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AI-Tpack and the Pre-Service Teacher: Mapping the Structural Disconnect Between Personal AI Use and Instructional Design

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ABSTRACT

The rapid infusion of Artificial Intelligence (AI) into education requires empirical evidence on the readiness of pre-service teachers across disciplines. This descriptive-correlational study examined the AI-TPACK (Artificial Intelligence-Technological Pedagogical Content Knowledge) readiness of 264 pre-service teaching interns enrolled in Bachelor of Elementary Education (BEEd) and Bachelor of Secondary Education (BSE) programs, majoring in English, Mathematics, and Science, at Taguig City University. Using an instrument adapted from Ning et al. (2024), the study assessed participants across seven domains: Content Knowledge (CK), Pedagogical Knowledge (PK), AI-Technological Knowledge (AI-TK), Pedagogical Content Knowledge (PCK), AI-Technological Content Knowledge (AI-TCK), AI-Technological Pedagogical Knowledge (AI-TPK), and integrated AI-TPACK. It further examined whether the purpose of respondents' personal AI use (educational, social media, or media/video) predicted their instructional design readiness, and whether readiness varied across program cohorts. Descriptive results showed high self-reported competency in CK (94.3%) and PK (93.2%), and somewhat lower but still high competency in the AI-integrated domains (82.5%–87.9%). However, multiple linear regression analyses revealed that personal AI use patterns did not significantly predict any AI-TPACK indicator ($p > 0.05$, $R^2 \leq 0.016$), and one-way ANOVA revealed no significant differences across program cohorts. These findings point to a structural disconnect between personal familiarity with AI and professional instructional design readiness, underscoring the need for teacher education institutions to move beyond passive exposure to technology toward explicit, discipline-embedded AI-TPACK instruction.

Keywords: *AI-TPACK, pre-service teachers, AI usage, teaching design*

INTRODUCTION

The rapid infusion of Artificial Intelligence (AI) into education requires empirical evidence on the readiness of pre-service teachers across disciplines. This descriptive-correlational study examined the AI-TPACK (Artificial Intelligence-Technological Pedagogical Content Knowledge) readiness of 264 pre-service teaching interns enrolled in Bachelor of Elementary Education (BEEd) and Bachelor of Secondary Education (BSE) programs, majoring in English, Mathematics, and Science, at Taguig City University. Using an instrument adapted from Ning et al. (2024), the study assessed participants across seven domains: Content Knowledge (CK), Pedagogical Knowledge (PK), AI-Technological Knowledge (AI-TK), Pedagogical Content Knowledge (PCK), AI-Technological Content Knowledge (AI-TCK), AI-Technological Pedagogical Knowledge (AI-TPK), and integrated AI-TPACK. It further examined whether the purpose of respondents' personal AI use (educational, social media, or media/video) predicted their instructional design readiness, and whether readiness varied across program cohorts. Descriptive results showed high self-reported competency in CK (94.3%) and PK (93.2%), and somewhat lower but still high competency in the AI-integrated domains (82.5%–87.9%). However, multiple linear regression analyses revealed that personal AI use patterns did not significantly predict any AI-TPACK indicator ($p > 0.05$, $R^2 \leq 0.016$), and one-way ANOVA revealed no significant differences across program cohorts. These findings point to a structural disconnect between personal familiarity with AI and professional instructional design readiness, underscoring the need for teacher education institutions to move beyond passive exposure to technology toward explicit, discipline-embedded AI-TPACK instruction.

DISCUSSION

Deconstructing the Structural Disconnect Between Personal Use and Instructional Design

The empirical findings of this study expose a distinct structural disconnect between the personal technology habits of pre-service teachers and their professional instructional design capabilities. This disconnect is characterized by high levels of self-assessed efficacy within the AI-TPACK matrix, alongside a near-complete absence of predictive power in actual, routine AI usage profiles. Descriptively, pre-service teaching interns demonstrate strong confidence, with cumulative positive conformance ratings frequently breaking past the 85% threshold across all subdomains. Despite this implication, the structural regression model results indicate that the frequency and purpose of AI tool usage (e.g., educational use, social media use, media creation) vary little across the four core technical-pedagogical domains ($R^2 < 0.016$). This total disconnect suggests

that interns' self-perceived readiness for formal classroom instructional planning occurs regardless of their frequency of AI tool use in daily life.

