NETWORKED LEARNING BEHAVIOR IN HIGHER EDUCATION: A MODERATED MEDIATION ANALYSIS OF TPACK AND AI READINESS

COMPORTAMENTO DE APRENDIZAGEM EM REDE NO ENSINO SUPERIOR: UMA ANÁLISE DE MEDIAÇÃO MODERADA DO TPACK E DA PRONTIDÃO PARA IA

COMPORTAMIENTO DE APRENDIZAJE EN RED EN LA EDUCACIÓN SUPERIOR: UN ANÁLISIS DE MEDIACIÓN MODERADA DEL TPACK Y LA PREPARACIÓN PARA LA IA

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ABSTRACT: This study examines the structural relationships among artificial intelligence (AI) readiness, technological pedagogical content knowledge (TPACK), and networked learning behavior among faculty members at Indian public universities. Using a cross-sectional quantitative survey design, the study tests a moderated mediation model in which TPACK mediates the relationship between AI readiness and networked learning behavior, while institutional digital infrastructure moderates this indirect effect. Structural equation modeling was employed to assess the hypothesized relationships. The results show that AI readiness significantly increases TPACK, which, in turn, strongly predicts networked learning behavior. TPACK constitutes the main mechanism through which AI readiness influences collaborative online learning practices, and the indirect effect is significantly stronger in institutions with well-developed digital infrastructure. The study highlights the importance of integrating faculty AI readiness, pedagogical competence, and institutional digital support, with practical implications for faculty development programs and strategic investments in digital infrastructure in higher education settings.

KEYWORDS: Networked learning. TPACK. AI readiness. Higher education. Digital infrastructure.

RESUMO: *Este estudo examina as relações estruturais entre a prontidão para a inteligência artificial (IA), o conhecimento tecnológico pedagógico do conteúdo (TPACK) e o comportamento de aprendizagem em rede entre docentes de universidades públicas indianas. Por meio de um delineamento quantitativo transversal, baseado em levantamento, testa-se um modelo de mediação moderada no qual o TPACK medeia a relação entre a prontidão para IA e o comportamento de aprendizagem em rede, enquanto a infraestrutura digital institucional modera esse efeito indireto. A modelagem de equações estruturais foi utilizada para avaliar as relações hipotetizadas. Os resultados mostram que a prontidão para IA aumenta significativamente o TPACK, que, por sua vez, prediz fortemente o comportamento de aprendizagem em rede. O TPACK constitui o principal mecanismo dessa relação, e o efeito indireto é mais forte em instituições com infraestrutura digital bem desenvolvida. O estudo destaca implicações para formação docente e investimentos estratégicos em infraestrutura digital institucional.*

PALAVRAS-CHAVE: *Aprendizagem em rede. TPACK. Prontidão para IA. Ensino superior. Infraestrutura digital.*

RESUMEN: *Este estudio examina las relaciones estructurales entre la preparación para la inteligencia artificial (IA), el conocimiento tecnológico pedagógico del contenido (TPACK) y el comportamiento de aprendizaje en red entre docentes universitarios de la India. Con un diseño cuantitativo transversal, prueba un modelo de mediación moderada en el que el TPACK media la relación entre la preparación para la IA y el comportamiento de aprendizaje en red, mientras que la infraestructura digital institucional modera este efecto indirecto. Se empleó el modelado de ecuaciones estructurales para evaluar las relaciones. Los resultados muestran que la preparación para la IA incrementa significativamente el TPACK, que, a su vez, predice fuertemente el comportamiento de aprendizaje en red. El TPACK constituye el principal mecanismo, y el efecto indirecto es mayor en instituciones con infraestructura digital desarrollada. El estudio destaca la importancia de integrar la preparación para la IA, la competencia pedagógica y el apoyo digital institucional.*

PALABRAS CLAVE: *Aprendizaje en red. TPACK. Preparación para la IA. Educación superior. Infraestructura digital.*

INTRODUCTION

Networked learning refers to learning activities facilitated through digital connections, allowing individuals to exchange messages and materials with other participants, instructors, and information archives (Goodyear et al., 2004; Hodgson et al., 2020). This approach differs from conventional, instructor-centric models of instruction by emphasizing the socially situated and collaborative nature of knowledge construction, in which teachers act as facilitators and co-participants within a networked ecology of learners, tools, and resources (Siemens, 2005). Within this ecology, educators' capability to work purposefully with technological instruments becomes a crucial determinant of successful learning outcomes. One influential framework for understanding this capability is Technological Pedagogical Content Knowledge (TPACK), developed by Mishra and Koehler (2006) on the basis of Shulman's (1986) construct of pedagogical content knowledge.

