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Construction and Validation of a Five-Dimensional Structure Model for the Participation Level of Pre-service Teachers in Generative AI-Based Online Learning—An Empirical Study Based on Social, Collaborative, Behavioral, Emotional, and Cognitive Dimensions

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Abstract: *The present study aims to construct and validate a five-dimensional structure model for pre-service teachers' engagement in generative artificial intelligence (GenAI)-driven online learning. A total of 1,478 pre-service teachers were selected as research participants, and the measurement scale encompasses five core dimensions: social, collaborative, behavioral, emotional, and cognitive engagements. The study first established the measurement item system through exploratory factor analysis, followed by confirmatory factor analysis to assess data suitability and cross-group measurement equivalence. Results demonstrate: Firstly, the five-dimensional model exhibits strong suitability, with all fit indices meeting standards after modification, and each dimension demonstrates robust unidimensionality and converge validity. Secondly, the model shows high cross-sample consistency between the estimation and validation groups. The present study provides empirical evidence supporting the five-dimensional structure model of GenAI-based online learning engagement among 1,478 pre-service teachers. Finally, the relevant issues are discussed based on the findings, and directions for future research are proposed.*

Keywords: *Pre-service teachers; Generative artificial intelligence; Online learning engagement; Structural model*

1. Introduction

With the rapid advancement of Generative Artificial Intelligence (GenAI) technology, large language models such as ChatGPT, DeepSeek, ERNIE Bot, and iFLYTEK SparkDesk are profoundly reshaping the landscape of higher education [1–2]. Centered on natural language interaction, these tools are capable of generating text, code, images, and even multimodal learning resources in real time, thereby providing learners with unprecedented cognitive support and creative opportunities [3]. In the filed of teacher education, the widespread integration of GenAI has not only transformed the learning methods of pre-service teachers, but also significantly influenced the development of their future teaching competencies. However, the technological sophistication of GenAI does not necessarily translate into improved learning quality, and whether learners can engage deeply in GenAI-powered online learning processes remains the key factor determining the full realization of technology's educational value [4].

Learning engagement is one of the core topics in the fields of educational psychology and the learning sciences. Since Astin (1984) proposed the student engagement theory [5], researchers have developed theoretical frameworks and empirically examined the learning engagement from multiple dimensions. Existing research generally agrees that learning engagement is a multidimensional construct encompassing three fundamental dimensions: behavioral, cognitive, and emotional [6]. With the advancement of collaborative learning theory and networked learning environment, some researchers have further incorporated social and collaborative dimensions [7–8]. However, with respect to online learning engagement within the specific technological context of Generative Artificial Intelligence, a comprehensive five-dimensional structure model has yet to be supported by a systematic

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theoretical framework and sufficient empirical evidence, leaving this research gap urgently to be addressed.

Research on measurement models for online learning engagement has evolved from a unidimensional to a multi-dimensional approach. Early studies primarily focused on behavioral engagement, using explicit behavioral indicators such as login frequency and assignment submission rates as proxy measures of engagement [9]. As research advanced, the Community of Inquiry (CoI) framework proposed by Garrison et al. (1999) categorizes the online learning experience into three core dimensions: social presence, cognitive presence, and instructional presence, thereby providing a crucial theoretical foundation for multidimensional engagement measurement [10]. In the collaborative dimension, the interdependence theory developed by Johnson D. W. and Johnson R. T. (1989) elucidates the mechanisms through which collaborative interactions facilitate deep learning [11], while Vygotsky's Zone of Proximal Development theory further underscores the critical role of social collaboration in cognitive construction. The introduction of the emotional engagement dimension stems from research on the relationship between emotion and learning [12]; Pekrun's (2011) theory of academic emotion regulation and value demonstrates that positive academic emotions can significantly predict learners' deep engagement behaviors [13].

