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Developing digital human capital: Formation mechanism and human resource development framework of pre-service teachers' AI integration competence

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Abstract: As the artificial intelligence (AI) technology is fully integrated into the education field, AI integration involves developing AI integration among the pre-service educators as the human resource of tomorrow. Education has been a determinant of the quality of education and the digital transformation of education. The study will focus on the research objectives, as follows, to investigate the contemporary status of pre-service teacher using AI-TPACK competencies, to study the differences by gender, grade, school level and years of teaching experience, to test the impact that school technical support, technological attitude and technological competence impose on AI-TPACK formation, and finally to generate an AI-TPACK theory of pre-service teacher human resources. The research gathered the data by conducting a questionnaire survey of 325 pre-service teachers in Chinese universities, but it mainly utilized structural equation modeling to analyze the data. The results showed that pre-service teachers display fairly high overall levels of AI-TPACK, but they do not show competencies in their technical knowledge (AI-TK) and technological integration (e.g., AI-TPK, AI-TCK). Technological support, attitudes, and technological competence in schools are important determinants of their AI-TPACK products and institutional level and teaching experience are critical external moderators. Based on these findings, this paper makes a systematic suggestion on how the AI integration capabilities of pre-service teachers can be developed based on the human resource development perspective. This framework includes four folds, namely optimization of curriculum, enhancement of practice, resource support and policy guidance.

Keywords: digital human capital; pre-service teachers; AI integration competency; AI-TPACK; human resource development

1. Introduction

Driven by the global digital transformation and the wave of artificial intelligence technology, the education sector is undergoing unprecedented, profound changes (Liu et al., 2020). The artificial intelligence (AI) not only changed the way instructional material is shown and the shape of educational spaces but also placed completely new challenges on the work and skillset of educators (Liang et al., 2023). Pre-service teachers, as the main human resource to the future education system, are put in a dilemma whether they can successfully sharpen knowledge and skills in AI technology, pedagogy, and subject content (i.e., AI-TPACK) or not. This has become a pivotal issue concerning the progress of educational modernization and the quality of human capital.

The history of the growth of the educational industry in the field of informatization of China has had three major stages. Phase One (the period between 2000 and 2010): Development of infrastructure. The School-to-School Selectivity Project (launched in 2000) was to bring 90 percent of the schools in primary and secondary schools into compliance with the internet by the year 2010. The government expended 30 billion yuan at the country level, and the local governments contributed the same sum of money. The top-down initiative made the deployment of infrastructure within a few seconds because it was resource-backed. Phase Two (2010-2018): Application Implementation. The Education Informatization 1.0 program put less emphasis on hardware and more on software, requiring all teachers to take 50 h of IT training every year. Teacher certification was made contingent upon information literacy. Phase Three (2018–2022): Intelligent Transformation. The Education Informatization 2.0 program is clearly focusing on the field of AI with the creation of 100 national smart education demonstration areas, as well as a requirement that universities should include AI literacy into the teacher education curriculum by 2022.

Pre-service teachers refer to learners who are undergoing professional training for the teaching profession but have not yet formally entered the teaching profession (Zaydn & Dindar, 2024). From the perspective of Human Resource Development (HRD), pre-service teachers are the most promising type of the so-called digital human capital in the system of the country's education. Digital human capital transcends traditional human capital concepts, specifically referring to the knowledge, skills, and competencies individuals possess to acquire, integrate, create, and transform value within digital environments (Lyu & Liu, 2021). Whether an organization can adjust to the digital economy era or not depends solely on the efficiency with which this capital is invested and developed. In the case of school organizations, the investment in AI-TPACK capabilities of pre-service teachers can be viewed as the prospective policy of developing educational human capital in the future. This would help them become more effective in their teaching post-employment, their performance in terms of innovation, and their professional flexibility, thus guaranteeing them long-term competitive advantages to educational institutions (Csizmadia, 2022; Ryazanova, 2022).

In recent years, strategic human resource management (SHRM) research has increasingly focused on the interplay between technology and human capital (Rodgers et al., 2023; Meijerink et al., 2021). It is a well-discussed fact among scholars that realizing technological value is squarely the goal of human capabilities. Organizations must leverage systematic development frameworks to transform technological empowerment into sustainable employee competencies (Banerjee, P., & Sharma, N., 2024; Olaitan, J., & Elshennawy, A., 2024). This has the implication that, in the context of teacher education, universities, which are the major institutions of pre-service teacher training, have a leading role in HRD to play (Christensen, A., & Jerim, J., 2025; Peng, 2024).

Despite the fact that the theoretical background of AI-TPACK has been formulated, the current literature is still analyzing the structure and affecting factors of AI-TPACK primarily through the disciplinary prism of pedagogy or information technology. There remains a lack of systematic analysis from an integrated human

resource management and development viewpoint, particularly at the level of “digital human capital” formation. How is AI integration competency formed among pre-service teachers? What roles do its key influencing factors play within the HRD framework? How can an effective development mechanism be constructed to systematically enhance this core capital?

Consequently, the proposed paper uses a quantitative cross-sectional survey among the pre-service teachers in the Chinese institutions of higher learning. The information was gathered with the help of a standardized questionnaire (research instrument) and processed with the help of structural equation modeling (SEM), a multivariate statistical method that compares theoretical models and empirical data. The research problem is to: (1) explore the present situation of the AI-TPACK integration capabilities of pre-service teachers; (2) Test the differences that can be attributed to gender, grade level, institutional level, and teaching experience; (3) Test the empirical mechanisms of the effects of organizational support (institutional technical support) and the individual capital (technological attitudes and competencies) on AI-TPACK; and (4) Construct a theoretical framework that will systematically investigate how to develop AI integration competencies in pre-service teachers in a human resource development view. This framework forms a conceptual base and programming route for higher institutions of learning and appropriate administrative authorities to maximize talent development mechanisms and create a superior quality of human capital in future teaching groups.