TPACK conceptualizes teacher knowledge as the dynamic interaction of three core domains, namely technological knowledge (familiarity with digital tools), pedagogical knowledge (understanding of teaching methods), and content knowledge (mastery of subject matter), together with the hybrid forms of knowledge that emerge at their intersections: technological content knowledge, or understanding of how technology and subject matter shape one another; technological pedagogical knowledge, or understanding of how particular tools change what teaching strategies are possible; pedagogical content knowledge, or understanding of how to represent a given subject so that it is teachable (Shulman, 1986); and, at the center of the model, TPACK itself, the integrated understanding of how technology, pedagogy, and content interact and constrain one another in a specific teaching situation. In practical terms, TPACK describes how teachers select, adapt, and combine digital tools with appropriate pedagogical strategies to teach specific subject content effectively, and it has become one of the most widely used frameworks for explaining why some educators integrate technology successfully while others do not.

TPACK is typically assessed through validated self-report instruments (Schmidt et al., 2009) and is used by teacher educators and instructional designers both diagnostically, to identify which knowledge domain is holding back effective technology integration, and formatively, to structure professional development so that technological training is never delivered in isolation from pedagogy and content (Kimmons & Hall, 2016; Valtonen et al., 2021). Its relevance for networked learning specifically follows from the logic of the framework itself: engaging productively with a networked ecology of learners and tools is not simply a matter of being comfortable with technology, but of knowing how to weave that technology into pedagogically sound, content-appropriate practice, which is exactly the integrative competence TPACK describes. In other words, TPACK is not treated here as a peripheral background variable but as the substantive knowledge base that should, in principle, convert a teacher's general orientation toward technology into a specific, situated capacity to teach and collaborate through digital means. While a substantial body of research has examined TPACK in K-12 settings, the connection between TPACK and networked learning behavior in higher education has received comparatively little attention, especially considering emerging AI-based solutions (Chai et al., 2019).

A second, closely related construct is AI readiness, defined as individuals' cognitive, motivational, and behavioral predisposition to work with AI-based educational solutions, encompassing awareness of AI's potential, a positive attitude toward its use, and the behavioral intention to adopt it in professional practice (Ayanwale et al., 2022). Unlike general digital literacy, which describes familiarity with technology in the abstract, AI readiness is specific to the affective and motivational stance a person takes toward a class of tools whose behavior is adaptive and, to a degree, opaque, which is why awareness of what the technology can and cannot do, and of the ethical questions it raises, is treated as a component of the construct rather than a separate add-on (Long & Magerko, 2020).

The authors treat AI readiness as sitting closer to disposition than to skill, in the same sense that self-efficacy beliefs precede and motivate the effortful acquisition of a competence rather than constituting that competence themselves (Bandura, 1986), and in the same sense that behavioral intention is theorized in technology acceptance research as the proximal driver of the effort a person is willing to invest in learning to use a new tool (Venkatesh et al., 2003). Applied to the present context, this reasoning positions AI readiness as an antecedent of technology-related competence rather than as a competence in its own right: faculty members who are more aware of, and receptive to, AI are more likely to invest the effort required to build the technological, pedagogical, and content knowledge that TPACK represents. In other words, the disposition to engage with AI is expected to precede and feed into the development of TPACK-related skills, which should, in turn, translate into observable networked learning practices; readiness by itself supplies motivation, but TPACK is what supplies the capability that readiness is theorized to produce.

