructional design.
- TPK2: I can choose appropriate technologies to optimize teaching.
- TPK3: I can guide students to use information technology to complete assignments or activities.
- TPK4: I can apply different teaching methods when using information technology.
- TPACK1: I can select technology and create a teaching plan based on learning objectives.
- TPACK2: I can adapt information technology on the basis of factors such as student learning situations.
- TPACK3: I can offer online courses through online platforms.
- TPACK4: I can use information technology tools to promote collaborative learning.

2.2 Wearable sensor data collection

We recruited ten English teachers who participated in the questionnaire survey to take part in a sensor-based data collection experiment. In the experiment, the teachers simulated teaching tasks. The task involved designing a 15-minute instructional activity using a designated English practice application to deliver simulation lectures. Throughout the entire process, each teacher wore a portable near-infrared imaging system (fNIRS) (Lightnirs, Shimadzu Corporation, Kyoto, Japan). The system consists of 16 optical probes, including eight emitters and eight detectors, with a spacing of 30 mm between the emitters and detectors. This device evaluates teachers' cognitive activity and brain function changes while they perform teaching tasks by measuring changes in hemoglobin concentration in specific areas of the cerebral cortex.

The system synchronously collects data at a sampling frequency of 13.3 Hz. The data is collected in real-time using kernel-based NIRS (kNIRS) software and then processed using fNIRS analysis software. The processing flow includes steps such as data format conversion, artifact removal, and signal filtering to ensure data quality. The processed data is segmented into time windows corresponding to specific AI teaching tasks. Then, key indicators such as the average concentration changes of oxygenated hemoglobin and deoxygenated hemoglobin were extracted from these windows and exported to Statistical Package for the Social Sciences (SPSS) software. Finally, we used statistical methods such as correlation analysis and multiple analysis of variance (MANOVA) to conduct in-depth analysis of these brain activity indicators and the AI-TPACK questionnaire results of teachers, in order to explore the relationship between the two.

The physiological variables recorded by the Empatica E4 and related sensing platforms were selected in accordance with the multidimensional stress model.[18] By capturing data from both the autonomic nervous system [heart rate (HR) and electrodermal activity (EDA)] and cortical activity (α/β ratio), the system provides data on the internal state that self-reported questionnaires cannot capture.[19] HR was used as a recognized proxy for physiological arousal. HR is linked to the pedagogical friction that teachers experience when managing unexpected technological failures or complex AI interactions. In previous studies, HR was successfully used to differentiate between veteran and novice teachers' stress levels during active instruction.[20] EDA, or skin conductance level, is sensitive to the sympathetic nervous system's fight-or-flight response. It is used to detect microstressors in human–computer interaction. EDA is an immediate indicator of the cognitive effort required to process AI-generated feedback compared with traditional teaching methods.[21] The α/β ratio is a standard electroencephalography-derived metric for monitoring mental workload. A decrease in the ratio (increased β power relative to α) indicates high cognitive processing and potential mental fatigue. Studies in teacher professional development have utilized this ratio to evaluate the usability of new educational technologies.[22]

2.3 Data analysis

The data collected was analyzed using SPSS and Analysis of Moment Structures (AMOS) software. The mean and standard deviation of scores for each dimension were calculated to obtain an overview of teachers' AI-TPACK use levels. Reliability, validity, and internal consistency were determined by computing Cronbach's α coefficients. Confirmatory factor analysis (CFA) was performed, with convergent validity evaluated using reliability and average variance extracted (*AVE*). Discriminant validity was assessed by comparing the square root of *AVE* for each construct with the correlations between that construct and other latent variables.

To construct a structural equation model (SEM) for AI-TPACK adoption, parameters were estimated using the maximum likelihood method, and the model fit was evaluated using the chi-square to degrees of freedom ratio, goodness-of-fit index (*GFI*), adjusted goodness-of-fit index (*AGFI*), comparative fit index (*CFI*), and root mean square error of approximation (*RMSEA*). Finally, Pearson correlation analysis was performed to examine the relationships between preprocessed sensor data and the corresponding scores of TPK and AI-TPACK obtained from the questionnaire survey results.