In the era of GenAI, the connotation and structure of online learning engagement have exhibited new characteristics. The inherent feature of generative artificial intelligence, i.e. dialogical interaction, generativity, and personalization, impose more complex cognitive processing demands on learners, requiring high cognitive flexibility in critical evaluation, creative application, and reflective integration [14]. At the social and collaborative level, GenAI tools—as "artificial intelligence entities" —have redefined traditional interpersonal collaboration models, blurring the boundaries between human-machine and peer collaboration to form a unique "human-machine-peer" tripartite collaborative ecosystem [15]. At the emotional level, learners 'trust in GenAI, usage anxiety, and technology acceptance attitudes collectively shape a complex landscape of emotional engagement [16]. At the behavioral level, emerging learning practices such as Prompt Engineering have fundamentally transformed pre-service teachers' engagement patterns [17]. However, systematic empirical research on the multidimensional structure of learning engagement in this emerging context remains scarce, particularly with respect to the validation of measurement instruments that integrate the aforementioned five dimensions for pre-service teacher populations.

The pre-service teacher population hold unique strategic value in research on generative artificial intelligence (GenAI) applications in education. On one hand, they represent the core force behind future educational innovation, and the quality of their GenAI literacy development directly impacts the digital learning experiences of the next generation of students [18]. On the other hand, pre-service teachers are at a critical stage of professional knowledge construction, and GenAI tools exert profound shaping effects on their cognitive development, learning habits, and professional identity [19]. At present, some studies have examined pre-service teachers' adoption intentions toward GenAI from the perspective of the Technology Acceptance Model (TAM) [20], while others have investigated ChatGPT's influence on writing skills or critical thinking [21], systematic validation using the five-dimensional structure of learning engagement as the core variable through structural equation modeling remains scarce, necessitating further exploration.

In light of this, based on a systematic review of literature on learning engagement theory and GenAI educational applications, and incorporating the Inquiry Community Framework, Self-Determination Theory [22], and the Emotion-Cognition Integration Theory, the present study proposes and constructs a five-dimensional structure model of GenAI-based online learning engagement for pre-service teachers. The model encompasses five core dimensions: social engagement, collaborative engagement, cognitive engagement, behavioral engagement, and emotional engagement. An itemization system was developed through exploratory factor analysis, and the construct validity of the model was empirically tested using confirmatory factor analysis (CFA) and structural equation modeling (SEM). Additionally, cross-validation was performed across different groups of pre-service teachers to assess its generalizability.

Based on the aforementioned research background, the present study focuses on the following four specific research questions:

Research Question 1: Does the five-dimensional structure model of pre-service teachers' GenAI-based online learning engagement developed in the present study meet the fundamental prerequisites for path analysis?

Research Question 2: How applicable and effective is the five-dimensional structure model of

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pre-service teachers' GenAI-based online learning engagement? Can this model effectively fit the empirical data?

Research Question 3: What are the conceptual structural relationships among the latent variables in the five-dimensional structure model of pre-service teachers' GenAI-based online learning engagement? Do the dimensions demonstrate acceptable levels of reliability and validity?

Research Question 4: Does the five-dimensional structure model of pre-service teachers' GenAI-based online learning engagement exhibit cross-group measurement equivalence across different populations—that is, does the model remain fully consistent across various groups?

2. Research Methods

2.1 Research Subject

The present study employed a random sampling method and performed the questionnaire survey via the wjx platform (https://www.wjx.cn). During the pilot stage, 196 pre-service teachers were recruited, comprising 38 males and 158 females. At the formal survey stage, a total of 1,478 pre-service teachers from domestic higher education institutions were included, with the sample composition as follows: 448 males (30.3%) and 1,030 females (69.7%); in terms of academic background, 602 were in science and engineering (40.7%), 614 in liberal arts (41.5%), and 262 in arts, sports, and other disciplines (17.8%).

2.2 Research Tools

The present study employed a questionnaire comprising 20 observed variables to measure participants 'online learning engagement. The scale's theoretical foundation stems from the three-dimensional engagement model proposed by Fredricks et al. [23], which was later expanded by Redmond et al. into an assessment framework encompassing five dimensions: emotional, social, cognitive, collaborative, and behavioral, and further revised and validated by Getenet et al. [24–25]. Building on this framework and tailored to the specific research context, the scale was reviewed and refined by three domain experts, resulting in a formal instrument for measuring pre-service teachers' GenAI-based online learning engagement.