Despite this conceptual proximity, very few studies have empirically examined how AI readiness and TPACK relate to one another and, more importantly, whether this relationship helps explain networked learning behavior, understood here as the concrete, observable use of digital connections for professional collaboration and knowledge exchange. This gap is compounded by the growing adoption of adaptive learning systems, intelligent tutoring systems, and generative AI tools in universities, which makes the intersection of AI readiness and TPACK an especially fertile area for investigation.

At the same time, relatively little is known about how contextual factors, such as institutional digital infrastructure, shape these associations. The authors regard this omission as consequential rather than incidental: sociotechnical systems theory holds that individual competence and organizational structure jointly, not separately, determine whether a given behavior is enacted (Trist, 1981), and ecological accounts of educational technology make the same point more specifically, arguing that a teacher's technology-related behavior is constrained by the affordances of the surrounding system as much as by what the teacher personally knows or intends (Zhao & Frank, 2003).

Applied here, this means that even a faculty member whose AI readiness has already been converted into strong TPACK may be unable to translate that competence into networked learning behavior if the surrounding hardware, connectivity, and learning-management infrastructure will not support it; institutional digital infrastructure is therefore treated not as a background control variable but as a boundary condition that determines how much of the AI readiness-to-TPACK-to-behavior pathway can actually surface as observed practice.

This gap is especially pronounced in developing countries with rapidly digitizing higher education sectors but persistent infrastructural constraints (UNESCO, 2023). To address these gaps, the present study tests a moderated mediation model in which TPACK serves as a mediator between AI readiness and networked learning behavior, while institutional digital infrastructure acts as a boundary condition moderator. The general research question guiding this analysis is as follows: Does TPACK mediate the relationship between AI readiness and networked learning behavior among higher education faculty, and if so, does institutional digital infrastructure moderate this mediated relationship?

REVIEW OF LITERATURE

AI Readiness among Educators

In educational contexts, AI readiness refers to individual awareness of the technology's potential, willingness to adopt AI in professional practice, and intention to do so (Ayanwale et al., 2022). AI readiness stands distinct from general digital literacy because it involves a deeper awareness of how to apply the technology and of ethical implications. Recent research indicates that AI readiness positively influences the intention to adopt technologies (Sánchez-Prieto et al., 2023) and drives innovation (Chen et al., 2022).

The relevance of the AI readiness construct for the present study lies in the strong connection between AI readiness and TPACK. Specifically, AI readiness would be expected to increase individuals' technological knowledge in TPACK because such individuals are willing and able to use innovative technologies like AI for instruction (Mishra & Koehler, 2006).

Institutional Digital Infrastructure as a Moderator

Contextual factors play a crucial role in shaping individuals' technology adoption behavior. In the case of educational institutions, digital infrastructure—which involves availability of hardware, internet connectivity, Learning Management System (LMS) capacity, and institutional Information Technology (IT) infrastructure—creates affordances and constraints within which individuals can act based on their skills and knowledge (Bates, 2015). Institutions with fewer resources may hinder even individuals with higher TPACK scores from engaging in networked learning behavior, whereas resource-rich institutions would enhance their behavior. The moderation hypothesis follows principles of sociotechnical systems theory (Trist, 1981) and educational technology ecological frameworks (Zhao & Frank, 2003). By incorporating digital infrastructure as a moderator, the current study will account for contextual constraints in which individual competencies are enacted.

Research Gaps

Based on the review of existing literature, research gaps were identified. No study to date has examined the link between AI readiness and TPACK through a mediation model focusing on networked learning behavior. These gaps are significant and need to be addressed to achieve sustainable education.

HYPOTHESES OF THE STUDY

Drawing on the TPACK framework (Mishra & Koehler, 2006), with frameworks assessing AI readiness (Ayanwale et al., 2022) and sociotechnical systems theory (Trist, 1981), the study was conducted using a moderated mediation model. The model assumes that AI readiness has an indirect influence on networked learning behavior via TPACK (mediation), and that this mediated relationship is moderated by institutional digital infrastructure (moderated mediation).

H1: AI readiness positively correlates with TPACK among higher education faculty.

H2: TPACK positively correlates with networked learning behavior.

H3: TPACK mediates the relationship between AI readiness and networked learning behavior.