3. Results

3.1 Baseline competency

The teachers rated themselves highly in traditional knowledge domains. CK and PK showed high scores [mean (M) = 3.77, standard deviation (SD) = 0.70, and M = 3.73, SD = 0.64], reflecting confidence in subject expertise and teaching practices. In contrast, AIK and TCK showed low scores, indicating challenges in mastering emerging technologies such as AI. The overall AI-TPACK competency was moderate (M = 3.52, SD = 0.76), suggesting awareness of AI integration but limited proficiency (Table 3).

Item-level analysis results (Table 4) showed that the teachers were proficient in basic office software (M = 3.84, SD = 0.88), but struggled with subject-specific technologies (M = 2.72, SD = 0.95). While the teachers could use technology to present content (M = 3.80, SD = 0.73), they

Table 3
Descriptive statistics of scores of variables of AI-TPACK.

Dimension	Variable	Number of items	*M*	*SD*	Minimum score	Maximum score
Basic knowledge	AIK	4	3.20	0.81	1.50	5.00
	CK	4	3.77	0.70	2.00	5.00
	PK	4	3.73	0.64	2.25	5.00
Integrated knowledge	PCK	3	3.72	0.71	2.00	5.00
	TCK	7	3.39	0.74	2.00	5.00
	TPK	4	3.42	0.73	1.25	5.00
Core competency	AI-TPACK	4	3.52	0.76	2.00	5.00

Table 4
Average scores and *SD*s of variables of AI-TPACK.

Variable	Item	*M*	*SD*
AIK	AIK1	3.84	0.88
	AIK2	3.23	0.87
	AIK3	3.03	0.89
	AIK4	2.72	0.95
CK	CK1	3.97	0.73
	CK2	3.86	0.76
	CK3	3.79	0.81
	CK4	3.47	0.95
PK	PK1	3.92	0.69
	PK2	3.74	0.71
	PK3	3.66	0.74
	PK4	3.60	0.75
PCK	PCK1	3.93	0.71
	PCK2	3.80	0.75
	PCK3	3.43	0.88
TCK	TCK1	3.80	0.73
	TCK2	3.28	0.87
	TCK3	3.32	0.91
	TCK4	3.19	0.91
	TCK5	3.51	0.79
	TCK6	3.33	0.86
	TCK7	3.29	0.89
TPK	TPK1	3.53	0.82
	TPK2	3.54	0.78
	TPK3	3.33	0.87
	TPK4	3.27	0.83
AI-TPACK	TPACK1	3.70	0.77
	TPACK2	3.48	0.80
	TPACK3	2.99	1.05
	TPACK4	3.90	0.81

scored lower in critical reflection and adoption of new tools (TCK4–TCK7). For AI-TPACK, confidence was moderate in designing technology-enhanced lessons (M = 3.70, SD = 0.75), but lowest in offering online courses (M = 2.99, SD = 0.91), reflecting infrastructure and preparedness gaps.

3.2 Reliability and validity of AITPACK framework

The model demonstrated strong reliability as presented in Table 5. Cronbach's α values ranged from 0.851 (CK) to 0.934 (TCK), with AI-TPACK at 0.972, all exceeding the 0.70 threshold (Table 6). Composite reliability values (0.853–0.935) confirmed internal consistency.

Table 5
Reliability and convergence testing results.

Variable	Cronbach's α	Composite reliability	*AVE*	Square root of *AVE*
AIK	0.883	0.885	0.658	0.811
CK	0.851	0.853	0.592	0.769
PK	0.890	0.891	0.672	0.820
PCK	0.902	0.903	0.756	0.869
TCK	0.934	0.935	0.698	0.835
TPK	0.915	0.916	0.731	0.855
AI-TPACK	0.927	0.928	0.764	0.874

Table 6
Standardized factor loadings for items.