2. Literature review

As the use of the contribution of the artificial intelligence technology in education became widespread, the conventional TPACK framework has turned out to be incapable of being used to represent the needs of a full-scale involvement of the AI technology in the teaching process. Therefore, researchers have come up with the AI-TPACK framework that builds upon TPACK to present a better depiction of the knowledge structure that teachers ought to acquire in the era of AI (Ning et al., 2024). Within AI-TPACK, there are seven dimensions, namely, Content Knowledge (CK), Pedagogical Knowledge (PK), AI Technological Knowledge (AI-TK), Pedagogical Content Knowledge (PCK), AI Technological Content Knowledge (AI-TCK), Pedagogical Knowledge (AI-TPK), and AI-TPACK. This framework does not just enlarge the traditional TPACK, but also points out the special purpose of the AI technology in the instructional design, implementation, and assessment. To give an example, in an empirical study, Hava and Babayigit (2024) discovered that AI-TPACK proficiency of teachers is directly linked to their digital literacy, which is, in turn, dependent on the technical support and attitude of teachers and their experience of teaching. Moreover, the work by Chen et al. (2024) used the structural equation modeling approach, which disclosed that AI-TPACK proficiency of pre-service teachers significantly depends on their years of study, curriculum design, and the experience of teaching practice. These studies provide empirical support for the theoretical construction of AI-TPACK. All these aspects make up the core dimensions of the intelligent educational environment of pre-service teachers that identify their future teaching performance and innovation in the intelligent classroom (Hava &

Babayigit, 2024). Regarding human capital, AI-TPACK is not only a stock of knowledge and skills of a particular person but also a strategic resource that can be valued as a result of an investment and development (Jarrahi et al., 2023).

In the context of AI-TPACK, it is possible to distinguish between the external environmental factors and individual intrinsic factors influencing the development of pre-service teachers' competency level. The main external factors include technological support in schools, curriculum design, practical opportunities, and organisational culture; the internal ones include the attitude of teachers to AI technologies, self-efficacy, motivation to learn, and professional identity (Chen et al., 2024). Combined with the others in the context of HRD, these aspects constitute the prerequisites of the emergence of the digital human capital of pre-service teachers. This capital directly depends on the quality of their future effectiveness in teaching, their capacity to be innovative, and their professional flexibility in intelligent educational settings (Hava & Babayigit, 2024). Thus, the consideration of the AI-TPACK development among pre-service teachers is an essentially strategic investment into the education system of the future human capital in order to make educational organizations more efficient and innovative in general.

Technical support as a critical organizational tool has a pronounced effect on the enhancement of the AI-TPACK competencies of pre-service teachers. Studies show that infrastructure and technical education and resource provisions made by the school of higher order significantly boost the confidence and practical skills of teachers in the area of integrating technology (Bai & Guo, 2023). Moreover, the AI-TPACK development is also dependent on the rationality and the practicality of curriculum design. Pre-service teachers would be better able to incorporate AI technology into teaching subjects through the use of project-based learning, instructional design work, and practical internships (Koehler & Mishra, 2005).

Recent research has broadened the knowledge on AI-TPACK and digital human capital. Empirical studies conducted by Hava and Babayigit (2024) determined that the proficiency of AI-TPACK teachers is strictly connected to their digital literacy, which is conditioned by the technical assistance of schools, attitudes of teachers and their experience of teaching. Using structural equation modeling, Chen et al. (2024) discovered that the proficiency of pre-service teachers based on AI-TPACK is related to the years of study experience, curriculum design, and teaching practice experience. Ning et al. (2024) uncovered the network relationship among knowledge factors in the framework of AI-TPACK and presented evidence of the interdependence of the seven dimensions of the framework.

As a human resource development conceptualization, Jarrahi et al. (2023) conceived AI competencies as strategic organizational resources that can be valued by investment, as it is the same conceptualization of digital human capital present in Lyu and Liu (2021). In the field of strategic HRM, Meijerink et al. (2021) and Banerjee and Sharma (2024) have highlighted the pivotal role of technology and human capital in its particular interactions, such that the development of technological value realisation comes down to human capabilities development. Rodgers et al. (2023) and Olaitan and Elshennawy (2024) also eagerly emphasized the need to have systematic development structures to convert technological empowerment into sustainable competencies by the employees.

Despite these advances, the current research is mainly discipline-based pedagogy or information technology. The systematic analysis based on the combined perspective of human resource management and development is still lacking, especially at the stage of forming digital human capital. In particular, none of the previous research has: (1) conceptualized AI-TPACK as digital human capital subject to HRD investment; (2) analyzed the development mechanisms under the dual prism of organizational support and individual capital; (3) developed a holistic HRD model, converting the implicative research results into systematic development policies. This paper solves these gaps by employing the HRD theory and AI-TPACK empirical studies.

Through systematic analysis of relevant literature, this study clarifies the external factors influencing the structural development of pre-service teachers' AI-TPACK competency. These primarily include pre-service teachers' attitudes toward AI technology application, their capacity to apply AI technology, and the level of AI technology support provided by their schools. Therefore, based on the AI-TPACK theory, this study proposes a hypothetical model (**Figure 1**) by incorporating three latent variables: pre-service teachers' technological attitudes, technological competencies, and institutional technological support.

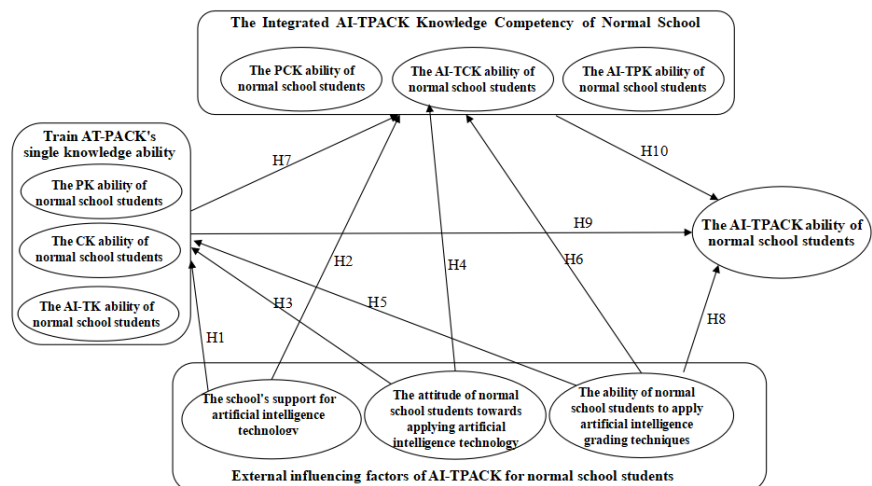


Figure 1. Hypothesis model of this study.