H4: Institutional digital infrastructure moderates the relationship between TPACK and networked learning behavior in the sense that the relationship will be stronger for faculty working in digitally equipped institutional environments.

H5: The indirect influence of AI readiness on networked learning behavior via TPACK will be moderated by institutional digital infrastructure (moderated mediation).

METHODOLOGY

Population and Sampling

The target population consisted of higher education faculty engaged in online or blended learning for at least one year across four recognized universities in Kolkata, India. Stratified random sampling was employed, with strata defined by geographic region (North, South, East, and West Kolkata), institution type (research- or teaching-oriented), and academic discipline (STEM, social sciences, and humanities).

Out of 530 distributed questionnaires, 412 usable responses were returned, yielding a response rate of 77.7%. Of the sample, 54.6% were men and 45.4% were women. The participants' mean age was 41.3 years (SD = 8.6). Years of work experience ranged from 2 to 25 (M = 14.2, SD = 7.9). Participants were distributed across three disciplinary groups: STEM (38.3%), social sciences (31.1%), and humanities and arts (30.6%).

RESEARCH ETHICS

This study followed established ethical procedures for research involving human participants. The research protocol, including the survey instrument and data collection procedures, received prior approval from the Institutional Ethics Review Committee at the authors' university. Prior to participation, all faculty members were provided with an informed consent statement outlining the purpose of the study, the voluntary nature of participation, and their right to withdraw at any point without penalty. Participation was entirely voluntary, and no incentives or institutional pressure were applied to encourage responses. Respondent anonymity was ensured throughout: no personally identifying information (such as name, email address, or employee identification number) was collected, and questionnaire responses were stored and analyzed only in aggregated, de-identified form. Data were accessible only to the research team and were used exclusively for the purposes of this study.

MEASURES

All measures in this research used a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Networked learning behavior was measured using a 12-item scale adapted from Goodyear et al. (2004) for the context of AI-mediated learning. An example item was "I use digital media to interact with fellow teachers from other universities on a regular basis." Cronbach's alpha for the scale was .91.

TPACK was measured using a 28-item TPACK Survey adapted for higher education purposes (Schmidt et al., 2009; Chai et al., 2019). The scale assesses seven TPACK components (TK, CK, PK, TCK, TPK, PCK, TPACK). Cronbach's alpha was .93.

AI readiness was assessed with the 15-item AI Readiness Scale for Educators (ARSE) designed by Ayanwale et al. (2022). It measures educators' levels of awareness, attitudes, and behavioral intentions regarding the use of AI tools in their work. Reliability of the scale was found to be high (α = .88).

Institutional digital infrastructure was measured using an 8-item scale designed specifically for this research. The items were related to availability of sufficient hardware, broadband internet, a properly functioning LMS, and effective IT support services. The reliability of the scale was high (α = .86).

Common Method Bias and Data Quality

Because the study used a quantitative self-report survey, common method bias (CMB) was assessed using Harman's single-factor test and the common latent factor approach in confirmatory factor analysis (CFA). According to Harman's test, a single factor explained 23.4% of the variance, well below the 50% cutoff point. In addition, the CFA common latent factor method showed no substantial loading inflation; thus, CMB was not identified in the data. No multivariate outliers were identified according to the Mahalanobis distance measure, and the assumption of multivariate normality was met.

ANALYTICAL STRATEGY

Data analysis was performed in three steps. First, confirmatory factor analysis (CFA) was conducted using AMOS 27 to evaluate the measurement model. Model fit was evaluated using the following indices: Comparative Fit Index (CFI) >.95, Tucker–Lewis Index (TLI) >.95, Root Mean Square Error of Approximation (RMSEA) <.06, Standardized Root Mean Square Residual (SRMR) <.08 (Hu & Bentler, 1999). Next, structural equation modeling (SEM) was used to test H1-H3. Finally, moderation and mediation effects in the path models were examined using the PROCESS macro (Hayes, 2022). Moderation and mediation were examined using an SEM-based moderated mediation testing approach (Preacher et al., 2007).

