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Validation of the Teachers AI-TPACK Scale for the Indian Educational Setting

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Abstract: Educators work in extremely dynamic and complex classroom environments where they must continuously alter and update their understanding. Specifically, possession of rich, organised, and integrated knowledge from various domains including knowledge on subject-matter, knowledge of students' thinking and learning, and, increasingly, knowledge of technology is essential. By integrating these three aspects, Mishra and Koehler developed the Technological Pedagogical and Content Knowledge (TPACK) framework in 2006 which offers a thorough and comprehensive method for incorporating technology into the education setting. On the parallel, use of information technology has rapidly increased in the field of education, especially with the introduction of Artificial Intelligence (AI). Thus, the Technological Pedagogical Content Knowledge (TPACK) framework needed to be updated to reflect the growing incorporation of AI into educational standards. Hence, investigator Ning and colleagues in the year 2024 built a framework for incorporating AI into TPACK and developed a robust scale titled *Teachers AI-TPACK Scale* that measures the teachers competencies in incorporating AI into their teaching environment. The objective of this work was to test the validity of the scale in the Indian educational setting. With a sample size of 660 teaching faculties in universities and colleges across India, this study followed the routine stages such as construct validity analysis in the form of Exploratory Factor Analysis using SPSS V27, followed by Confirmatory Factor Analysis in AMOS software. The original scale with 39 items across seven dimensions were retained throughout the validation process and resulted in a high reliability score of 0.907. This provides compelling evidence for the validity and reliability of the teachers AI-TPACK scale in measuring Indian educators' knowledge and skills at the juncture of AI with pedagogy, technology and content. This is currently the only scale available to measure this construct in India.

Introduction

Contextual Background

The principal effect of Information and Communications Technologies (ICT) has revolutionised the way people perceive and discuss education (Bhattacharya and Sharma, 2007; Choudhury et al., 2024), learning designs, pedagogy, students' learning outcomes and achievements in the twenty-first century. According to academics and policymakers, the development of students' higher-order skills should be emphasised in this current century' education programmes (Roussinos and Jimoyiannis, 2019; Gupta et al., 2024), among them are critical thinking, creativity, problem-solving, communication, teamwork, and digital competency skills, all of which are important for students to master in order to thrive in society (Dede, 2011; Laurillard, 2008; Lavi et al., 2021; Mahmud and Wong, 2022; Gupta et al., 2023; Voogt et al., 2013). Thus, according to Mishra et al. (1996) and Spiro and Jehng (2012), the teaching profession mandates that teachers use advanced knowledge structures across many contexts and settings to meet this requirement. This is also true since educators work in extremely dynamic and complex classroom environments where they must

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continuously alter and update their understanding (Leinhardt and Greeno, 1986). Specifically, possession of rich, organised and integrated knowledge from various domains is essential for effective teaching (Glaser, 1984; Shulman, 1986), which includes knowledge of students' thinking and learning, knowledge of subject matter and, increasingly, knowledge of technology.

By integrating these three aspects, Mishra and Koehler developed the Technological, Pedagogical and Content Knowledge (TPACK) framework in 2006, offering a thorough and comprehensive method for incorporating technology into the education setting. Prior to this, pedagogical content knowledge (PCK), as defined by Shulman (1986), emphasised the integration of pedagogy and content knowledge as a necessary component of effective teaching. This served as the foundation of developing TPACK framework. In order to meet the growing significance of digital tools in the educational landscape, Mishra and Koehler expanded this model by adding technology as a third essential component which conceived TPACK (Mishra and Koehler, 2006).

What is TPACK?

Three key areas of teacher expertise are identified in this paradigm (Figure 1): technology (TK), pedagogy (PK), and content (CK). The relationships between and among these units of knowledge, which are represented by the terms TCK (technological content knowledge), PCK (pedagogical content knowledge) and TPK (technological pedagogical knowledge) and TPACK (Technology, Pedagogy, and Content Knowledge), are equally significant to the model. Each one of these has distinct features like: Teachers' knowledge of the material to be taught or learned is referred to as Content Knowledge (CK); Teachers who possess an in-depth understanding of teaching and learning procedures, practices, and strategies are said to possess Pedagogical Knowledge (PK). They include, among several others, the general goals, values, and objectives of education. A teacher's comprehension of different technologies and how they may be used to enhance teaching and learning processes in the classroom is referred to as Technology Knowledge (TK). This includes being aware of digital tools, having technical skills, employing technology, and being adaptable. Regarding the interactions- TCK is an understanding of how technology and content impact and restrict one another; TPK is an understanding of how teaching and learning can change when particular technologies are used in particular ways and PCK is consistent with and reminiscent of Shulman's idea of knowledge of pedagogy that is pertinent to the teaching of certain content which entails understanding the limitations and educational potential of various technology tools in relation to disciplinarily and