The scale encompasses five latent variables: social, collaborative, behavioral, emotional, and cognitive engagement, totaling 20 observed variables, all scored using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The KMO value is 0.982, and the Bartlett's test for sphericity is significant ($p < .001$), indicating good suitability for factor analysis. The Cronbach's α coefficients for the latent variables are: social engagement (0.877), emotional engagement (0.892), collaborative engagement (0.881), behavioral engagement (0.882), and cognitive engagement (0.874). The overall scale has α coefficient of 0.971, reflecting good internal consistency reliability [26].

2.3 Research Procedure

Through a literature review, an initial scale framework encompassing five dimensions, i.e. social, collaborative, cognitive, behavioral, and emotional engagement, was established. Following the completion of the initial formulation of observational variables, three domain experts were invited to review and validate the scale content. Based on their feedback, relevant items were revised and refined based on the experts' feedback.

The scale validation process proceeds sequentially through two stages: pre-test and formal test. Upon completion of formal data collection, exploratory factor analysis (EFA) is employed to assess the structural validity of the scale, followed by confirmatory factor analysis (CFA) to evaluate its construct validity. Additionally, multi-group CFA is performed to systematically assess the measurement equivalence of the model across population variables in both the estimation and validation groups, ensuring its cross-group applicability among different pre-service teacher populations.

2.4 Data Processing

The sample data were processed using SPSS version 26.0, while AMOS version 26.0 was employed to examine the five-dimensional structure model of pre-service teachers’ engagement in GenAI-based

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online learning, including analyses of model fit, reliability, validity, and measurement invariance..

3. Research Findings

3.1 Condition Analysis of the Five-Dimensional Structure Model for Pre-service Teachers' Participation in GenAI Online Learning

To validate the applicability of the five-dimensional structure model for measuring pre-service teachers' engagement in GenAI-based online learning, the present study examined the data from the following aspects. Firstly, the correlation coefficients among all observed variables ranged from 0.780 to 0.831, all below the critical threshold of 0.90, indicating moderate intervariable correlation. Secondly, basic statistical analyses revealed mean values between 3.81 and 4.01, standard deviations of 0.780–0.900, absolute skewness values ranging from 0.549 to 0.699, and absolute kurtosis values between 0.299 and 1.08 (see Table 1). Both skewness and kurtosis values fell within the acceptable range of −2 to +2, and no multicollinearity was observed among the variables. In conclusion, the study data meet the normal distribution assumption [27] and satisfy the fundamental requirements for conducting path analysis.

Table 1: Means, Standard Deviations, Reliability, and Kurtosis of the Five-Dimensional Structure Model for Pre-Service Teachers' GenAI-based Online Learning Engagement (n=1478)

observable variable	n	mean	standard bias	skewness	Peakness	observable variable	n	mean	standard bias	skewness	Peakness
SE1	1478	3.87	0.850	-0.617	0.702	CE3	1478	3.94	0.840	-0.648	0.685
SE2	1478	3.86	0.900	-0.602	0.299	CE4	1478	3.86	0.890	-0.652	0.587
SE3	1478	3.94	0.830	-0.576	0.478	BE1	1478	3.92	0.860	-0.690	0.781
SE4	1478	3.81	0.900	-0.549	0.326	BE2	1478	3.97	0.830	-0.634	0.611
EE1	1478	3.93	0.810	-0.699	1.083	BE3	1478	3.93	0.840	-0.630	0.648
EE2	1478	3.94	0.830	-0.604	0.604	BE4	1478	3.95	0.830	-0.671	0.859
EE3	1478	3.97	0.840	-0.602	0.483	CET1	1478	3.95	0.800	-0.619	0.860
EE4	1478	3.97	0.830	-0.671	0.795	CET2	1478	3.96	0.840	-0.642	0.617
CE1	1478	3.91	0.840	-0.651	0.709	CET3	1478	4.01	0.780	-0.653	1.024
CE2	1478	3.93	0.850	-0.599	0.492	CET4	1478	3.93	0.860	-0.653	0.640

3.2 Validation of the Five-Dimensional Structure Model for Pre-service Teachers' Participation in GenAI Online Learning

The present study hypothesizes that the model is theoretically grounded in previous researches and evaluates its applicability and validity using empirical data. If the model's applicability fails to meet acceptable standards, it is revised based on the model fit results. The study employs the Maximum Likelihood (ML) estimation method to systematically validate the hypothesized model.