Results and Hypothesis Testing

The results are presented in five subsections: (5.1) descriptive statistics and bivariate correlations; (5.2) measurement model fit; (5.3) structural path coefficients; (5.4) mediation and moderated mediation effects; and (5.5) the path diagram. A comprehensive hypothesis-testing summary is provided in the final subsection.

Descriptive Statistics and Correlations

Table 1 presents means, standard deviations, and interconstruct correlations for all variables used in the analysis. Alpha reliabilities are indicated on the diagonal in parentheses. All interconstruct correlations were significant at the $p < .01$ level, and the directions of these associations gave initial evidence supporting the hypotheses before structural testing.

Table 1.
Descriptive Statistics and Inter-Construct Correlations (N = 412)

Variable	M	SD	1. AIR	2. TPACK	3. NLB	4. DI
1. AI Readiness (AIR)	4.83	0.91	*(.88)*			
2. TPACK	4.61	0.87	.49**	*(.93)*		
3. Networked Learning Behavior (NLB)	4.72	0.94	.43**	.57**	*(.91)*	
4. Digital Infrastructure (DI)	4.39	1.02	.31**	.38**	.44**	*(.86)*

Note. AIR = AI Readiness; TPACK = Technological Pedagogical Content Knowledge; NLB = Networked Learning Behavior; DI = Digital Infrastructure. Reliability coefficients (α) appear on the diagonal in parentheses. ** $p < .01$ (two-tailed).

Measurement Model Fit

Before the structural analysis, confirmatory factor analysis (CFA) was conducted. The goodness-of-fit indices for the measurement model and the structural model are shown in Table 2. All fit indices satisfied the expected criteria (Hu & Bentler, 1999), indicating adequate model fit before hypothesis testing.

Table 2.
Model Fit Indices for Confirmatory Factor Analysis and Structural Equation Model

Model	χ^2/df	CFI	TLI	RMSEA [90% CI]	SRMR
Measurement Model (CFA)	1.87	.96	.95	.046 [.042, .051]	.057

Structural Model (SEM)	1.88	.96	.95	.047 [.043, .052]	.059
Recommended Threshold	**< 3.0**	**> .95**	**> .95**	**< .060**	**< .080**

Note. CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual. χ^2/df = chi-square divided by degrees of freedom. Thresholds based on Hu & Bentler (1999).

Structural Path Coefficients

Table 3 shows the standardized regression weights (β), standard errors, t-statistics, and 95% confidence intervals for all paths in the structural model. H1 and H2 were supported. The direct effect of AI readiness on networked learning behavior dropped to non-significance after TPACK was added to the model, supporting the mediation model specified in H3. The interaction between TPACK and digital infrastructure supported H4.

Table 3.
Standardized Structural Path Coefficients (N = 412)

Pathway	**β**	**SE**	**t**	**p**	**95% CI**
AI Readiness → TPACK (H1)	0.47	0.05	9.40	< .001	[0.37, 0.57]
TPACK → Networked Learning Behavior (H2)	0.53	0.06	8.83	< .001	[0.41, 0.65]
AI Readiness → NLB (direct, controlling TPACK)	0.11	0.07	1.57	.117	[−0.03, 0.25]
TPACK × Digital Infrastructure → NLB (H4)	0.19	0.07	2.71	< .01	[0.05, 0.33]

Note. β = standardized path coefficient; SE = standard error; NLB = Networked Learning Behavior; DI = Institutional Digital Infrastructure. Two-tailed significance. 95% CIs based on maximum-likelihood estimation. Non-significant path shown in italics.

Mediation and Moderated Mediation Effects

Table 4 displays bootstrapped indirect effects (with 5,000 samples). The indirect effect of AI readiness on networked learning behavior mediated by TPACK was significant (supporting H3); the mediator explained 69.4% of the total effect. The nonsignificant direct effect was consistent with full mediation. The conditional indirect effects at both high and low levels of institutional digital infrastructure (DI) were significant, although the effect was stronger at high DI levels. A significant index of moderated mediation supported H5.