To fully explain this disconnect, the research team has presented three justifications: (1) the relatively consistent results across all subscales lead to inference of inflated self-reports resulting from the self-reporting methodology, as participants are aware of how to respond to the questions without any definable or measurable qualitative impacts, (2) the fact that these participants have reached the end of their formal teacher training program entails a psychological state of mind whereby people will tend to over-inflate their professional competence when asked to self-respond to questions that are based on classroom use of educational technology; i.e., this tendency to over-report competency with TPACK self-reports is well-known (Xie & Luo, 2022), and (3) this issue illustrates a significant statistical concern with how the dependent variable is defined for all four groups of participants to calculate the covariance resulting from this research.

Using standard deviations from 0.559 to 0.860 on a five-point scale, the dependent variable did not provide enough variance for the covariance calculated as expected. Consequently, some numbers are close to zero (i.e., regression coefficients are consistently low when using this number of participants in this survey (N=264). This indicates that using the Likert scale has created significant challenges in determining the precision with which the data on pre-service teachers' level of technical readiness can be established.

Also, the data on present AI applications used by the interns, as well as how various instructional designs have required a large number of detailed cognitive processing systems to be developed to design practical curriculum needs. Most interns have only used products from general-purpose consumer platforms: Canva AI (82.20%), ChatGPT (80.30%), and Grammarly (80.30%) for rather elementary productivity needs. Specific designs, such as specialized teaching systems and classroom simulations (AI), have attracted a small percentage of interns (31.06%). As a result, while interns frequently apply AI products in their workflow activities, they generally do not use domain-specific products to help them develop effective lesson design; thus, program use does not always translate into highly sophisticated pedagogical understanding (Ning et al., 2024; Runge et al., 2025).

Comparative Literature Review

Compared with international literature, this study's baseline findings confirm and expand recent international studies grounded in the AI-TPACK framework. The finding that foundational knowledge (CK and PK) exceeds advanced technology adoption (AI-TCK and AI-TPK) is consistent with structural agreements reached in the seminal examination of this framework by Ning et al. (2024). The findings of this study reveal that such advanced constructs require a degree of mastery across converging fields, making them far more difficult to master than the general use of technological tools.

More importantly, the absence of predictive validity found with the routine usage patterns within this study is consistent with the systematic review conducted by Runge et al. (2025), which concluded that incidental or personal experience with generative AI systems does not develop an adequate level of instructional effectiveness unless proper institutional scaffolding has been applied.

While one would expect there to be differences between the cohorts documented in Table 13, the results of this study are in contrast with some of the case study literature from East Asia that found that secondary science and mathematics majors exhibited a much greater level of technical self-efficacy than elementary majors (Xie & Luo, 2025). The consistent institutional-level exposure to technology at Taguig City University indicates that the curriculum provides equal exposure to technology across all disciplines.

Within the localized Philippine context, this study represents a significant contribution to recent regional literature. The positive attitudes and device saturation exhibited by participants mirror the findings of Alejandro et al. (2024), who found a similar level of readiness among teacher candidates. Nonetheless, the gaps that are defined in the regression analyses employed in this investigation demonstrate the operating difficulties established by Lumala et al. (2025) and Bautista et al. (2024), who posited that the absence of formal pedagogical simulation and practical experience limits Filipino pre-service educators in their ability to do more than create basic text. This research provides empirical evidence supporting the provincial studies of Ilagan et al. (2025). It shows that, even in an urban college with adequate device availability and constant Internet access, technology use is still inhibited by a lack of discipline-specific integration in the curricula.

Theoretical and Practical Implications for Instructional Design

The theoretical implications of the current study focus on adjusting the structural architecture of the AI-TPACK model in teacher preparation institutions. Our findings suggest that AI-TPACK is a distinct cognitive framework with its own understanding and cannot be considered a mere incidental result of regular personal technology use. The regression model constants are statistically significant ($p < 0.001$) in all domains, confirming that a certain level of preparedness exists, which may stem from general pedagogical studies but remains independent of users' actual behavior in primary activities. Thus, AI-TPACK should be viewed as an independent curricular objective that needs to be taught explicitly through systematic instruction rather than through general digital literacy exposure (Ning et al., 2024).

Practically, these extracted implications provide a precise roadmap for higher education institutions and national policymakers that want to develop or redesign instructional design courses. Since consumers' usage habits do not correlate with professional competency, TEIs need to rethink their approach and move away from generic

technology workshops in favor of a more structured approach based on discipline-specific interventions. Based on the national goals set by DepEd through the E-CAIR (Department of Education, 2025) initiative and quality expectations specified in EDCOM II (2025), teacher preparation institutions should build their curricula on prescribed training patterns involving a series of mandatory micro-teaching modules concerning AI-assisted lesson planning and creating collaborative partnerships with local schools for presenting automated evaluation systems. Moreover, it is vital to incorporate ethical aspects related to data privacy protection, copyright issues, and algorithmic biases into the current curriculum to support teaching excellence.