3. Research method

This paper used a quantitative cross-sectional survey design to examine the current situation, the factors affecting and the formation process of AI-TPACK competencies among pre-service teachers located in Chinese institutions of higher education. To begin with, the study relied on the study scales and research-based studies to create a Survey Questionnaire on Pre-service Teachers AI Technology Integration Content Knowledge survey questionnaire that targets pre-service educators directly. The questionnaire has three key parts: Part One involves the basic demographics that will be conducted in four items, where the respondent is required to specify his/her gender, grade level, school level, and teaching experience. Part Two presents the AI-TPACK Competency Structure Scale. This scale was developed based on Schmidt et al.'s (2009) TPACK measurement tool. While Schmidt's scale targeted

pre-service teachers in mathematics, science, social studies, and literature, this study included pre-service teachers across multiple disciplines. Consequently, certain items from Schmidt's scale were appropriately reduced. The adapted Schmidt scale contained fewer items for PCK and TCK, making it insufficient to accurately reflect pre-service teachers' PCK and TCK levels. Therefore, this study integrated the characteristics of AI-TPACK, drawing on Archambault & Crippen's (2009) TPACK knowledge survey questionnaire and relevant content from Cambazoğlu et al.'s (2013) pre-service science teacher technological content knowledge scale to develop the AI-TPACK Competency Structure Scale for Pre-service Teachers. The third component is the Pre-service Teacher AI-TPACK Competency Structure Development Influencing Factors Scale. The scale was built by taking a version of the Karaca et al. (2013) Technology Competency Scale and modifying it to create the Pre-service Teacher AI-TPACK Competency Structure Development Influencing Factors Scale.

According to Hair et al. (2010), the appropriate sample size for studies employing structural equation modeling should range between 150 and 400. Additionally, the previous studies by Wilson et al. (2018) and Wilson and Keni (2018) indicate a need to choose samples of more than 200. Therefore, the sample size established for this study exceeds 300.

Subsequently, to ensure the validity and reliability of subsequent research, after the initial questionnaire was drafted, this study sought feedback from experts at Chinese universities, incorporating their suggestions for revisions and refinements. Following this, focus group discussions were conducted with 10 pre-service teachers in their third year or above, modifying the wording of questionnaire items to ensure participants understood their meaning. The final version comprises a 28-item AI-TPACK Competency Structure Scale for pre-service teachers and a 13-item AI-TPACK Competency Structure Development Influencing Factors Scale. The questionnaire employs a seven-point Likert scale (Strongly Disagree = 1, Disagree = 2, Somewhat Disagree = 3, Neutral = 4, Somewhat Agree = 5, Agree = 6, Strongly Agree=7) for each observed variable. Specific items corresponding to each dimension of the pre-service teacher AI-TPACK survey are presented in **Table 1**.

This study conducted reliability and validity tests on the questionnaire. First, analysis revealed (**Table 2**) that the overall Cronbach's alpha coefficient for the designed scale was 0.956, indicating excellent reliability and demonstrating stability or consistency across all items. Second, validity was assessed using KMO and Bartlett's sphericity test. Results showed KMO = 0.941 and Bartlett's sphericity test yielded $\chi^2 = 14391.120$, $df = 1485$, $p < 0.001$. This implies that the variables observed with respect to each of the measurement items of the dimensions have common factors; thus, the data can be analyzed using factor analysis.

Table 1. Items of the Pre-service Teacher AI-TPACK Survey Questionnaire.

Research variables		Number of questions	Reference resources
Primary indicators	Secondary indicators		
AI-TPACK Internal knowledge structure	AI-TK	3	Schmidt et al. (2009)
	CK	3	Schmidt et al. (2009)
	PK	3	Schmidt et al. (2009)
	PCK	4	Canbazoglu et al. (2013)
	Integrating AI-TCK	4	Archambault et al. (2009)
	Integrating AI-TPK	4	Canbazoglu et al. (2013)
	Integrating AI-TPACK	4	Schmidt et al. (2009)
External influencing factors	Attitude toward the application of AI technology (AT)	4	Karaca et al. (2013)
	Ability to apply AI technology (AB)	4	
	School technical support (STS)	5	
Demographic characteristics	Gender, grade, school level, teaching experience	4	

Table 2. Reliability statistics for each dimension of the scale.

Potential variables	Cronbach's alpha	Number of items
AI-TK	0.815	3
CK	0.819	3
PK	0.828	3
PCK	0.911	4
AI-TCK	0.883	4
AI-TPK	0.894	4
AI-TPACK	0.918	4
AT	0.913	4
AB	0.918	4
STS	0.939	5
Total	0.965	38

After ensuring the questionnaire's validity and reliability met established standards, this study conducted a second large-scale formal questionnaire distribution. The distribution primarily relied on the Questionnaire Star platform. The survey participants were pre-service teachers in their third year or above at Chinese universities. A total of 357 questionnaires were collected, of which 325 were valid, yielding a validity rate of 91%.

4. Research finding

This section analyzes the questionnaire results. First, descriptive statistical analyses are conducted on the basic characteristics of the surveyed Chinese pre-service teachers, their AI-TPACK competency structures, and influencing factors. Second, the variations in the AI-TPACK competency structures of pre-service teachers are investigated. Lastly, the structural equation modeling is used to dig deeper into the

contemporary state of AI-TPACK competency structures among pre-service teachers and the connection between multiple factors affecting them.

4.1. Current status of AI-TPACK competencies among pre-service teachers

To understand the specific details of the research sample, this study first compiled statistics on the personal information of 325 survey participants. This primarily included participants' gender, grade level, university tier, and teaching experience. The sample of the pre-service teachers included institutions divided into: World-Class University Construction Institutions, World-Class Discipline Construction Institutions, Regular First-Tier Universities, Regular Second-Tier Universities, and Higher Vocational Colleges. Some categories carried small samples, and so the disciplinary layers were restructured into three groups, namely, Key First-Tier Universities, Regular First-Tier Universities, and Regular Second-Tier Universities.