Table 4.
Bootstrapped Mediation and Moderated Mediation Effects (Bootstrap N = 5,000)

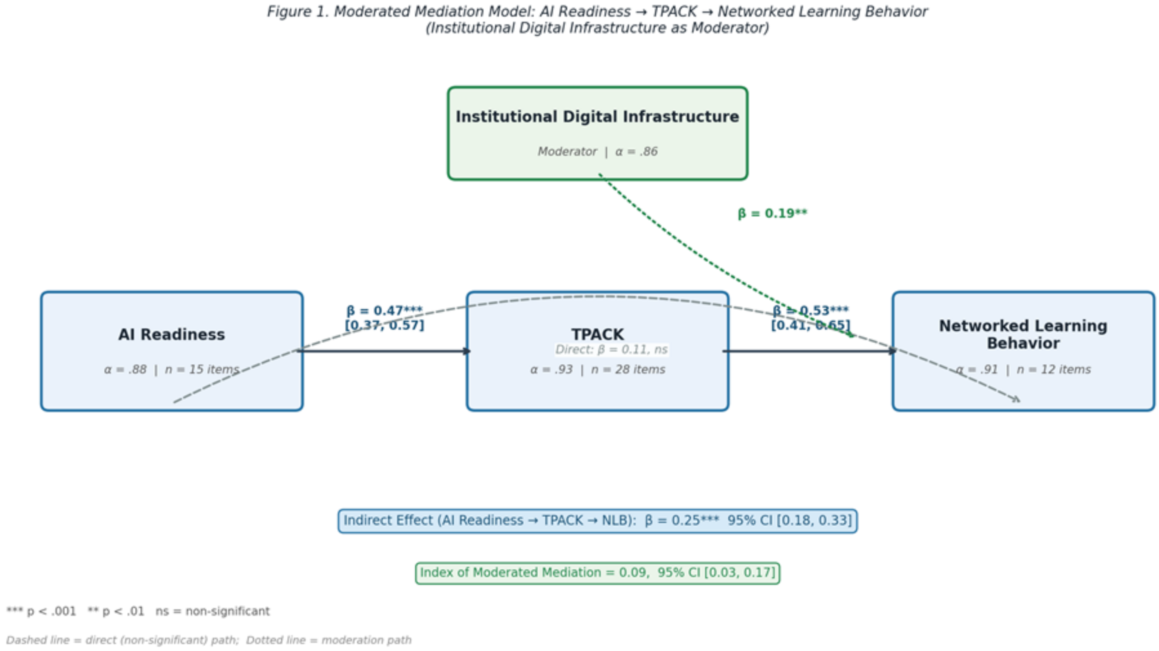
Effect	β	95% Boot CI	SE	% Mediated	Sig.
Indirect Effect (AIR→TPACK→NLB) (H3)	0.25	[0.18, 0.33]	0.04	69.4%	Yes
Indirect @ High DI (+1 SD)	0.32	[0.22, 0.43]	0.05	—	Yes
Indirect @ Low DI (−1 SD)	0.18	[0.10, 0.28]	0.05	—	Yes
Index of Moderated Mediation (H5)	0.09	[0.03, 0.17]	—	—	Yes

Note. Boot CI = bias-corrected bootstrap confidence interval; DI = Institutional Digital Infrastructure; High DI = +1 SD above mean; Low DI = −1 SD below mean. All confidence intervals exclude zero, confirming statistical significance.

PATH DIAGRAM

Figure 1 presents the complete moderated mediation model. Solid lines denote statistically significant pathways; the dashed line represents the non-significant direct effect of AI readiness on networked learning behavior when TPACK is included. The dotted line from institutional digital infrastructure indicates the moderation pathway on the TPACK–networked learning behavior relationship. Standardized path coefficients are displayed on each pathway.

Figure 1.
Path Diagram



Note. Moderated mediation model with standardized path coefficients. AI Readiness → TPACK → Networked Learning Behavior, moderated by Institutional Digital Infrastructure. *** $p < .001$; ** $p < .01$; ns = non-significant (dashed).

Hypothesis Testing Summary

Table 5 summarizes the five research hypotheses, key statistical findings, decisions regarding the null hypotheses, and final evaluations. All five hypotheses were empirically supported. In each case, the null hypothesis was rejected based on the prespecified alpha level of .05.