Table 2 Comparison of Fit Indices for the Five-Dimensional Structure Model of Pre-Service Teachers' GenAI-based online learning Engagement (n = 1478)

	x2 (df , p)	Q(NC)	TLI	CFI	SRMR	RMSEA	
						LO90	HI90
initial model	1248.723(175, p < 0.000)	7.136	0.954	0.958	0.028	0.061	0.068
Model Correction	799.497(163, p < 0.000)	4.905	0.971	0.975	0.024	0.048	0.055
critical value	p > .05	Q(NC) < 5	GFI > 0.9	GFI > 0.9	SRMR < 0.05	LO90 ≤ 0.05	HI90< 0.10

The validation results of the model's goodness of fit are presented in Table 2. For the initial model, the χ^2/df value was 7.136, TLI was 0.954, CFI was 0.958, SRMR was 0.028, and RMSEA with its 90% confidence interval ranged from 0.061 to 0.071. Although TLI, CFI, and SRMR all met acceptable criteria, the χ^2/df and RMSEA values slightly exceeded the critical thresholds, indicating that the model's local fit required optimization. Subsequently, appropriate adjustments were made to the model structure using the Modified Index (MI), resulting in a significant improvement in fit quality (see Table 2 and Figure 1) [28]. The modified model met all fit criteria: χ^2/df = 4.905, TLI = 0.971, CFI = 0.975, SRMR = 0.024, and RMSEA with its 90% confidence interval ranged from 0.048 to 0.055. All fit metrics complied with critical thresholds, demonstrating a marked enhancement in the model's applicability. It is evident that the modified model's applicability and validity have been fully validated, making it the final research model for the present study.

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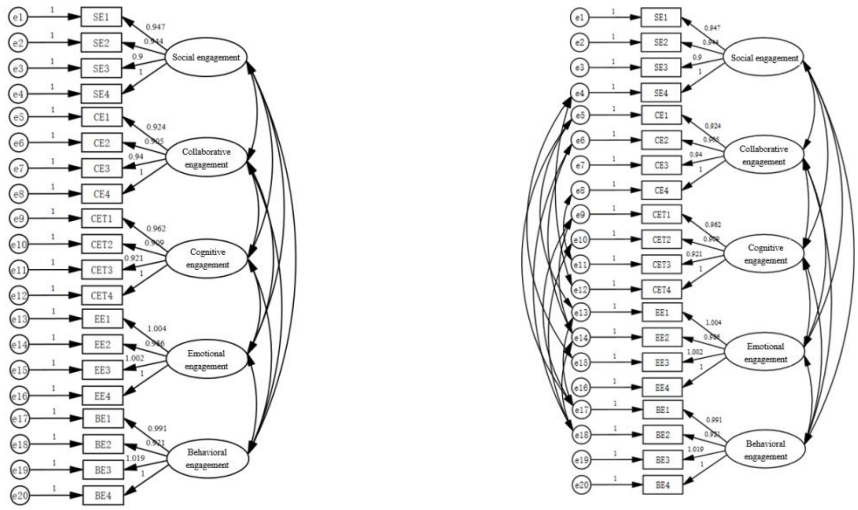

<Initial Model> <Revised Model> <Initial Model> <Revised Model>

Figure 1: Five-dimensional Structure Model of Pre-Service Teachers' GenAI-based Online Learning Engagement (Standardized Coefficients)

3.3 Analysis of the Conceptual Structural Relationships and Reliability/ validity of the Five-Dimensional Structure Model for Pre-service Teachers' GenAI Online Learning Engagement

Table 3: Factor Loadings and Reliability/ Validity Indicators of the Five-Dimensional Structure Model for Pre-service Teachers' GenAI Online Learning Engagement