Methodological Limitations

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CONCLUSION AND RECOMMENDATIONS

Conclusion

In summary, the results reveal an adequate self-assessed readiness level of pre-service teachers from Taguig City University regarding the AI-TPACK framework; this is evidenced by the significant e-automation experience of the target participants but does not predict their ability in designing instructional learning activities. This unique segregation is evident in the findings of multiple linear regression analysis ($R^2 = 0.016$). Therefore, the study needs to ensure that the self-promoted and repeated use of consumer AI tools, such as Canva AI, ChatGPT, and Grammarly, does not lead to a well-rounded understanding that supports engagement in the discipline-specific use of innovative technologies. Finally, the lack of substantial variation between academic fields indicates that this issue is universal, not unique to one academic program. Consequently, the study explicates the importance of moving beyond general exposure to personal technology toward structured, institution-wide training grounded in ethical and moral principles.

Recommendations

In light of these conclusions, the following actionable recommendations are formulated for curriculum designers, institution administrators, and future researchers:

1. Curriculum Overhaul: Teacher Education Institutions should completely revamp the curriculum they utilize for integrating technology to go beyond generic productivity applications to incorporate specialized software for education, like intelligent tutoring systems and AI simulations in the course management system.

2. Performance-Based Assessment Requirement: Institutions should require the use of objective, performance-based tasks, like an analysis of lesson plans, a micro-teaching portfolio, and AI tool selection guidelines, among others.

3. Policy Alignment: Teacher Education Institutions should create formal partnerships with the Department of Education's Education Center for Artificial Intelligence Research (E-CAIR) to begin trialing AI-assisted technology in clinical practice to ensure that university training and course management systems utilize national quality standards defined by EDCOM II.

4. General Methodological Expansion for Future Research: Future research should take larger and more balanced multi-institution samples and employ a better survey design that uses reverse-scored items and conducts longitudinal studies.

Functional Distribution of AI Tools by Purpose

AI Software Tool	Edu. Count	Edu. %	Soc. Count	Soc. %	Med. Count	Med. %
Canva AI (e.g., Magic Write)	217	82.20%	81	30.68%	75	28.41%
ChatGPT	212	80.30%	77	29.17%	40	15.15%
Grammarly	212	80.30%	42	15.91%	18	6.82%
Quillbot	193	73.11%	39	14.77%	20	7.58%
Google Bard / Gemini	119	45.08%	37	14.02%	23	8.71%
Meta AI	112	42.42%	86	32.58%	36	13.64%
Google Gemini	105	39.77%	36	13.64%	20	7.58%
AI Classroom Simulators	82	31.06%	24	9.09%	15	5.68%
Microsoft Copilot	74	28.03%	21	7.95%	18	6.82%
Duolingo Max	69	26.14%	35	13.26%	21	7.95%
Perplexity AI	55	20.83%	27	10.23%	19	7.20%
Deep Seek	54	20.45%	27	10.23%	22	8.33%
Pi, by Inflection	46	17.42%	30	11.36%	17	6.44%

Anthropic Claude 3	44	16.67%	26	9.85%	20	7.58%

Table No. 1. Functional Distribution of AI Software Tools by Personal Use Purpose (N = 264)

Descriptive AI-TPACK Domain Readiness Profile

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Strong understanding of core discipline concepts.	42.0 %	52.3 %	4.2%	1.5%	0.0%
2. Complete comprehension of historical concept evolution.	37.9 %	51.5 %	8.7%	1.9%	0.0%
3. Knowledgeable about everyday real-world applications.	49.6 %	42.4 %	6.4%	1.5%	0.0%
4. Deep understanding of content knowledge structures.	42.8 %	45.5 %	9.8%	1.9%	0.0%
5. Substantial knowledge depth and curriculum familiarity.	37.1 %	51.9 %	9.1%	1.9%	0.0%

Table No. 2. Pre-Service Teaching Interns' Readiness in Content Knowledge (CK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Capable of executing diverse classroom teaching methods.	43.9 %	47.7 %	7.2%	1.1%	0.0%
2. Selects appropriate methods based on content.	45.1 %	43.6 %	9.8%	1.5%	0.0%
3. Adjusts methods dynamically based on pupil feedback.	46.2 %	47.0 %	5.7%	1.1%	0.0%
4. Possesses knowledge of effective classroom management.	40.2 %	47.7 %	11.0 %	1.1%	0.0%
5. Accounts for student background, interest, and motivation.	49.6 %	41.7 %	7.2%	1.5%	0.0%