Variable	Item	Standardized factor loading
AIK	AIK1	0.785
	AIK2	0.833
	AIK3	0.849
	AIK4	0.771
CK	CK1	0.728
	CK2	0.754
	CK3	0.817
	CK4	0.778
PK	PK1	0.793
	PK2	0.840
	PK3	0.835
	PK4	0.809
PCK	PCK1	0.859
	PCK2	0.902
	PCK3	0.844
TCK	TCK1	0.821
	TCK2	0.855
	TCK3	0.799
	TCK4	0.840
	TCK5	0.863
	TCK6	0.812
	TCK7	0.808
TPK	TPK1	0.870
	TPK2	0.888
	TPK3	0.814
	TPK4	0.846
AI-TPACK	TPACK1	0.861
	TPACK2	0.899
	TPACK3	0.843
	TPACK4	0.889

CFA results showed construct validity, with acceptable fit indices (χ^2/degree of freedom (df) = 2.15, *GFI* = 0.90, *CFI* = 0.95, and *RMSEA* = 0.07). *AVE* values (0.592–0.764) and high standardized loadings (0.728–0.902) confirmed convergent validity. Discriminant validity was satisfied, as the square root of *AVE* exceeded interconstruct correlations (Tables 7 and 8).

3.3 Path of SEM

SEM revealed significant pathways among AI-TPACK constructs. AIK strongly influenced TCK ($\beta = 0.42$, $p < 0.001$) and TPK ($\beta = 0.38$, $p < 0.001$), while CK affected TCK ($\beta = 0.25$, $p < 0.001$) and PCK ($\beta = 0.33$, $p < 0.001$). PK showed the strongest effects, predicting both TPK ($\beta = 0.45$, $p < 0.001$) and PCK ($\beta = 0.51$, $p < 0.001$). TPK was the most influential predictor of AI-TPACK ($\beta = 0.47$, $p < 0.001$), followed by PCK ($\beta = 0.28$, $p < 0.001$) and TCK ($\beta = 0.21$, $p < 0.01$). These results underscore the pivotal role of pedagogical expertise and technology–pedagogy integration in advancing AI-TPACK competency (Table 9).

The explanatory power of the model was high. CK and PK explained 63.2% of PCK variance, AIK and CK explained 54.8% of TCK, and AIK and PK explained 60.5% of TPK. Together, PCK, TCK, and TPK accounted for 78.1% of AI-TPACK variance, confirming the robustness of the framework. Because of the established reliability and validity of the measurement model, we constructed the SEM of AI-TPACK to test the proposed hypotheses. The model fit indices were as follows: $\chi^2/df = 2.48$, $GFI = 0.89$, $AGFI = 0.86$, $CFI = 0.93$, and $RMSEA = 0.07$. These values meet recommended thresholds, indicating that the theoretical model demonstrates an acceptable fit with the observed data (Tables 10 and 11).

Table 7
Discriminancy of variables (HTMT criterion).

	AIK	CK	PK	PCK	TCK	TPK	AI-TPACK
CK	0.589	—	—	—	—	—	—
PK	0.697	0.781	—	—	—	—	—
PCK	0.669	0.810	0.863	—	—	—	—
TCK	0.830	0.745	0.802	0.825	—	—	—
TPK	0.856	0.722	0.847	0.865	0.893	—	—
AI-TPACK	0.806	0.786	0.891	0.899	0.879	0.891	—

Table 8
Correlation coefficients and discriminative validity test results of variables ($p < 0.01$).

	AIK	CK	PK	PCK	TCK	TPK	TPACK
AIK	0.811	—	—	—	—	—	—
CK	0.521	0.769	—	—	—	—	—
PK	0.610	0.683	0.820	—	—	—	—
PCK	0.588	0.712	0.754	0.869	—	—	—
TCK	0.734	0.650	0.701	0.723	0.835	—	—
TPK	0.755	0.631	0.742	0.760	0.821	0.855	—
TPACK	0.710	0.689	0.780	0.791	0.805	0.852	0.874

Table 9
Structural model path coefficients and hypothesis testing results.

Influence path	Unstandardized coefficient (B)	Standard error	t-value	Standardized path coefficient (β)	Hypothesis test result
AIK → TCK	0.395	0.067	5.89	0.42	Supported
CK → TCK	0.284	0.077	3.67	0.25	Supported
AIK → TPK	0.329	0.064	5.12	0.38	Supported
PK → TPK	0.493	0.079	6.21	0.45	Supported
CK → PCK	0.360	0.072	4.98	0.33	Supported
PK → PCK	0.589	0.082	7.15	0.51	Supported
PCK → AI-TPACK	0.301	0.075	4.02	0.28	Supported
TCK → AI-TPACK	0.216	0.069	3.11	0.21	Supported
TPK → AI-TPACK	0.529	0.081	6.55	0.47	Supported

Table 10
Effect of variables in SEM.