As shown in **Table 3**, among the surveyed sample, 59 respondents were male, accounting for 18.2%; and 266 female students, accounting for 81.8%. Overall, female pre-service teachers were more prevalent. By academic year: 68 pre-service teachers were in the third year of the graduate school (20.9%); 88 were in the fourth year of the graduate school (27.1%); 51 pre-service teachers were first year graduate students (15.7%); 55 pre-service teachers were second year graduate students (16.9%) and 46 pre-service teachers were third year graduate students (14.1%). The survey participants spanned different academic years from the third year onwards. Regarding the tier of institutions attended by pre-service teachers: 126 were from key first-tier universities (38.8%); 100 pre-service teachers were from ordinary first-tier universities (30.8%); 99 pre-service teachers were from ordinary second-tier universities (30.4%). The surveyed pre-service teacher group covered different university tiers. In terms of teaching experience, 172 pre-service teachers were identified to possess relevant teaching experience, including internships or teaching, which represented 53 and 153 pre-service teachers had a relatively very limited teaching experience, respectively.

Descriptive statistical analysis of the component factors within the AI-TPACK competency structure of pre-service teachers reveals that all seven knowledge categories are at a moderately high level overall. However, significant room for improvement remains across each knowledge domain. Specific statistical results are presented in **Table 4**. The overall average score for pre-service teachers' AI-TPACK was 4.46, exceeding 4. This indicates that their overall AI-TPACK level is above average. There are substantial differences between the different components of AI-TPACK, namely: $PCK > PK > CK > AI-TCK > AI-TPACK > AI-TPK > AI-TK$. Subject-related PCK, PK, and CK all portray high scores, which implies that pre-service teachers possessing single-subject coursework and training in teacher education can be proficient in single-knowledge subject-teaching material. The AI-TPACK sub-score that has the lowest mean is AI-TK, which means that the pre-service teachers have quite weak AI technical knowledge when revolving around intelligent education. This highlights the reason they must emphasize the development of AI skills in their day-to-day learning and teaching to increase their technical

knowledge of AI. The average scores of AI-TCK and AI-TPK, indicating the same AI-TK, were 4.70 and 4.60, respectively, which were higher than the mean score of AI-TK. This indicates that while pre-service teachers' AI technical knowledge requires improvement, they can effectively integrate AI technical knowledge with subject knowledge or pedagogical knowledge during daily teaching practices. Their overall competency with AI technology in employing it in teaching particular subjects, however, is quite low and should undergo improvement and advancement.

Table 3. Statistical Table of Basic Information of Survey Participants ($n = 325$).

Variable	Type	Number of samples	Percentage (%)
Gender	Male	59	18.2
	Female	266	81.8
	Junior	68	20.9
	Senior	88	27.1
Grade	First-year graduate student	51	15.7
	Second-year graduate student	55	16.9
	Third-year graduate student	46	14.1
	Doctoral student	17	5.3
School Level	Key first-tier university	126	38.8
	Ordinary first-tier university	100	30.8
	Ordinary second-tier university	99	30.4
Teaching Experience	Yes	172	53
	No	153	47

Table 4. Descriptive statistics of AI-TPACK factors for teacher-training students ($n = 325$).

Dimension	Minimum value	Maximum value	Average value	Standard deviation
AI-TK	1	7	4.46	1.07
AI-TPK	1	7	4.60	0.90
AI-TPACK	1	7	4.62	0.92
AI-TCK	1	7	4.70	0.94
CK	2	7	4.72	0.88
PK	2	7	4.85	0.81
PCK	3	7	5.01	0.81

4.2. Differential analysis by background variables

To reflect how different background factors influence pre-service teachers' AI-TPACK competency structures, this study will conduct differential analyses based on pre-service teachers' gender, grade level, school level, and teaching experience. Specifically, independent samples t-tests will be used to analyze the effects of gender and teaching experience on AI-TPACK competency structures. One-way ANOVA will be employed to examine the effects of grade level and school level on AI-TPACK competency structures.

4.2.1. Analysis of gender differences

According to **Table 5**, the gender variable among pre-service teachers did not reach statistical significance in any of the seven dependent variable tests ($p > 0.05$). This indicates no significant differences in AI-TK, CK, PK, PCK, AI-TCK, AI-TPK, or AI-TPACK competencies between male and female pre-service teachers, meaning gender has no impact on the AI-TPACK competency structure of pre-service teachers. From HRD perspective, this implies that when cultivating AI integration competencies in pre-service teachers, the differential effects of gender need not be considered. Instead, emphasis should be placed on other more influential factors to comprehensively enhance the digital human capital of pre-service teachers.

Table 5. Comparison of differences between male and female teacher-training students in the various dimensions of AI-TPACK.

Test variable	Gender	Number	Average	Standard deviation	t value
AI-TK	Male	59	4.56	0.948	0.382
	Female	266	4.44	1.092	
CK	Male	59	4.78	0.942	0.558
	Female	266	4.71	0.863	
PK	Male	59	4.83	0.815	0.829
	Female	266	4.86	0.814	
PCK	Male	59	4.99	0.811	0.809
	Female	266	5.02	0.808	
AI-TCK	Male	59	4.64	0.901	0.584
	Female	266	4.71	0.947	
AI-TPK	Male	59	4.55	0.952	0.614
	Female	266	4.62	0.894	
AI-TPACK	Male	59	4.58	0.938	0.703
	Female	266	4.63	0.919	

4.2.2. Analysis of grade differences

The paper used a one-way ANOVA to test the hypothesis that the grade level of pre-service teachers affected the AI-TPACK competency structure. **Table 6** provides differences between the dimensions of AI-TPACK. To do post-hoc comparisons, the Significant Differences Method was used to correspond to the overall significance level of the *F*-test.

The response rate was used as the statistical analysis variable to show that differences in CK competence were significant among pre-service teachers based on the grade level ($p = 0.001 < 0.05$) and the doctoral candidates showed a very high level of subject knowledge compared to third and fourth-year undergraduates and also to students in the first year of a graduate program. But grade level did not have any significant effect on other dimensions of AI-TPACK competence structure.

Table 6. Analysis of variance of teacher-training students in different grades in each dimension of AI-TPACK.