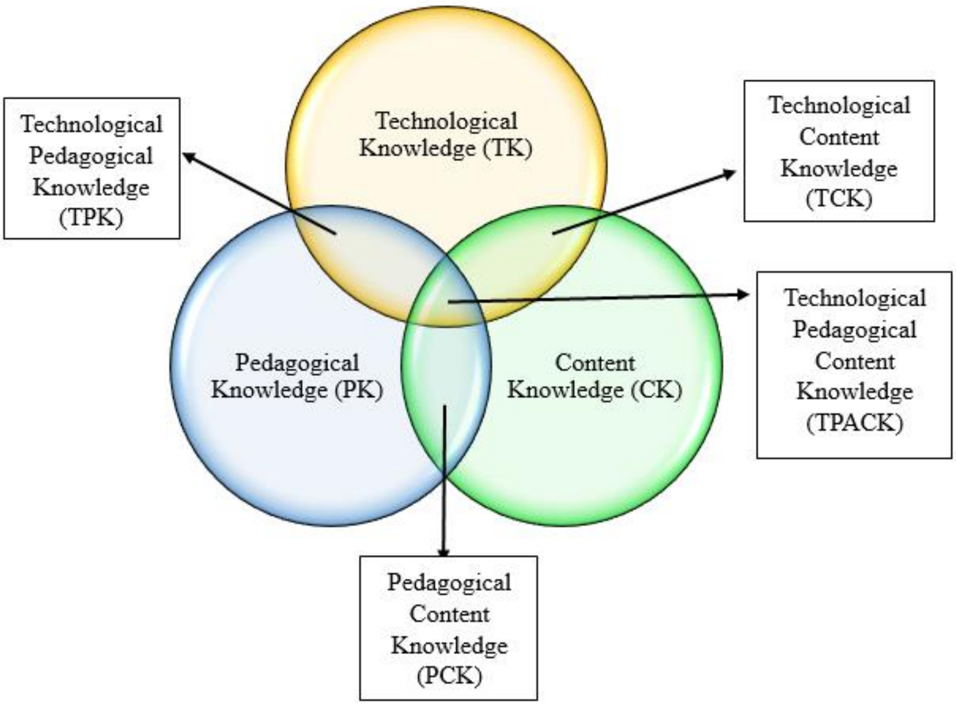

Figure 1. The TPACK Framework and its Knowledge Components (Source: Koehler and Mishra, 2009).

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developmentally appropriate pedagogical designs and strategies. Finally, TPACK stands for the foundation of successful technology-based education, necessitating comprehension of how concepts are represented through technologies, instructional strategies that make use of technology to teach topics in a productive way and understanding what constitutes concepts' learning style—hard or simple—and how technology might assist in addressing some of the issues that students encounter, awareness of students' past learning and epistemological frameworks, and understanding of the ways in which technologies can advance and strengthen current knowledge or develop novel epistemologies.

Initially, pedagogy and content were treated independently from technology, which was viewed as an add-on. This idea was contested by Mishra and Koehler's TPACK approach, which suggested that comprehending the intricate interactions among three fundamental elements—Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK)—is necessary for effective technology-based instruction. The main argument put forth by the concept of TPACK is that ICT should not be seen as a stand-alone component that can be added to conventional teaching methods. Rather, TPACK offers an integrated framework of teacher's knowledge that clarifies the crucial elements affecting improved student learning and successful teaching using digital technology (Mishra and Koehler, 2006). The TPACK approach was designed to emphasise that integrating technology into education requires more than just knowing how to use it; it also requires understanding how to combine technology with pedagogical approaches and content-specific knowledge to improve learning outcomes. This integrated approach acknowledged that, when carefully integrated into the curriculum, technology may revolutionise the ways that people teach and learn (Koehler and Mishra, 2009).

Significance of AI and its Integration into TPACK Framework

The TPACK theoretical framework has been in use for nearly two decades now, during which time information technology has rapidly improved, especially with the introduction of artificial intelligence (AI). With the advancement of technology, society has successfully moved from the information era to a new one marked by greater intelligence (Holmes et al., 2019; Roll and Wylie, 2016). However, replacing a teacher with AI in the future is not anticipated, according to Hrastinski et al. (2019). This is due to the fact that teacher-student interaction is essential to both the advancement of learning and the personal growth of each student (Cheng and Tsai, 2019). However, because AI and its related sectors are developing so quickly, teaching and learning settings will be surrounded by them (Ng et al., 2021; Xu, 2020). As a result, in order to implement AI-based instruction, teachers' professional expertise will change (Seufert et al., 2021). According to this perspective, the ability to use AI-based systems, both technologically and pedagogically, is essential for those in the teaching profession in order to successfully integrate this potent technology into teaching (Celik, 2023).

The crucial question in this situation is whether the current TPACK model is still appropriate given the changing needs of education and educators' need for professional growth (Kanbul et al., 2022). The Technological Pedagogical Content Knowledge (TPACK) framework needed to be updated to reflect the growing incorporation of AI into educational standards. Furthermore, the incorporation of AI technology inside the TPACK framework will bring about innovative modifications to teaching strategies, learning environments, and associated elements. Thus, due to its significance, Ning et al. (2024) perceived a necessity to add new meanings to the TPACK framework in the age of AI. In summary, the development of a unique TPACK framework anchored in the era of artificial intelligence has made it imperative to re-evaluate the relationships between pedagogy, technology and subject matter. In this framework, subject matter and pedagogy knowledge are secondary to technology as the most dynamic component. It conjectured that this part of knowledge would change accordingly, i.e., the evolution of Technological Pedagogical Knowledge (TPK) would occur (Ning et al., 2024).