Table No. 3. Pre-Service Teaching Interns' Readiness in Pedagogical Knowledge (PK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Familiar with common AI tools in education contexts.	42.0 %	46.6 %	9.5%	1.1%	0.8%
2. Capable of easily acquiring necessary educational AI.	35.6 %	51.5 %	10.6 %	1.5%	0.8%
3. Frequently incorporates AI tools in pedagogy.	25.8 %	56.4 %	14.0 %	2.7%	1.1%

4. Proficient in using AI to enhance instruction.	31.1 %	50.0 %	15.9 %	2.3%	0.8%
5. Knowledgeable about using AI for interactive teaching.	31.8 %	53.4 %	12.5 %	1.5%	0.8%

Table No. 4. Pre-Service Teaching Interns' Readiness in AI-Technological Knowledge (AI-TK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Proficient at formulating curriculum plans with ease.	26.9 %	58.0 %	12.5 %	2.3%	0.4%
2. Well-acquainted with focal points and teaching challenges.	27.3 %	60.6 %	10.6 %	1.5%	0.0%
3. Differentiates instruction based on learning scenarios.	40.5 %	50.4 %	7.6%	1.5%	0.0%
4. Capable of designing engaging small-group activities.	40.2 %	48.9 %	9.5%	1.5%	0.0%
5. Aware of common errors students make during learning.	43.6 %	46.6 %	8.0%	1.9%	0.0%

Table No. 5. Pre-Service Teaching Interns' Readiness in Pedagogical Content Knowledge (PCK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Familiar with domain-specific AI like tutoring systems.	28.8 %	53.8 %	14.8 %	2.3%	0.4%
2. Capable of effortlessly using AI in academic fields.	25.8 %	57.2 %	14.0 %	2.7%	0.4%
3. Proficient in using AI to update disciplinary knowledge.	28.4 %	56.4 %	12.5 %	2.3%	0.4%
4. Selects appropriate AI tools based on subject matter.	31.1 %	56.4 %	10.2 %	1.9%	0.4%
5. Adept at using AI to enhance material comprehension.	28.4 %	53.4 %	15.9 %	1.9%	0.4%

Table No. 6. Pre-Service Teaching Interns' Readiness in AI-Technological Content Knowledge (AI-TCK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Capable of using AI to expand pedagogical views.	35.6 %	52.7 %	10.2 %	1.5%	0.0%
2. Able to apply appropriate AI across diverse activities.	28.0 %	57.6 %	12.5 %	1.9%	0.0%

3. Capacity to select AI to sustain student motivation.	31.8 %	54.5 %	10.6 %	2.7%	0.4%
4. Can apply AI structures to assess pupil learning outcomes.	28.8 %	54.9 %	13.3 %	2.7%	0.4%
5. Proficient in optimizing instructional management via AI.	27.7 %	54.5 %	14.8 %	3.0%	0.0%

Table No. 7. Pre-Service Teaching Interns' Readiness in AI-Technological Pedagogical Knowledge (AI-TPK)

Subscale Indicators	A (%)	B (%)	C (%)	D (%)	E (%)
1. Integrates AI, content, and pedagogy for efficiency.	36.4 %	51.5 %	9.5%	2.7%	0.0%
2. Selects appropriate methods and AI based on content.	29.5 %	55.7 %	11.7 %	2.7%	0.4%
3. Uses AI to simulate and adapt complex class scenarios.	30.3 %	54.5 %	12.1 %	3.0%	0.0%
4. Deploys personalized AI to guide practical learning.	28.4 %	55.3 %	12.9 %	3.0%	0.4%
5. Utilizes AI for self-directed professional development.	34.8 %	51.1 %	11.7 %	2.3%	0.0%

Table No. 8. Pre-Service Teaching Interns' Readiness in Integrated AI-TPACK

3.4 Inferential Relational Modeling: Multiple Linear Regression

Predictor Variable	Unstandardized (β)	Standardized (Beta)	t-value	p-value	Status
Constant	3.695	—	18.42	<0.001	Significant
Education-Related Personal Use	0.044	`	1.93	0.055	Not Significant
Social Media-Related Personal Use	0.052	0.037	0.56	0.573	Not Significant
Media/Video-Related Personal Use	-0.015	-0.011	-0.17	0.865	Not Significant

Table No. 9. Multiple Linear Regression Model Predicting AI-TK Readiness

Model Fit: $R = 0.127$, $R^2 = 0.016$, $SE = 0.67$, $F(3, 260) = 1.41$, $p = 0.241$