Test variable		Sum of squares	Degree of freedom	Average square	F	Post-hoc comparison HSD method
AI-TK	Between groups	9.209	5	1.842	1.633	n.s.
	Within the group	359.702	319	1.128		
	Total	368.911	324			
CK	Between groups	14.004	5	2.801	3.798*	Doctoral student > Junior
	Within the group	235.218	319	0.737		Doctoral student > Senior
	Total	249.222	324			Doctoral student > First year of graduate school
PK	Between groups	4.900	5	0.980	1.493	
	Within the group	209.356	319	0.656		n.s.
	Total	214.256	324			
PCK	Between groups	3.821	5	0.764	1.175	
	Within groups	207.422	319	0.650		n.s.
	Total	211.243	324			
AI-TCK	Between groups	2.493	5	0.499	0.563	
	Within groups	282.314	319	0.885		n.s.
	Total	284.808	324			
AI-TPK	Between groups	3.830	5	0.766	0.937	
	Within groups	260.863	319	0.818		n.s.
	Total	264.693	324			
AI-TPACK	Between groups	3.563	5	0.713	0.838	
	Within groups	271.247	319	0.850		n.s.
	Total	274.811	324			

Note: *: $p < 0.05$

4.2.3. Analysis of school-level differences

Further, variation in the school levels could reveal the inequality between the institutions in terms of educational resources, curriculum framework, staff skill, and approach towards the use of AI technology, in HRD terms. This study tested the hypothesis of the impacts of school levels of pre-service teachers on their competency structure of AI-TPACK using one-way analysis of variance. **Table 7** depicts comparative differences of AI-TPACK dimensions. Statistical analysis reveals that school tier significantly influences pre-service teachers' PK, PCK, AI-TCK, AI-TPK, and AI-TPACK competency structures ($p < 0.05$). There is also a much higher knowledge level of pre-service teachers in major first-tier universities as compared to the ordinary second-tier universities. When the means are compared, it can be seen that the pre-service teachers of typical second-tier universities have much lower levels of AI-TPACK competencies in all dimensions than those of other tiers of universities.

Table 7. Analysis of variance of teacher-training students at different school levels in each dimension of AI-TPACK.

Test variable	Sum of squares	Degree of freedom	Average square	F	Post-hoc comparison	HSD method
AI-TK	Between groups	1.512	2	0.756	0.663	n.s.
	Within groups	367.399	322	1.141		
	Total	368.911	324			
CK	Between groups	3.672	2	1.836	2.408	n.s.
	Within groups	245.549	322	0.763		
	Total	249.222	324			
PK	Between groups	4.059	2	2.029	3.109*	Key first-tier universities > Ordinary second-tier universities
	Within groups	210.198	322	0.653		
	Total	214.256	324			
PCK	Between groups	4.156	2	2.078	3.231*	Key first-tier universities > Ordinary second-tier universities
	Within groups	207.087	322	0.643		
	Total	211.243	324			
AI-TCK	Between groups	5.494	2	2.747	3.167*	Key first-tier universities > Ordinary second-tier universities
	Within groups	279.314	322	0.867		
	Total	284.808	324			
AI-TPK	Between groups	6.232	2	3.116	3.882*	Key first-tier universities > Ordinary second-tier universities
	Within groups	258.461	322	0.803		
	Total	264.693	324			
AI-TPACK	Between groups	8.794	2	4.397	5.322*	Key first-tier universities > Ordinary second-tier universities
	Within groups	266.017	322	0.826		
	Total	274.811	324			

Note: *: $p < 0.05$

4.2.4. Analysis of differences in teaching experience

From the perspective of digital human capital formation, teaching experience can be regarded as a crucial practical training opportunity. It provides pre-service teachers with a platform to integrate theoretical knowledge with teaching practice, enabling them to continuously explore and apply AI technologies in practice, thereby enhancing their AI integration capabilities. An independent samples t-test analyzed whether pre-service teachers' teaching experience influenced their AI-TPACK competency structure. Comparisons of differences across AI-TPACK dimensions are presented in **Table 8**. Statistical analysis revealed significant differences in CK, PK, and PCK between pre-service teachers with and without teaching experience. The p-values for CK, PK, and PCK dimensions among those with teaching experience were 0.025, 0.001, and 0.019, respectively, all less than 0.05. Furthermore, the mean scores across all AI-TPACK dimensions were higher for pre-service teachers with teaching experience compared to those with limited experience.

Table 8. Comparison of differences in teacher-training students' AI-TPACK dimensions based on teaching experience.

Test variable	Teaching experience	Number of cases	Average value	Standard deviation	t value
AI-TK	Yes	172	4.49	1.064	0.535
	No	153	4.42	1.073	
CK	Yes	172	4.82	0.829	2.253*
	No	153	4.60	0.917	
PK	Yes	172	4.99	0.779	3.270*
	No	153	4.70	0.826	
PCK	Yes	172	5.11	0.788	2.354*
	No	153	4.90	0.817	
AI-TCK	Yes	172	4.75	0.935	1.009
	No	153	4.64	0.941	
AI-TPK	Yes	172	4.63	0.922	0.615
	No	153	4.57	0.885	
AI-TPACK	Yes	172	4.64	0.940	0.543
	No	153	4.59	0.901	

Note: *: $p < 0.05$

4.3. Influencing factors and formation mechanisms

To explore how three external variables, including attitudes of pre-service teachers toward AI technology, their capacity to use AI technology, and technical support in schools, affect all the dimensions of AI-TPACK, the study used AMOS 24.0 software to establish a structural equation model. A measurement model was used to describe the relationships between observed variables and latent variables. The tests are mostly parameter tests and goodness-of-fit tests. Parameter tests included significance tests ($p < 0.05$) and plausibility tests (variance and standard deviation of parameter estimates both greater than 0; standardized regression coefficients not exceeding 1).

Maximum likelihood estimation results determined the model fit, as shown in **Table 9**: CMIN/DF = 2.07 indicates parsimonious fit; RMSEA = 0.057 signifies acceptable fit; GFI=0.832 denotes acceptable path diagram-to-data fit; AGFI is 0.803, indicating acceptable results; IFI is 0.925, indicating good fit between the model path diagram and actual data; TLI is 0.915, indicating a favorable value-added fit index; CFI is 0.924, indicating a favorable comparative fit index.

Table 9. Fit indices for the initial structural model ($n = 325$).