Path	Direct effect	Indirect effect	Total effect
Basic Knowledge → Integrated Knowledge			
AIK → TCK	0.420	—	0.420
CK → TCK	0.250	—	0.250
AIK → TPK	0.380	—	0.380
PK → TPK	0.450	—	0.450
CK → PCK	0.330	—	0.330
PK → PCK	0.510	—	0.510
Integrated Knowledge → AI-TPACK			
PCK → AI-TPACK	0.280	—	0.280
TCK → AI-TPACK	0.210	—	0.210
TPK → AI-TPACK	0.470	—	0.470
Basic Knowledge → AI-TPACK			
AIK → AI-TPACK	—	0.267	0.267
CK → AI-TPACK	—	0.145	0.145
PK → AI-TPACK	—	0.354	0.354

Table 11
R^2 and explanatory power of variables in SEM.

Variable	R^2	Predictor
PCK	0.632	CK, PK
TCK- AI	0.548	AIK, CK
TPK- AI	0.605	AIK, PK
AI-TPACK	0.781	PCK, TCK, TPK

3.4 Correlation analysis of sensor data and questionnaire data

The results of this study provide objective neuroscience validation of the AI-TPACK ability by analyzing brain functional activity data of ten teachers during simulated teaching processes. The data analysis focuses on the blood oxygen changes in the prefrontal cortex (PFC), which are closely related to advanced cognitive functions. Descriptive statistical results show that during teaching tasks, the PFC region of teachers exhibits significant activation patterns, with an average change in oxygenated hemoglobin concentration (Δ[Oxy Hb]) of 0.18 μ mol/L and a change in deoxyhemoglobin concentration (Δ[Deoxy Hb]) of −0.09 μ mol/L, reflecting moderate cognitive investment and effective brain resource mobilization (Table 12).

The correlation analysis results revealed a significant correlation between brain activity indicators and AI-TPACK questionnaire scores (Table 13). The results showed that higher TPK (technical teaching knowledge) and AI-TPACK comprehensive ability scores were significantly positively correlated with stronger activation levels in the PFC (i.e., higher Δ[Oxy Hb]) (r=0.582 to 0.651, p<0.01) and significantly negatively correlated with Δ[Oxy Hb] (r=−0.551 to −0.624, p<0.01). This indicates that teachers with higher technological integration capabilities have more optimized brain efficiency and cognitive resource allocation when performing AI teaching tasks.

After controlling for confounding variables such as teaching experience and age, partial correlation analysis confirmed the results (Table 14). The positive correlation between AI-TPACK score and Δ[Oxy Hb] remained significant (r=0.618, p<0.001), which supports the AI-

Table 12
Descriptive statistics of fNIRS indicators in simulation teaching.

fNIRS Indicator	Abbreviation (unit)	Measurement Item	*M*	*SD*	Minimum value	Maximum value
Oxygenated Hemoglobin Change	Δ[Oxy-Hb] (μmol/L)	Cognitive activation/ mental workload; higher values indicate stronger activation	0.18	0.07	0.05	0.32
Deoxygenated Hemoglobin Change	Δ[Deoxy-Hb] (μmol/L)	Neuronal oxygen consumption; more negative values indicate stronger activation	−0.09	0.04	−0.18	−0.02
Total Hemoglobin Change	Δ[Total-Hb] (μmol/L)	Regional cerebral blood volume change	0.09	0.05	0.01	0.19

Table 13
Correlation analysis between fNIRS data and questionnaire scores.

	Mean Δ[Oxy-Hb]	Mean Δ[Deoxy-Hb]
TPK Score	0.612	−0.588
AI-TPACK Score	0.651	−0.624

Table 14
Partial correlation coefficients between AI-TPACK and fNIRS indicators after controlling for teaching years and age.