Table 5.
Summary of Hypothesis Testing Results

H	Hypothesis Statement	Key Statistical Evidence	Decision	Verdict
H1	AI readiness will be positively associated with TPACK among higher education faculty.	$\beta = 0.47$, $SE = 0.05$, $t = 9.40$, $p < .001$ 95% CI [0.37, 0.57]	Reject H0 ($p < .001$)	**Supported**
H2	TPACK will be positively associated with networked learning behavior.	$\beta = 0.53$, $SE = 0.06$, $t = 8.83$, $p < .001$ 95% CI [0.41, 0.65]	Reject H0 ($p < .001$)	**Supported**
H3	TPACK will mediate the relationship between AI readiness and networked learning behavior.	Indirect $\beta = 0.25$, 95% Boot CI [0.18, 0.33]	Reject H0	**Supported**

		% Mediated = 69.4% (full mediation)	(CI excludes 0)	
H4	Institutional digital infrastructure will moderate the TPACK → NLB relationship (stronger at high DI).	Interaction β = 0.19, SE = 0.07, t = 2.71, $p < .01$ 95% CI [0.05, 0.33]	Reject H0 ($p < .01$)	**Supported**
H5	The indirect effect of AI readiness on NLB via TPACK will be moderated by institutional digital infrastructure (moderated mediation).	Index of MM = 0.09 95% Boot CI [0.03, 0.17]	Reject H0 (CI excludes 0)	**Supported**

Note. H = Hypothesis; NLB = Networked Learning Behavior; DI = Institutional Digital Infrastructure; MM = Moderated Mediation; Boot CI = bootstrapped confidence interval. Verdicts are based on two-tailed significance tests and bootstrap CI exclusion of zero. All hypotheses supported at $p < .01$ or stronger.

SUMMARY OF FINDINGS

Overall, the findings present substantial evidence for the moderated mediation model. AI readiness had a significant positive effect on TPACK (H1: β = 0.47, $p < .001$), which in turn significantly predicted networked learning behavior (H2: β = 0.53, $p < .001$). The mediated pathway via TPACK was also statistically significant and explained a substantial proportion of the total effect (H3: β = 0.25, 69.4% mediation). Institutional digital infrastructure was found to significantly moderate both the direct TPACK-networked learning behavior link (H4: β = 0.19, $p < .01$) and the mediated relationship itself (H5: index = 0.09, confidence interval (CI) [0.03, 0.17]). Together, these findings emphasize the key mediating role of TPACK in the AI readiness–networked learning behavior linkage, and reveal institutional digital infrastructure as an important boundary condition of this mechanism.

DISCUSSION

This study investigated whether the relationship between AI readiness and networked learning behavior among higher education faculty in India is mediated by TPACK and moderated by institutional digital infrastructure. The findings support the proposed moderated mediation model and offer several theoretical and practical insights.

AI Readiness as a Precursor to TPACK

The finding of a significant positive relationship between AI readiness and TPACK (H1 supported) contributes to theoretical scholarship in two ways. First, it positions AI readiness as an antecedent disposition that helps cultivate integrative TPACK competencies. As such, it supports theoretically the proposition made within the TPACK framework about the dynamic nature of technological knowledge (Mishra & Koehler, 2006). Specifically, faculty members with greater awareness of and more positive attitudes toward AI tools are expected to develop TPACK-related skills. The latter include knowledge of appropriate technological tools suitable for achieving certain pedagogical goals and working with certain curricular content. This finding also resonates with technology adoption literature, suggesting that attitudinal readiness is a gateway condition that triggers competency development and leads to subsequent technology use (Venkatesh et al., 2003). Practically, this result emphasizes the importance of the need for faculty development programs to focus on AI awareness and attitude formation as essential preconditions to TPACK skill development and further networked learning.