Model fit indicators	CMIN (χ^2)	DF	CMIN/DF	RMSEA	GFI	AGFI	IFI	TLI	CFI
Measurement model	1302.324	629	2.07	0.057	0.832	0.803	0.925	0.915	0.924

To test the research hypotheses proposed in this study, standardized regression coefficients β were estimated and tested at the α level of $p < 0.001$. This examined the influence of pre-service teachers' AI-TPACK component factors, pre-service teachers' attitudes toward AI technology application, their AI application competencies, and

school support for AI technologies on their AI-TPACK competency structure. School support for AI technologies did not significantly influence preservice teachers' CK, PCK, or AI-TCK levels; preservice teachers' AI application competencies did not significantly affect their AI-TK, CK, PK, or PCK levels; Pre-service teachers' attitudes toward AI technology application do not significantly affect their AI-TCK level; pre-service teachers' PK level does not significantly affect their AI-TPK level; school support for AI and related technologies, pre-service teachers' ability to apply AI technology, CK, PK, and PCK do not significantly affect pre-service teachers' AI-TPACK level. Therefore, these factors are removed from the initial structural model, yielding a simplified revised structural model, as shown in **Figure 2**.

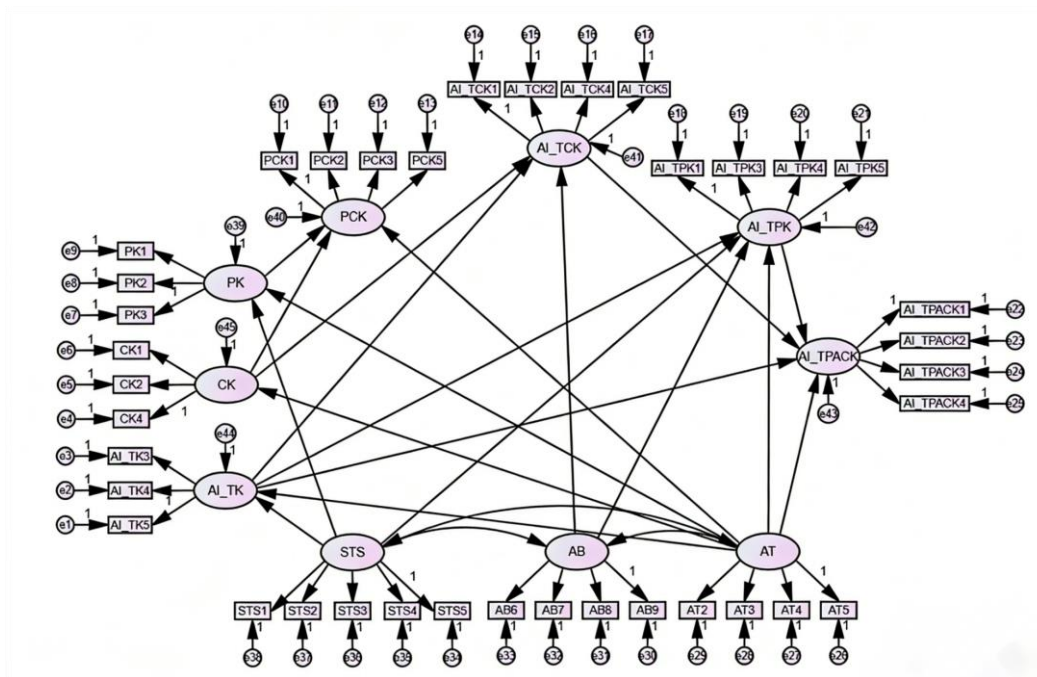


Figure 2. Modified structural model.

Table 10 shows the goodness-of-fit indices of the revised structural model in this study. As can be seen from the table, the test values of the revised structural model all meet the reference standard requirements (Jackson et al., 2009) and have good goodness-of-fit, indicating that the revised structural model is acceptable.

Table 10. Fit test of the modified model ($n = 325$).

Statistical test value	CMIN/DF	RMSEA	SRMR	GFI	AGFI	TLI	CFI
Matching standard value	$1 < \text{CMIN/DF} < 3$	< 0.05	< 0.08	> 0.9	> 0.9	> 0.9	> 0.9
Corrected model test value	1.404	0.035	0.052	0.906	0.901	0.969	0.971

Overall, technical support on the school level, attitude to technology, and technological competence have a strong effect on the AI-TPACK competencies of pre-service teachers. Moreover, school-level and teaching experience are vital external moderating variables because they play a major role in controlling the establishment and evolution of pre-service teachers. These results provide strong empirical support for the concept of developing a pre-service teacher AI integration competency

development framework based on the HRD perspective. They also align with the research findings mentioned in the abstract, indicating that pre-service teachers' AI-TPACK competencies are influenced by multiple factors, with complex formation mechanisms, requiring multidimensional systematic development and cultivation to comprehensively enhance the quality of pre-service teachers' digital human capital. This lays a solid talent foundation for the digital transformation of future education and the improvement of educational quality.

Based on the revised structural equation model, this study further analyzed the direct effects of each latent variable on pre-service teachers' AI-TPACK and its related dimensions, with results presented in **Table 11**.

Table 11. Direct Effects of Various Influencing Factors on Pre-service Teachers' AI-TPACK.

Latent Variables	Direct effects
PCK← STS	0.000
PCK← AT	0.212
PCK← CK	0.404
PCK← PK	0.325
AI- TCK← STS	0.000
AI- TCK← AB	0.306
AI- TCK← AT	0.000
AI- TCK← AI- TK	0.466
AI- TCK← CK	0.242
AI- TPK← STS	0.217
AI- TPK← AB	0.262
AI- TPK← AT	0.206
AI- TPK← AI- TK	0.344
AI- TPACK← STS	0.000
AI- TPACK← AB	0.000
AI- TPACK← AT	0.194
AI- TPACK← AI- TK	−0.198
AI- TPACK← CK	0.000
AI- TPACK← AI- TCK	0.332
AI- TPACK← AI- TPK	0.493

Regarding the single knowledge dimension, school support for technologies like AI positively promoted both AI-TK and PK among pre-service teachers. Meanwhile, pre-service teachers' attitudes toward applying AI significantly and positively influenced their AI-TK, CK, and PK.

Within the composite knowledge dimension, pre-service teachers' attitudes toward AI application exerted positive direct effects on both their PCK and AI-TPK. Their AI application ability positively influenced both AI-TCK and AI-TPK. Additionally, pre-service teachers' AI-TK significantly and positively influenced both

AI-TCK and AI-TPK; CK also exerted positive effects on PCK and AI-TCK; while PK directly promoted PCK.