Predictor Variable	Unstandardized (β)	Standardized (Beta)	t-value	p-value	Status
Constant	4.120	—	21.15	<0.001	Significant
Education-Related Personal Use	-0.066	-0.018	-0.30	0.766	Not Significant
Social Media-Related Personal Use	0.017	0.012	0.19	0.852	Not Significant
Media/Video-Related Personal Use	0.063	0.049	0.73	0.465	Not Significant

Table No. 10. Multiple Linear Regression Model Predicting AI-TCK Field Readiness

Model Fit: $R = 0.057$, $R^2 = 0.003$, $SE = 0.649$, $F(3, 260) = 0.29$, $p = 0.834$

Predictor Variable	Unstandardized (β)	Standardized (Beta)	t-value	p-value	Status
Constant	4.211	—	21.90	<0.001	Significant
Education-Related Personal Use	-0.115	-0.033	-0.53	0.598	Not Significant
Social Media-Related Personal Use	-0.015	-0.012	-0.17	0.863	Not Significant
Media/Video-Related Personal Use	0.090	0.070	1.05	0.294	Not Significant

Table No. 11. Multiple Linear Regression Model Predicting AI-TPK Field Readiness

Model Fit: $R = 0.075$, $R^2 = 0.006$, $SE = 0.641$, $F(3, 260) = 0.53$, $p = 0.660$

Predictor Variable	Unstandardized (β)	Standardized (Beta)	t-value	p-value	Status
Constant	4.204	—	21.85	<0.001	Significant

Education-Related Personal Use	-0.083	-0.024	-0.38	0.705	Not Significant
Social Media-Related Personal Use	0.009	0.007	0.11	0.915	Not Significant
Media/Video-Related Personal Use	0.031	0.024	0.36	0.716	Not Significant

Table No. 12. Multiple Linear Regression Model Predicting Integrated AI-TPACK Readiness

Model Fit: R = 0.036, R^2 = 0.001, SE = 0.641, F(3, 260) = 0.11, p = 0.954

3.5 Program Cohort Variance Analysis: One-Way ANOVA

AI-TPACK Domain	BEEd (n=119)	BSE-Eng (n=82)	BSE-Math (n=52)	BSE-Sci (n=11)*	F-value	p-value
AI-TK Readiness	4.089 (0.68)	4.198 (0.67)	4.177 (0.64)	4.236 (0.72)	0.547	0.651
AI-TCK Design	4.085 (0.61)	4.163 (0.66)	4.064 (0.65)	3.985 (0.79)	0.450	0.718
AI-TPK Design	4.109 (0.64)	4.169 (0.62)	4.138 (0.71)	4.061 (0.56)	0.184	0.907
Integrated AI-TPACK	4.114 (0.63)	4.217 (0.56)	4.123 (0.72)	4.018 (0.86)	0.604	0.613

Table No. 13. One-Way ANOVA: AI-TPACK Domain Readiness Across Program Cohorts

Note: Standard deviations are enclosed in parentheses.

DISCUSSION

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The empirical findings of this study expose a distinct structural disconnect between the personal technology habits of pre-service teachers and their professional instructional design capabilities. This disconnect is characterized by high levels of self-assessed efficacy within the AI-TPACK matrix, alongside a near-complete absence of predictive power in actual, routine AI usage profiles. Descriptively, pre-service teaching interns demonstrate strong confidence, with cumulative positive conformance ratings frequently

breaking past the 85% threshold across all subdomains. Despite this implication, the structural regression model results indicate that the frequency and purpose of AI tool usage (e.g., educational use, social media use, media creation) vary little across the four core technical-pedagogical domains ($R^2 < 0.016$). This total disconnect suggests that interns' self-perceived readiness for formal classroom instructional planning occurs regardless of their frequency of AI tool use in daily life.

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Recommendations

In light of these conclusions, the following actionable recommendations are formulated for curriculum designers, institution administrators, and future researchers:

1. Curriculum Overhaul: Teacher Education Institutions should completely revamp the curriculum they utilize for integrating technology to go beyond generic productivity applications to incorporate specialized software for education, like intelligent tutoring systems and AI simulations in the course management system.

2. Performance-Based Assessment Requirement: Institutions should require the use of objective, performance-based tasks, like an analysis of lesson plans, a micro-teaching portfolio, and AI tool selection guidelines, among others.

3. Policy Alignment: Teacher Education Institutions should create formal partnerships with the Department of Education's Education Center for Artificial Intelligence Research (E-CAIR) to begin trialing AI-assisted technology in clinical practice to ensure that university training and course management systems utilize national quality standards defined by EDCOM II.

4. General Methodological Expansion for Future Research: Future research should take larger and more balanced multi-institution samples and employ a better survey design that uses reverse-scored items and conducts longitudinal studies.

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