In light of this, presuming that the TPACK framework, when aligned with the technological and pedagogical influences of AI, will provide a robust framework for better understanding teacher knowledge for AI-based instruction, investigators Ning et al., (2024) built a framework for incorporating the Technological Pedagogical Content Knowledge of Artificial Intelligence Technology (AI-TPACK). The goal was to clarify the intricate relationships and mutually reinforcing effects of subject-specific content, pedagogical approaches, and AI technology in education. Thus, AI- TPACK framework was formulated with- TPK turning into AI-TPK, TCK turning into AI-TCK, and TPACK into AI-TPACK.

Need for Adopting AI-TPACK Framework in the Indian Educational Context

Because of the distinct possibilities and challenges that the Indian education system presents, the AI-TPACK

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framework (Figure 2) must be used for the Indian educational context. Large and diverse student populations are a common feature of Indian classrooms, making successful technology integration and personalised learning difficult (Dubey et al., 2022; Kasinathan and Yogesh, 2019). When successfully incorporated into the AI-TPACK framework, AI-powered tools have the ability to overcome these issues by offering individualised learning experiences that are responsive to the demands of each individual student. AI can, for example, improve educational outcomes, support individualised instruction, provide personalised feedback, and modify learning methods in response to student performance (Chen et al., 2020; Vinay, 2023; Zawacki-Richter et al., 2019). Teachers may use AI technology to build more effective and interesting learning environments by integrating them with content knowledge and pedagogical practices.

these tools efficiently, educators frequently lack the assistance and training they need (Aithal and Aithal, 2019; Irrinki, 2021; Sharma and Singh, 2010). They can benefit from an organised approach to professional development by utilising the AI-TPACK framework, which can help them enhance their technological, pedagogical, and subject expertise in a coherent way. This modification can guarantee that teachers are prepared to make the most of AI tools, which will ultimately result in better teaching methods and student outcomes in the Indian setting. Therefore, a tool with the AI-TPACK framework is imperative in this scenario. With that being said, the most recent educator-focused tool with optimal criteria for evaluating their understanding of all the AI-TPACK components was developed by Yimin Ning, Cheng Zhang, Binyan Xu, Ying Zhou and Tommy Tanu Wijaya in China, 2024.

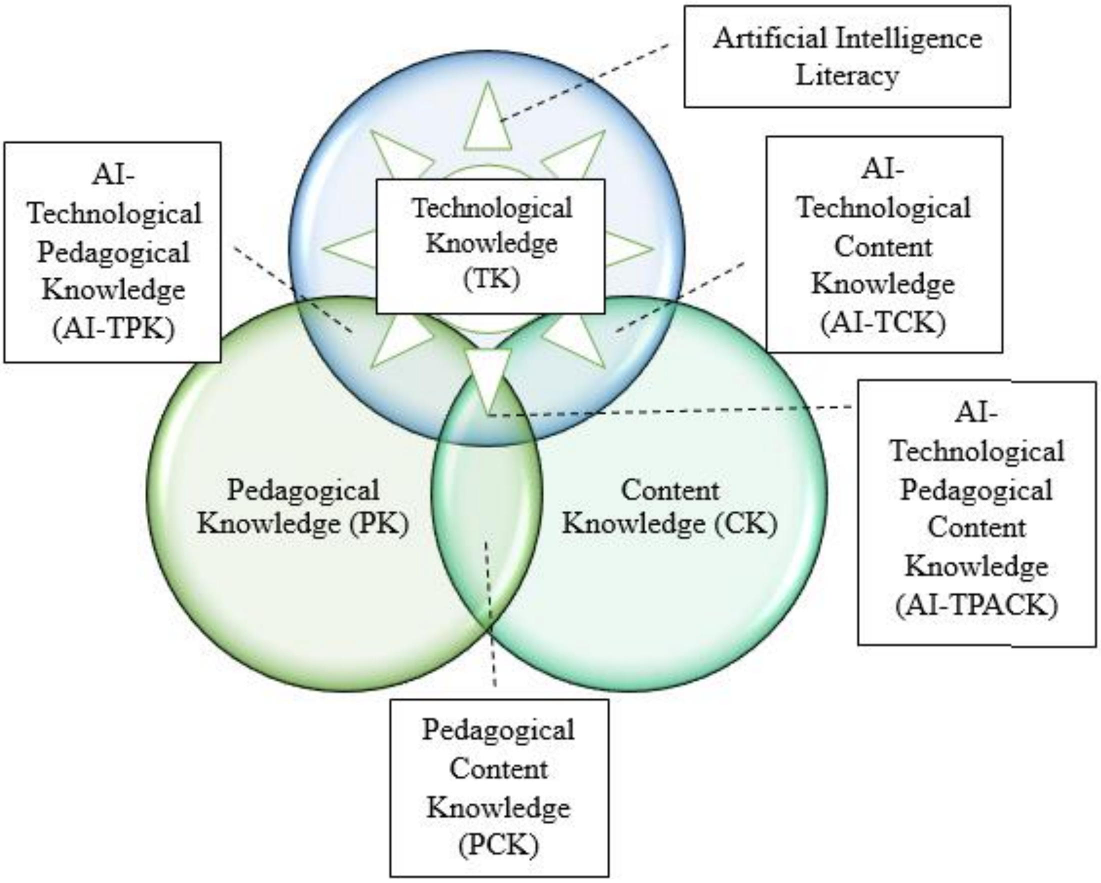

Figure 2. AI-TPACK Structural Diagram by Ning et al., 2024.