At the overall AI-TPACK level, pre-service teachers' attitude toward applying AI had a positive direct effect on AI-TPACK, whereas AI-TK exhibited a negative effect. Within the composite knowledge dimension, both AI-TCK and AI-TPK exert significant positive effects on AI-TPACK, with AI-TPK demonstrating the most pronounced impact ($\beta = 0.493$), followed by AI-TCK ($\beta = 0.332$).

The strength of influence on direct effects by factors is as follows: the largest factor by magnitude effects is AI-TPK, AI-TCK, attitude toward AI application, AI application ability, school technical support (STS) and CK are the closest factors, and AI-TK influences negatively. This indicates that AI-TPK plays the most critical role in advancing pre-service teachers' AI-TPACK development. It suggests that efforts should focus on strengthening pre-service teachers' pedagogical knowledge construction and competency enhancement in integrating artificial intelligence technologies, thereby boosting their digital literacy and adaptability to educational transformation.

4.4 Human Resource Development Framework

Based on the aforementioned research findings, this study adopts an HRD perspective to construct a systematic HRD framework (**Figure 3**). This framework aims to comprehensively enhance the quality of pre-service teachers' digital human capital, laying a solid talent foundation for the digital transformation of future education and the improvement of educational quality. This model is holistic and thoroughly reflects on the processes and determinants of the AI-TPACK competencies of pre-service teachers. It is methodically organized in the 4 dimensions of such qualities as the optimization of the curriculum, the reinforcement of practice, the support of resources, and the guidance of policy, so that it can promote the overall development of the AI integration potential in pre-service educators.

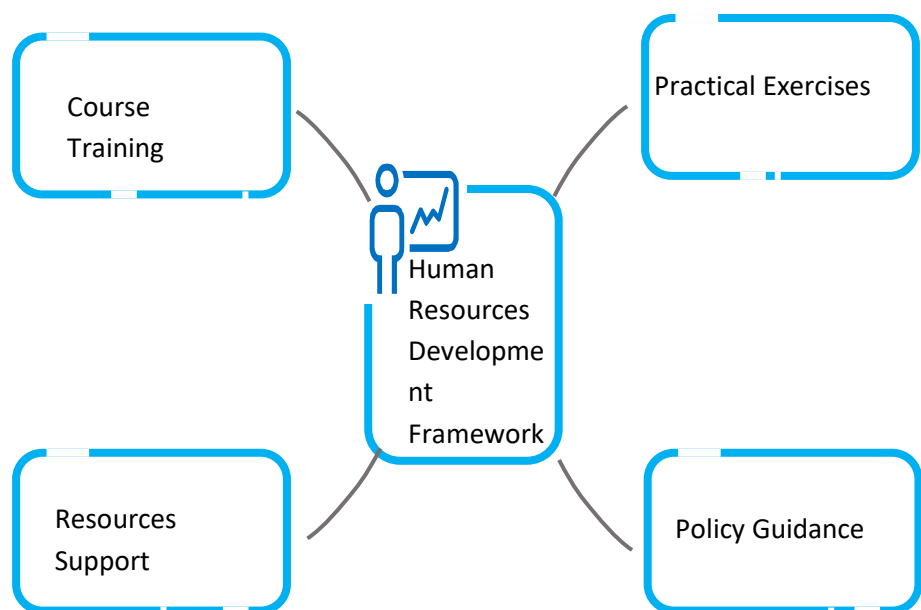


Figure 3. Pre-service Teacher Human Resource Development Framework.

The study shows that pre-service teachers demonstrate rather poor AI-TK ($M = 4.46$), which is a discrepancy in the digital human capital of the teachers. Thus, educational establishments must increase the amount of AI-related courses including AI fundamentals, AI applications in education, data science and analytics, to expand the knowledge and application skills of AI technologies in pre-service teachers. The coursework must incorporate the core principles of the AI, algorithms, and tools, and how they can be used in education to assist pre-service teachers to establish a strong base of knowledge in AI technology. AI-TPACK competency by pre-service teachers should not be limited to technical expertise only, but also integrate AI technology with teaching material about a particular subject. In such a way, curriculum planning ought to focus on interdisciplinary integration, the integration of AI technology and subject-specific teaching materials, with the purpose of assisting pre-service teachers to build an AI-TPACK knowledge system. To illustrate, with the use of case studies and project-based learning, pre-service teachers may be informed about incorporating AI technology into particular instructional design and implementation in practice and, consequently, develop their overall application skills better.

The study reported that teaching experience improves AI-TPACK competencies of pre-service teachers. Therefore, pre-service teachers should have more opportunities in internships and teaching practice at universities that allow them to learn and apply AI technologies to real-life situations. These experiences can not only assist with the combination of theoretical material with the teaching practice but also increase their insight into the reality of the educational effect of AI, as well as possible challenges (Cheng et al., 2025). Institutions of higher learning can launch an educational research project that implements AI with pre-service teachers. These projects may explore AI applications across disciplines, the development and evaluation of AI educational tools, and more (Alejandro et al., 2024; Karataş & Yüc, 2024). By engaging in research, pre-service teachers can not only develop their research skills but also test AI applications in practice, thus developing their skills of integrating AI.

The results of the research show that pre-service teachers' technical support in schools has a strong positive impact on the competencies of AI-TPACK. Thus, higher educational institutions need to put more effort and resources into educational technology by availing new AI equipment and AI software to aid learning and practice of pre-service teachers, including intelligent education programs and the use of AI resources (Bautista et al., 2024). Such resources not only increase the skills of teachers in terms of technological application, but also give their teaching practice strong incentives to work. Higher education institutions should establish specialized technical support teams to provide technical consultation and training services for pre-service teachers during AI technology application (Crompton, H., & Burke, D., 2023). In these teams, it is possible to conduct technical training workshops frequently to assist pre-service teachers in solving technical problems and enhancing their application skills. Alongside that, technical support teams have the capability of providing online support to deal with the problems faced by pre-service teachers in their practice in a timely manner (Bautista et al., 2024).