Partial correlation	r	Adjusted r	Coefficient change	p
TCK and Δ[OxyHb]	0.553	0.521*	−0.032	0.005
TPK and Δ[OxyHb]	0.612	0.582*	−0.030	0.002
AITPACK and Δ[OxyHb]	0.651	0.618**	−0.033	<0.001
TCK and Δ[DeoxyHb]	−0.520	−0.495*	+0.025	0.008
TPK and Δ[DeoxyHb]	−0.588	−0.551*	+0.037	0.003
AITPACK and Δ[DeoxyHb]	−0.624	−0.597**	+0.027	<0.001
TCK and Δ[TotalHb]	0.491	0.466*	−0.025	0.011
TPK and Δ[TotalHb]	0.575	0.543*	−0.032	0.004
AITPACK and Δ[TotalHb]	0.603	0.579**	−0.024	0.002

(Note: * $p < 0.01$, ** $p < 0.001$)

TPACK ability as a key factor in predicting teachers' cognitive efficiency in technology-enhanced teaching environments.

The results of MANOVA confirmed significant differences in brain activity indicators between the high and low AI-TPACK ability groups (Wilks' Lambda = 0.653, $F = 7.521$, $p < 0.001$, $\eta^2 p = 0.342$) (Table 15). High-scoring teachers showed significantly higher levels of frontal lobe activation. Finally, the regression analysis results further indicate that AI-TPACK–related abilities can effectively predict brain activity indicators. Among them, TPK showed the strongest independent predictive factor in multiple models, with significant predictive power for changes in Δ [Oxy Hb] and Δ [Deoxy Hb] (Table 16).

4. Discussion

The teachers demonstrated strong traditional knowledge but limited AI-related competencies. SEM results highlighted the central role of pedagogical expertise and technology–pedagogy integration in shaping AI-TPACK. Physiological data validated these findings, showing that higher AI-TPACK proficiency is associated with lower stress and more adaptive cognitive responses. The results confirm that wearable sensors provide valuable, objective insights into teachers' readiness for AI-integrated instruction.

4.1 Adaptability and dynamics of AI-TPACK model

The results of this study confirm that the AI-TPACK framework is robust for understanding how English teachers transition to intelligent education. The teachers who participated in this study showed confidence in their expertise (CK, $M = 3.77$) and pedagogical skills (PK, $M = 3.73$), yet they faced challenges in employing AI technology (AIK, $M = 3.20$). This suggests that current professional development mainly focuses on general-purpose digital tools rather than the transformative potential of AI. The SEM results reveal a hierarchical generation path for AI-TPACK. Foundational knowledge, such as AIK, CK, and PK, is not directly related to the improvement of AI-TPACK. Instead, its influence is mainly mediated through the intersectional

Table 15
MANOVA analysis results of fNIRS indicators in AI-TPACK groups.

Indicator	Statistic	Value	*F*-value	*df*	*p*	η^2p
MANOVA	Wilks' Lambda	0.653	7.521	3, 46	<0.001	0.342
	Pillai's Trace	0.347	7.521	3, 46	<0.001	0.342
ANOVA						
Δ[Oxy-Hb]	F-statistic	23.83	—	1, 48	<0.001	0.331
Δ[Deoxy-Hb]	F-statistic	20.39	—	1, 48	<0.001	0.298
Δ[Total-Hb]	F-statistic	21.99	—	1, 48	<0.001	0.312

Table 16
Regression analysis results of fNIRS indicators for AI-TPACK integration.

Dependent variable	Model	Predictor	β	t	p	R^2	Adjusted R^2	ΔR^2
Δ[Oxy Hb]	Model 1	AI-TPACK	0.651	4.882	<0.001	0.424	0.412	—
	Model 2	PCK	0.142	1.288	0.204	0.513	0.478	0.089*
		TCK	0.231	1.950	0.057			
		TPK	0.405	3.511	0.001			
Δ[Deoxy Hb]	Model 1	AI-TPACK	0.624	4.515	<0.001	0.389	0.376	—
	Model 2	PCK	0.166	1.521	0.135	0.477	0.439	0.088*
		TCK	0.203	1.745	0.087			
		TPK	0.381	3.322	0.002			

variables of TCK, TPK, and PCK. Notably, TPK emerged as the strongest predictor of core competency (β = 0.47). This indicates that the ability to strategically align AI tools with instructional methods is critical for successful integration rather than technical AI knowledge alone.