Furthermore, the Indian Government's emphasis on technology-enhanced learning and digital literacy highlights the necessity for frameworks like AI-TPACK that assist teachers in successfully incorporating AI into their lesson plans. In order to increase quality, equity, and access in education, initiatives like the National Education Policy (NEP) 2020 highlight how important it is to integrate technology (NEP_ Ministry of Human Resource Development, 2020). However, in order to use

Objectives of the Study

To validate the Teachers' AI-TPACK scale by Ning et al. (2024) in the Indian educational context

Review of Literature

Research has shown that TPACK is an extensive beneficial framework for the following purposes: a) investigating teachers' knowledge and abilities to incorporate ICT into their teachingl methods (Chai et al.,

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2013; Voogt et al., 2013); b) creating and evaluating teacher education and professional development programs which are aimed at fostering the use of digital technologies into teaching (Chai et al., 2017; Foulger et al., 2017; Graham, 2011; Jimoyiannis, 2010); and c) offering teachers substantial suggestions regarding the design of crucial, subject-specific practices by utilising the affordances of particular digital tools (Koh et al., 2015; Doering et al., 2014; Niess, 2013).

Research Gap

Many TPACK related research projects conducted in the last few years have concentrated on developing instruments for evaluating teachers' TPACK aspects. Chai et al., 2010, Koh et al., 2013, Schmidt et al., 2009, etc. are few examples. On the other hand, research on TPACK scale in the context of AI is a dynamic and ever-evolving venture in the academic sector. One such AI-TPACK Scale, created to evaluate instructors' ethical understanding of AI by Celik added an ethical component to TPACK (Celik, 2023). This is not directly focused on the seven dimensions of TPACK framework. Clearly, the scale created in 2024 by Ning et al. is the only AI-TPACK scale currently widely available and focuses solely on its dimensions. The scale was originally developed and validated in China. Other than this scale, there is a dearth of scales to measure AI-TPACK. This research gap mandates an immediate validation of the existing scale since AI-TPACK is a crucial component in this century and a scale to measure the same in the Indian context is paramount.

Need for Cross-culturally Validation of Scales/Measurement Tools

Scales and measurement instruments must be validated before being used in different nations and situations in order to guarantee their validity, reliability, and cultural applicability. Firstly, due to variations in language, educational systems, and cultural norms, instruments created in one context may not adequately reflect constructs in another, thus making cultural sensitivity essential (Cheung and Rensvold, 2000). Secondly, to ensure that translated items transmit the same meaning as the original, linguistic equivalency must be preserved while considering idioms and contextual nuances (Behling and Law, 2000). Next, simple translation is not sufficient in this regard. Validation is also required because of institutional and educational disparities, since measuring instruments must consider the particulars of various educational contexts to prevent imprecise evaluations (Perry et al., 2004). Next, psychometric validation is essential to guarantee consistent and accurate measurement in the new setting because psychometric qualities like validity and reliability might differ among populations (Van de Vijver and Leung, 2021). Furthermore, it is crucial to guarantee that the tool's outputs are interpreted consistently in various contexts so that accurate comparisons and insightful inferences may be drawn (Hambleton et al., 2004). If appropriate validation is not obtained, the instrument's effectiveness in various cultural and educational contexts may be compromised by biased, inaccurate, and non-generalizable results. Thus, in order to properly adapt measurement instruments to a variety of contexts and ensure that they fulfil their intended purpose, cross-cultural validation is an essential step.

Materials and Methods

Study Area and Participants

The study included a total of 660 university and college faculty members who were either professors, associate professors, or assistant professors. Because of this stratification, the various seniorities and degrees of academic expertise within the education system could be fully represented. The data was collected from samples across 23 states of India, with Odissa, Assam, West

Table 1. Demographic Characteristics of Study Participants (N = 660).

Characteristics	Category	Frequency	Percentage
Gender	Male	312	47.3
	Female	348	52.7
Subject Category	Science	197	29.8
	Arts	411	62.3
	Commerce	52	7.9
Teaching Experience	0-5 years	342	51.8
	6-10years	90	13.6
	11-15years	82	12.4
	16years and above	146	22.1
Location of University/ College	Odissa	72	10.9
	Assam	43	6.5
	West Bengal	120	18.2
	Jharkhand	111	16.8
	Others	314	47.6

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Bengal and Jharkhand contributing more than half of the total. These diverse geographical participants give a scope for a complete representation of the country's academic landscape since samples were collected across North, South, East and West states. Regarding the locale, respondents from West Bengal and Jharkhand comprised 35% of the total 660 respondents. The others option consisted of 47.6% of participants and the following were the states: Haryana, Uttar Pradesh, Tamil Nadu, Goa, Maharashtra, Meghalaya, Manipur, Nagaland, Arunachal Pradesh, Mizoram, Delhi, Karnataka, Madhya Pradesh, Bihar, Gujarat, Himachal Pradesh, Punjab, Kerala and Jammu & Kashmir. The other demographic details are showcased in Table 1.