Finally, the policy environment serves as an external safeguard for the development of pre-service teachers' digital human capital. Higher education

institutions and educational administrative departments should formulate relevant policies to guide and encourage pre-service teachers in developing AI integration capabilities (Chan, 2023). For instance, dedicated funds can be established to support research and practice projects related to AI education; incentive mechanisms can be created to recognize and reward pre-service teachers actively engaged in AI education practice and research; and relevant standards and norms can be developed to guide pre-service teachers' AI education training and practical work. Through policy guidance, a favorable environment conducive to the development of pre-service teachers' digital human capital can be fostered, promoting the rational allocation and efficient utilization of educational resources, and driving the comprehensive enhancement of pre-service teachers' AI integration capabilities.

5. Discussion

The results show that the pre-service teachers' overall AI-TPACK set of competencies is in the upper-middle range, although there is a lot of difference in dimensions. In particular, they have higher competencies in PCK, PK and CK, whereas AI-TK and competencies involving integration (AI-TPK and AI-TCK, etc.) are relatively low. This observation is consistent with Schmidt et al.'s (2009) observation that technological knowledge is commonly the weakest aspect of TPACK competencies among teachers. Moreover, the pre-service educators' AI-TPACK competencies are greatly dependent on the institutional level and teaching experience: teachers of the major universities are much better in terms of their AI-TPACK competencies when compared with their peers in the average second or third-tier institutions, and teachers with a certain teaching experience show better CK, PK, and PCK abilities. It is similar to what Archambault and Crippen (2009) pointed out, that knowledge structures of teachers can be integrated with the help of practical experience and the support of institutional resources. Despite their lesser level of AI-TK levels, pre-service teachers show rather high levels of AI-TCK and AI-TPK. This suggests they possess preliminary abilities to integrate AI technology with teaching practices, though their technological foundations require further strengthening (Hava, K., & Babayigit, Ö., 2024). The implication of the given finding is rather relevant to the field of teacher training: it is important to focus more on the process of applying the technology to the teaching setting instead of training them on skills of technical operation (Ning et al., 2024).

Through differential analysis, this study revealed variations in AI-TPACK competency structures among pre-service teachers with different background characteristics. No significant differences ($p > 0.05$) were observed between male and female pre-service teachers across AI-TK, CK, PK, PCK, AI-TCK, AI-TPK, or AI-TPACK competencies, indicating that gender has no significant impact on their AI-TPACK competency structures. This is consistent with the past findings. As an example, a similar observation is made by M. Haziq Saharuddin et al. (2025), who found that there are no significant gender variations among TPACK dimensions, and thus, TPACK professional development may be tailored without other variance versions based on gender. Moreover, the results of Naaz & Khan (2018) also revealed

no significant differences in TPACK between males and girls among pre-service teachers, which also serves the results of this research.

Significant differences exist in CK abilities among pre-service teachers across different academic years ($p = 0.001 < 0.05$), with doctoral candidates demonstrating significantly higher subject knowledge levels than third-year undergraduates, fourth-year undergraduates, and first-year graduate students. However, the academic year did not significantly influence other dimensions of AI-TPACK. School level significantly influenced the PK, PCK, AI-TCK, AI-TPK, and AI-TPACK competency structures of pre-service teachers ($p < 0.05$). The level of knowledge exhibited by pre-service teachers on these dimensions in important first-tier universities was very high compared to other second-tier universities. This result matches the observation of Qin et al. (2022), who have observed that degrees of lower (but paradoxically even the lowest) degrees of technology integration go hand in hand with high levels of TPACK in pre-service teachers. Such an incongruity could be the result of such factors as the institutional facilities, faculty training, and curriculum design (Aglibot et al., 2025). Pre-service teachers with teaching experience demonstrated significantly higher levels in CK, PK, and PCK dimensions ($p < 0.05$) and higher average scores across all AI-TPACK dimensions compared to those without teaching experience. This result is consistent with Wang (2018), who has suggested that the teaching experience has a strong effect on the subject knowledge, as well as on the pedagogical and content knowledge of a teacher.

These findings suggest a systematic framework of HRD that will be offered in this study to substantially increase the capabilities of pre-service teachers to integrate AI through four dimensions, such as curriculum optimization, practice reinforcement, resource support, and policy guidelines. This framework not only offers practical, concrete guidelines to the pre-service teacher training in the institutions of higher learning, but also empirical evidence that can be used by the education administrators to create applicable policies. It helps to develop and build digital human capital in the pre-service teachers and provides a strong platform for how the future education will be digital and helps in the advancement of the quality of education.

It is important to acknowledge that significant disparities exist between urban and rural educational contexts in China. While this study did not specifically differentiate between urban and rural institutions, future research should explore how school location (urban vs. rural) influences AI-TPACK development. Rural schools may require targeted resource allocation, infrastructure investment, and specialized training programs to bridge the digital divide. Policy interventions should consider differentiated strategies that account for varying levels of technological access and support in different regional contexts. Additionally, although this study did not examine age as a factor, age may also influence the AI-TPACK competency structure of pre-service teachers. Future research should incorporate age as a key demographic variable and develop differentiated strategies tailored to teachers across different age groups.

6. Conclusion

In summary, as artificial intelligence technology becomes deeply integrated into the education sector, pre-service teachers' AI integration capabilities have become crucial for enhancing educational quality and driving digital transformation in education. Through empirical analysis, this study reveals the current state, influencing factors, and formation mechanisms of pre-service teachers' AI-TPACK competencies in Chinese universities. It constructs a systematic framework for developing AI integration capabilities from an HRD perspective. Findings indicate that while pre-service teachers exhibit above-average overall AI-TPACK levels, their technical knowledge and integration skills remain relatively weak. School technical support, technological attitudes, and technological competence significantly influence pre-service teachers' AI-TPACK competencies, with institutional level and teaching experience serving as important external moderators. Based on these findings, the study proposes specific strategies to enhance pre-service teachers' AI integration competencies across four dimensions: curriculum optimization, practice reinforcement, resource support, and policy guidance. These strategies aim to provide theoretical foundations and practical pathways for pre-service teacher training and teacher HRD education institutions. Although this study achieved certain theoretical and practical outcomes, limitations remain. Future research could expand sample sizes, refine measurement tools, adopt longitudinal designs, and explore cross-regional and cross-cultural studies, intervention research, and the interplay between technological and social factors. Such efforts would enable more comprehensive and in-depth investigations into the formation and development mechanisms of pre-service teachers' AI integration competencies, thereby providing stronger support and safeguards for educational digital transformation and quality enhancement.

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