TPACK as a Mediator

The significant mediation effect of TPACK found in the study (H3 supported) has a series of important theoretical implications. Namely, it demonstrates that the effects of AI readiness on networked learning do not occur without a proximal mediator in the form of TPACK. In other words, AI readiness alone cannot produce behavioral outcomes because TPACK constitutes an essential mechanism transforming distal dispositions into proximal actions. Practically, it implies that the absence of adequate TPACK skills among faculty members having positive attitudes toward AI prevents them from developing corresponding networked learning behavior—a conclusion consistent with intention–behavior gap found in technology adoption literature (Fishbein & Ajzen, 1975). This also positions TPACK not only as a competency framework useful for measurement, but also as a mechanism of action and cognition in the technology integration process.

Moderation Effect of Institutional Digital Infrastructure

The significant moderation effect observed in the current analysis (H4 and H5 supported) reveals the importance of contextual factors for the technology competency-behavior relationship. While TPACK had a significant impact on networked learning behavior regardless of the level of digital infrastructure, this relationship became substantially more pronounced for faculty working in institutions endowed with ample resources in this area. From a theoretical perspective, this finding supports sociotechnical systems theory (Trist, 1981) and eco-centric models of educational technology (Zhao & Frank, 2003). They emphasize the interactive nature of individual agency and structural aspects of technology integration and educational change. With regard to implications, the moderated mediation result (H5) highlights a particularly important aspect of this relationship.

Namely, even faculty members who are highly competent both in AI and TPACK still require the right environment to display networked learning behavior. It implies that investments in faculty development are necessary yet insufficient for promoting networked learning behavior in educational settings. Instead, educational administrators should complement these initiatives with investments in institutional infrastructure. From a policy-making perspective, this issue becomes especially relevant in the context of Indian higher education system, which is marked by substantial differences in digital infrastructure.

FINAL CONSIDERATIONS

This study set out to answer a question that has remained largely unaddressed in the literature: whether TPACK explains how AI readiness translates into networked learning behavior among higher education faculty, and whether this translation depends on the digital infrastructure faculty have access to. The answer, based on the data reported above, is yes on both counts. AI readiness on its own did not directly predict networked learning behavior once TPACK was accounted for; it operated almost entirely through TPACK, which explained close to 70% of the total effect. This pattern indicates that positive attitudes and willingness toward AI are not, by themselves, sufficient to generate networked learning practices. Faculty must first convert that disposition into concrete technological, pedagogical, and content knowledge before it shows up as observable collaborative behavior online.

This is precisely the gap this study set out to close: prior work had examined TPACK and AI readiness as separate lines of inquiry, leaving open the question of how, or even whether, they connect to one another and to a concrete behavioral outcome. By modeling TPACK as the mechanism that carries AI readiness forward into networked learning behavior, this study supplies the missing link between an attitudinal disposition and an observable practice, and it does so with a level of statistical specificity, indicating both the size of the mediated pathway and the conditions under which it strengthens, that has not previously been available.

The second contribution follows from the moderation results. Institutional digital infrastructure did not simply add to the model; it changed the strength of the TPACK-to-networked-learning-behavior link, and it changed the strength of the full indirect pathway from AI readiness to networked learning behavior. In practical terms, this means that faculty competence and institutional capacity are not interchangeable or additive; they interact. A faculty member with strong TPACK skills working in a poorly resourced institution will realize only part of the networked learning behavior that the same skills would produce in a well-resourced one.

This has a direct bearing on how universities, particularly in rapidly digitizing but infrastructurally uneven systems such as India's, should sequence their investments: faculty development programs focused on AI readiness and TPACK are necessary but will underperform unless paired with parallel investment in hardware, connectivity, and learning-management capacity. The significance of closing this gap, then, is not only theoretical. It gives administrators and policymakers a testable basis for prioritizing where limited resources will produce the largest gains in networked learning behavior, rather than treating faculty training and infrastructure spending as separate, competing budget lines.

Taken together, these findings extend the study of technology integration in higher education from a purely individual-competency framing toward one that treats competence and context as jointly determining behavior. The findings should nonetheless be read in light of the study's cross-sectional design, which restricts the strength of the causal claims that can be drawn, and its geographic focus on public universities in one Indian region, which restricts how far the results can be generalized. Longitudinal designs that track faculty over time, and comparative studies across institutional systems and countries, would help establish whether the pathway identified here holds as AI tools and infrastructure continue to evolve.

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