Inclusion and Exclusion Criteria

The 660 participants were allowed to take part based on inclusion and exclusion criteria to warrant relevance to the research objectives

Inclusion criteria-

1. Participant must be currently a faculty member (professor, associate professor, or assistant professor) at a recognized College/University in India.

2. Participant must be able to read and respond in English (as the survey was conducted in English).

Exclusion criteria-

1.Visiting faculty/guest lecturers or part-time instructors who were not full-time employees of their respective institutions.

2. Not a permanent resident of India.

Details of the Survey Instrument under Validation

The Teachers AI-TPACK scale developed and validated in the research paper "Teachers' AI-TPACK: Exploring the Relationship between Knowledge Elements" by Yimin Ning, Cheng Zhang, Binyan Xu, Ying Zhou, and Tommy Tanu Wijay (2024) originally included 42 items and seven dimensions. These dimensions integrated artificial intelligence as a crucial component and encompassed an array of technological, pedagogical, and subject matter expertise for teachers. Six items were included in each dimension, each of which was intended to gauge educator's ability to use AI in the classroom. Using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), the investigators used structural equation modelling (SEM) to investigate the interactions between the seven knowledge elements i.e., PK, CK, AI-TK, AI-TCK, AI-TPK, PCK, and AI-TPACK. The findings indicated that, to varied degrees of explanatory strength, each of the six knowledge elements function as a predictive factor for the AI-TPACK variables. Through composite knowledge elements (PCK, AI-TCK and AI-TPK), core knowledge elements (PK, CK, and AI-TK) indirectly influenced AI-TPACK. Notably, Content Knowledge (CK) was seen to reduce the explanatory power of PCK and AI-TCK, and non-technical knowledge sections have far lower explanatory power than technical ones. The scale used a 5-point Likert self-assessment rating system, ranging from Strongly Conformant to Strongly Non-conformant. Higher scores implied higher degrees of AI-TPACK competency. Three items were eliminated at the conclusion of the analysis, leaving a 39-item scale (Refer to https://www.mdpi.com/2071-1050/16/3/978 for full scale).

Data Collection Procedure

The data collection spanned a three-month period from May to July 2024. The researchers secured the required approvals from their individual universities' educational departments and ethical committees before beginning the data collection process. This vital stage ensured that the research technique as a whole and the AI-TPACK scale complied with the accepted academic and ethical norms. The questionnaire was meticulously created with Google Forms, an easily navigable and extensively available web application. The research team's extensive introduction, outlining their academic ties, opened the questionnaire. Subsequently, the study's aims were stated clearly and comprehensively, underscoring the significance of validating the Teachers AI-TPACK scale inside the Indian educational milieu.

Further, informed consent was ensured. Participants were given a comprehensive consent form to review before they could access the survey items. This included information about the study's objectives, the confidentiality procedures in place, and the voluntary nature of participation. Following this, every segment had detailed instructions, with particular emphasis placed on elucidating the grading system employed in the Teachers AI-TPACK scale. In order to ensure the validity of the study, participants were urged to provide truthful responses. The survey took an average of 20-minutes completion time per entry, which was intentionally designed to strike a balance between completeness and respondents' fatigue. It consisted two sections: A) Demographic details of participants; B) Teachers AI-TPACK scale. Initially, 672 responses were obtained. To guarantee data quality, a thorough cleaning procedure was carried out where duplicate entries were eliminated, responses were checked for completeness, and any outliers or discrepancies were addressed. Following this exhaustive data cleaning process, 660 samples were left i.e., around 98.2% of the initial responses.

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Statistical Analysis Applied

The elements and structure of the teacher's AI-TPACK scale were established and validated by a rigorous two-phase approach to data analysis. Two equal and homogeneous subsets (n = 330 each) of the entire sample (n = 660) were randomly selected to enable both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA).

Phase 1: EFA- SPSS v 27 was used to perform EFA on the first half of the sample (n = 330). Two preliminary tests were carried out to determine whether the data were suitable for factor analysis before the EFA was conducted, such as The Kaiser-Meyer-Olkin (KMO) Test of Sampling Adequacy and Bartlett's Test of Sphericity (BTS). According to Tabachnick and Fidell (2007), the latter test examines the hypothesis that the correlation matrix is an identity matrix that will ultimately suggest that the variables are independent of each other. The former test assessed the sample adequacy as per Hutcheson and Sofroniou (1999). After that, EFA was carried out in order to investigate the underlying psychometric structure among each of the 39 items in the scale. Principal component analysis with varimax rotation was employed as a commonly advised technique in scale validation methods (Costello and Osborne, 2019). Phase 2: To check if the factor structure produced by the EFA procedure was compatible with the data, it was subsequently checked again using CFA on the second half of the sample.

Not ending here, the final scale was then investigated for its reliability in statistics by measuring its Internal Consistency using Cronbach's alpha coefficient.