4.2 Biometric indicators

By incorporating wearable sensor data, evidence that aligns with teacher self-assessments was obtained. The negative correlations between AI-TPACK scores and physiological arousal (HR and EDA) suggest that high competency buffers the stress from technology integration. Teachers with high AI-TPACK proficiency possess higher self-efficacy that enables them to manage technology-rich environments with lower cognitive load and operational anxiety. Conversely, those with lower scores in AI-TPACK experienced physiological stress, which might impede effective classroom management and student engagement.

4.3 AI-TPACK and sensor technology

The integration of the Empatica E4 wristband in this study represents an intersection between sensor technology and educational psychology. By capturing PPG and electrodermal activity, the results provide physiological data and meaningful indicators of teacher performance. This aligns with recent advancements in the IoT for education, where sensors provide real-time data to AI systems for adaptive feedback and personalized professional development. The significant correlation between AI-TPACK proficiency and lower physiological arousal validates the potential of wearable sensors to assess the psychological status of teachers, offering a data-driven method to reduce anxiety through targeted training.

5. Conclusions and Future Work

Using the questionnaire data from 232 primary and secondary school English teachers and physiological sensor data from 10 participants, we examined the status of their AI-TPACK competencies in this study.

The overall AI-TPACK competency of English teachers was found to be at a moderate level. Their knowledge was characterized by relatively strong performance in traditional TPACK dimensions, such as CK, PK, and PCK, while performance was weaker for AI-related dimensions, including AIK, TCK, and TPK. The SEM constructed for AI-TPACK in this study demonstrated a good fit with the data, confirming its applicability to the investigation of the effectiveness of AI technology in education. Path analysis results revealed that basic knowledge, including AIK, CK, and PK, serves as a foundational prerequisite for the development of integrated knowledge dimensions, such as TCK, TPK, and PCK. These integrated domains collectively influence AI-TPACK competency, with TPK emerging as the most influential predictor.

The physiological data collected from wearable sensors showed that teachers with higher self-assessed AI integration capabilities exhibited lower levels of physiological arousal during technology-enhanced teaching tasks. These findings indicate the feasibility of combining subjective self-assessments with objective biometric data to evaluate teacher readiness and engagement.

In this study, the participants mainly comprised urban teachers from eastern and central areas of China. To generalize the results of this study, it is necessary to include more teachers from rural and suburban schools. Additionally, the sensor-based data collection involved only ten participants and was conducted in a simulated teaching environment. Correlation analysis also requires further validation with larger samples. The adapted TPACK questionnaire also needs to include items related to detailed AI integration. This leads to further studies to investigate the trajectory of teachers' AI-TPACK competencies before and after targeted professional interventions to assess training effectiveness.

The results of this study show that the AI-TPACK framework is a useful tool for evaluating teacher preparedness in AI-enhanced instruction. While pedagogical knowledge remains the most influential factor in developing AI-integrated teaching proficiency, teachers' self-perceived competence is mirrored in their physiological responses during instructional tasks. The results will contribute to the development of a sensor-based educational ecosystem. By demonstrating that physiological indicators such as SDNN and EDA are reliable predictors of AI-TPACK competency, the study results support the advancement of smart teacher training that incorporates wearable indicators in real-time monitoring. This method bridges the gap between psychological and physiological dimensions of teacher development, offering a holistic framework for professional growth.

Physiological data, classroom behavior video recordings, and student learning outcomes must also be integrated through machine learning to construct sophisticated models to explore the dynamic interplay among teacher competencies, instructional behaviors, and student performance. The methodology of this study can be applied to other subjects for comparative analysis of AI-TPACK. Through the creation of standardized, discipline-specific AI-TPACK measurement tools, the reliability and validity of the assessments using the method of this study can be enhanced. Sensor-based experiments also need to be conducted to explore the effects of technology on education in longitudinal, real-time classroom observation. As biometric technologies become increasingly unobtrusive and sophisticated, their integration with the AI-TPACK framework is essential for professional development and the cognitive and physiological well-being of teachers.

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