Table 2. KMO and Bartlett's Test of Sphericity.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.544
Bartlett's Test of Sphericity	Approx. Chi-Square	21960.118
	df	741
	Sig.	.000

Results and Discussion

Phase 1- Exploratory Factor Analysis (EFA)

Suitability of data

Finding common components in a dataset and assessing the construct validity of a scale are the primary goals of an Exploratory Factor Analysis (EFA) (Costello and Osborne, 2019). In this regard, it is crucial to determine whether the collected data are appropriate for this analysis to guarantee the EFA's validity (Conway and Huffcutt, 2003). As a result, in order to determine whether the data were suitable, two tests were run-

1. The Kaiser-Meyer-Olkin (KMO) Sampling Adequacy Measure: The KMO value obtained was 0.544, just above the minimum threshold of 0.50 as Kaiser (1974) suggested for factor analysis. However, in the same line, Hutcheson and Sofroniou (1999) mentioned that though the value is low, it still meets the bare minimum criteria for proceeding with factor analysis. Likewise, Field (2013) stated that while values between 0.5 and 0.7 are mediocre, they are still acceptable for factor analysis, especially in exploratory research. 2. Bartlett's Sphericity Test: A statistically significant result (χ^2 = 21960.118, df = 741, p <.001) was obtained from this test, suggesting that factor analysis is valid and that the correlation matrix is not an identity matrix (Table 2). Both these results point to the fact that the collected data was appropriate for performing EFA.

Total variance explained (Table 3) is vital for deciding the number of factors that need to be maintained for further analysis. Together, the seven factors that were kept accounted for 79.060% of the variance in the data. This is a respectable level of explained variance, indicating that these seven factors capture a significant percentage of the data. The following are the individual factor contributions: 23.788% of the variance is explained by factor 1, 14.653% by factor 2, 12.509% by factor 3, and the rest contributed progressively less to this total variance explained. A seven-factor structure accounted for 79% of the overall variance on the AI-TPACK scale. The rotated sums of squared loadings revealed a more evenly distributed variance explained among the factors ranging from 14.79% to 8.91%. This is a good outcome, displaying that the items were capturing unique and significant aspects of the AI-TPACK scale.

As the succeeding step in analysis, EFA (n=330) in the form of Rotated Component Matrix (Table 4) using Principal component analysis as the extraction method and Varimax with Kaiser normalization as the rotation method was employed for underlying factor structure. Principal Component Analysis (PCA) is the most widely used technique for factor extraction in SPSS software. It estimates the number of factors, gives these variables names, and provides post hoc interpretations after extracting common components from the data based on their intercorrelations (Ferguson and Cox, 1993). Rotations can be carried out in numerous statistical ways and in this survey, the investigators picked the varimax rotation method (Williams et al., 2010).

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Table 3. Total Variance Explained.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.277	23.788	23.788	5.769	14.793	14.793
2	5.715	14.653	38.442	5.118	13.123	27.916
3	4.878	12.509	50.950	4.413	11.314	39.230
4	3.858	9.893	60.844	4.387	11.249	50.480
5	3.028	7.765	68.609	4.074	10.446	60.925
6	2.143	5.495	74.103	3.596	9.220	70.145
7	1.933	4.956	79.060	3.477	8.915	79.060
8	.974	2.498	81.558			
9	.824	2.112	83.670			
10	.772	1.980	85.650			
11	.697	1.786	87.436			
12	.621	1.592	89.027			
13	.548	1.404	90.432			
14	.519	1.330	91.762			
15	.482	1.237	92.999			
16	.443	1.137	94.136			
17	.412	1.056	95.192			
18	.307	.786	95.978			
19	.303	.777	96.755			
20	.280	.719	97.474			
21	.221	.566	98.040			
22	.148	.379	98.419			
23	.141	.360	98.779			
24	.097	.248	99.028			
25	.085	.219	99.246			
26	.055	.140	99.386			
27	.045	.116	99.501			
28	.036	.094	99.595			
29	.035	.090	99.685			
30	.033	.084	99.769			
31	.022	.057	99.825			
32	.017	.044	99.870			
33	.016	.041	99.910			
34	.012	.031	99.941			
35	.009	.022	99.963			
36	.006	.014	99.977			
37	.004	.010	99.988			
38	.003	.009	99.997			
39	.001	.003	100.000			

Five principles guide item selection in EFA: removing items with factor loadings less than 0.5 (Kaiser, 1960), removing items with roughly equal loadings on two factors, removing misclassified items based on

Table 4. EFA Analysis Results- Rotated Component Matrix.

	Component						
	1	**2**	**3**	**4**	**5**	**6**	**7**
PCK_5	.978						
PCK_3	.975						
PCK_2	.974						
PCK_1	.963						
PCK_4	.962						
PCK_6	.949						
AI_TPK_4		.936					
AI_TPK_5		.933					
AI_TPK_2		.929					
AI_TPK_1		.927					
AI_TPK_6		.894					
AI_TPK_3		.883					
AI_TCK_5			.835				
AI_TCK_4			.824				
AI_TCK_2			.774				
AI_TCK_6			.772				
AI_TCK_1			.771				
AI_TCK_3			.708				
PK_6				.864			
PK_3				.849			
PK_5				.848			
PK_2				.836			
PK_4				.805			
PK_1				.801			
CK_4					.852		
CK_1					.850		
CK_5					.819		
CK_3					.818		
CK_2					.752		
AI_TPACK_1						.865	
AI_TPACK_4						.859	
AI_TPACK_2						.853	
AI_TPACK_5						.839	
AI_TPACK_3						.765	
AI_TK_4							.893
AI_TK_1							.890
AI_TK_5							.732
AI_TK_3							.727
AI_TK_2							.726
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							

predetermined conceptual factors, iteratively removing items and repeating EFA, and continuous item removal in accordance with these principles until a more distinct factor structure appears (Costello and Osborne, 2019; Ferguson and Cox, 1993; Hair, 2009). The factor loadings ranged between .978 ≥ λ ≥ .708, with a loading value of λ ≥ .50 considered appropriate as per benchmark (Hair et al., 2006). According to Hair et al. (2010), we noticed that each item is considered good since item loadings were greater than 0.70, indicative of excellent construct validity. Furthermore, there appeared to be no significant cross-loadings (loadings > 0.3 for several factors), indicating that the variables have good discriminant validity. Thus, all the 39 items were retained and further contributed to the construct underlying the factor.

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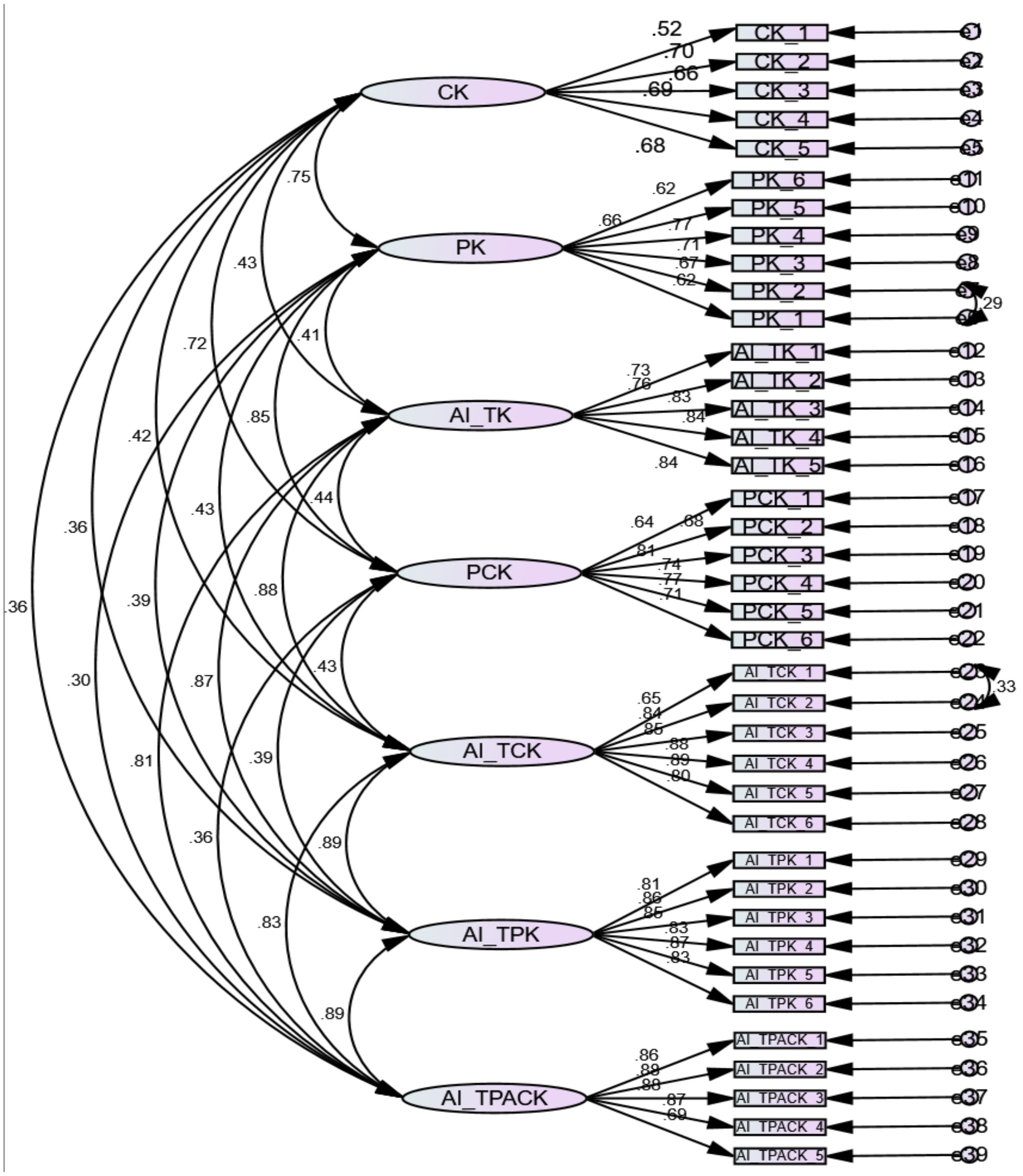

Figure 3. The Factor Structure of the Model with 39 items of AI- TPACK Scale.

Phase 2- Confirmatory Factor Analysis (CFA)

By utilizing Monte Carlo techniques, Gerbing and Hamilton (1996) realized that EFA can improve model formulation when used ahead of cross-validation using CFA (Figure 3). The investigators followed this. After which, CFA was advised as a subsequent test and the Factor structure of the model was analysed. The whole set of 39 items across seven dimensions was utilised to examine the likelihood that good factor loadings could be produced. Standardized Factor Loading with a minimum of .50 is acceptable and above .70 is considered excellent. The second part of the sample i.e., n=330 was utilized here. Several observable variables are used to measure each construct. Factor loadings ranged from very high (.89) to moderate (.52). The strongest correlations between latent constructs were observed between AI-TPK and AI-TPACK (.89). Between AI-TCK and AI-TPK (.89). This framework builds upon the theoretical underpinnings of TPACK as put forth by Mishra and Koehler (2006). Thus, as seen in figure 3, all the factor loadings were above 0.50 and fitness indices from CFA output were examined.

With regard to the CFA fit indices, the most commonly recorded measures were chosen (Table 5). CMIN/DF- Minimum Discrepancy Function by Degrees of Freedom divided was 2.260, i.e., within the

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recommended threshold value of <3 (Kline, 2023); RMSEA- The Root Mean Square Error of Approximation was 0.062 i.e., within the ideal threshold value of <0.08 and considered a good fit (Hu and Bentler, 1999); RMR- Root Mean Square residual was 0.032 i.e., <0.05 and is an acceptable model fit (Byrne, 2013); Looking at the GFI -Goodness of Fit index, the value obtained is 0.806 which is above 0.80 (Baumgartner and Homburg, 1996; Hooper et al., 2008) and is also considered as acceptable model fit due to a complex model; The PCFI - Parsimony Comparative Fit Index has resulted in 0.835 which is again acceptable since it is in the acceptable range of >0.80 (Mulaik et al., 1989). Likewise, the CFI - Comparative Fit Index value was 0.911 (>0.90), indicating a good model-data fit in general. Overall, these fitness estimates imply that the proposed AI-enhanced TPACK model for teachers is a good fit for the data.

Table 5. CFA Fit indices of Teachers AI-TPACK Scale under validation.

Measures	P value	CMIN/ DF	RMR	RMSEA	GFI	PCFI	CFI
Observed value	0.000	2.260	0.032	0.062	0.806	0.835	0.911
Benchmark	<0.05	<3	<0.05	<0.08	>0.80	>0.80	>0.90

Reliability Analysis

Internal consistency reliability was assessed using Cronbach's alpha for the retained 39 items (Table 6). Values above 0.70 are generally considered acceptable, with values above 0.80 indicating good reliability (DeVellis, 2003; Nunnally and Bernstein, 1994). The PCK dimension yielded the highest reliability (α = 0.990), while AI-TPACK had the lowest, though still excellent, reliability score (α = 0.898). The Cronbach's Alpha is 0.907 for the complete set of 39 items, showcasing the scale's internal consistency.

Based on the high-reliability coefficients, each item within each dimension and across other dimensions seem highly connected, most likely assessing the same underlying concept. This offers compelling proof of the validity of the AI-TPACK scale for use in the Indian educational context.

Conclusion and Implications

This study validated the Teachers AI-TPACK scale by Ning et al. (2024) in the Indian education context by utilizing a sample of 660 university and college faculty members across the nation. The results of the exploratory and confirmatory factor analyses, combined with high-reliability coefficients across the seven factors, provide compelling evidence for the validity and reliability of the teacher's AI-TPACK scale in measuring Indian educators' knowledge and skills at the juncture of AI with pedagogy, technology and content. As Chai et al. (2013) reason, context-specific TPACK measurements are important for comprehending the unique challenges and opportunities in different educational settings. Further, the final seven-factor structure with the 39 items aligns well with the theoretical foundations of TPACK (Mishra and Koehler, 2006) while effectively incorporating AI-specific knowledge domains, indicating the mounting importance of AI in educational technology (Holmes et al., 2019).

The validation of this scale has significant implications for practitioners, policymakers and researchers in Indian education. For the latter, this tool is a reliable instrument to examine and track the development of AI-related technological pedagogical content knowledge among Indian educators, possibly ending towards more targeted and valuable professional development programs. For the former, this validated scale responds to the demand for more AI-literate educators in the quickly changing digital ecosystem by providing them i.e. practitioners and policymakers with a framework to direct the incorporation of AI technology into teaching and learning processes (Roll and Wylie, 2016). But as Koehler et al. (2014) point out, TPACK is a dynamic and multifaceted concept that changes in tandem with pedagogical breakthroughs and technology

Table 6. Reliability Quotients of the Validated Teachers AI-TPACK Scale.

Dimension	Cronbach's Alpha (Dimension Wise)	Cronbach's Alpha (Total 39 items)
Content Knowledge (CK)	0.918	0.907
Pedagogical Knowledge (PK)	0.922	
AI- Technological Knowledge (AI-TK)	0.928	
Pedagogical Content Knowledge (PCK)	0.990	
AI- Technological Content Knowledge (AI-TCK)	0.908	
AI- Technological Pedagogical Knowledge (AI-TPK)	0.964	
AI- TPACK	0.898	

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improvements. Investigators, thus, suggest future studies to look at how AI-TPACK has developed over time among Indian educators and how it relates to better student outcomes and efficient teaching strategies in AI-enhanced learning settings.

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Conflict of Interest

The authors declare that there is no conflict of interest

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