Observe variable	**Potential Variable (Factor)**	**Loading Value**		**S.E.**	***t***	R^2	**Measure** Error a	CRb	AVEc
		Non-standardized Technique	**Standardization**						
SE1	Social engagement	1.000	0.816			0.665	0.335	0.877	0.642
SE2		1.018	0.780	0.030	34.130***	0.608	0.392		
SE3		0.969	0.805	0.027	35.674***	0.648	0.352		
SE4		1.047	0.803	0.029	35.529***	0.644	0.356		
CE1	Collaborative engagement	1.000	0.808			0.653	0.347	0.881	0.650
CE2		0.996	0.800	0.028	36.001***	0.640	0.360		
CE3		1.002	0.809	0.027	36.606***	0.655	0.345		
CE4		1.051	0.808	0.029	36.529***	0.653	0.347		
BE1	Behavioral engagement	1.000	0.818			0.669	0.331	0.883	0.653
BE2		0.920	0.780	0.026	35.390***	0.609	0.391		
BE3		0.972	0.805	0.026	37.036***	0.648	0.352		
BE4		0.982	0.829	0.025	38.694***	0.687	0.313		
EE1	Emotional engagement	1.000	0.826			0.683	0.317	0.872	0.673
EE2		1.005	0.811	0.027	37.151***	0.658	0.342		
EE3		1.021	0.813	0.027	37.295***	0.662	0.338		
EE4		1.029	0.831	0.027	38.505***	0.690	0.310		
CET1	Cognitive engagement	1.000	0.813			0.660	0.340	0.875	0.637
CET2		1.007	0.782	0.029	34.957***	0.611	0.389		
CET3		0.978	0.810	0.027	36.777***	0.656	0.344		
CET4		1.042	0.788	0.030	35.315***	0.620	0.380		

***p < .001

a. Measurement error = 1 – R²

b.CR: Construct Reliability (Construct Reliability)
c.AVE: Average Variance Extracted (Average Variance Extracted)

Assuming that the model fitting meets acceptable standards, the present study further performed an in-depth analysis of the causal relationships, reliability, and validity between latent and observed variables in the five-dimensional structure modeling framework, with results shown in Table 3. The standardized factor loadings of each observed variable on its corresponding latent variable ranged from 0.780 to 0.831, all reaching statistical significance (t> 33.455, p <0.001), while the R^2 values ranged from 0.608 to 0.690, indicating appropriate causal relationships between the latent and observed variables [27].

The reliability and validity analysis results indicate that the construct reliability (CR) of each latent variable ranges from 0.872 to 0.883, while the average variance extract (AVE) ranges from 0.637 to 0.673. Both values meet the criteria of CR> 0.700 and AVE> 0.500, demonstrating that the model exhibits strong internal consistency and converge validity [27]. This confirms the validity of the singularity of each latent variable in the five-dimensional structure model, providing robust empirical support for the model in the context of online learning for pre-service teachers.

However, the correlation coefficient analysis among latent variables revealed strong correlations between certain variables, such as social engagement and collaborative engagement (r = 0.938), collaborative engagement and cognitive engagement (r = 0.968), and emotional engagement and behavioral engagement (r = 0.927), raising concerns about multicollinearity among the variables. In the context of online learning, whether social engagement and collaborative engagement are independent concepts or exhibit significant conceptual overlap warrants further investigation based on the specific learning contexts of pre-service teachers.

3.4 Cross-validation Analysis of the Five-Dimensional Structure Model for Pre-service Teachers' Participation in GenAI Online Learning

To evaluate the external validity and cross-sample reliability of the five-dimensional structure model, the present study employed random split cross-validation [29]. By setting a fixed random number seed (seed = 20000), the total sample (N = 1478) was randomly reshuffled. According to the principle of precise sampling, the first 739 samples were assigned to the estimation group (Group A), and the subsequent 739 samples to the validation group (Group B), ensuring both randomness and reproducibility of the sampling [30].

1) Estimation group model fitting results

A confirmatory factor analysis was performed on the estimation group, yielding the following results: χ^2/df = 2.127, CFI = 0.988, TLI = 0.982, and RMSEA = 0.039 (90% CI: 0.033–0.040). All indicators met excellent standards, indicating that the model fit well in the estimation group [27].

2) Cross-validation results for the validation group model

The factor loadings obtained from the estimation group were used as fixed parameters for evaluation in the validation group. The results showed: χ^2/df = 2.866, CFI = 0.990, TLI = 0.986, RMSEA = 0.036 (90% CI: 0.031–0.040). All core indicators were highly consistent with those of the estimation group, with slight improvements, indicating that the five-dimensional structure model maintained stable fit performance across the new sample and demonstrated strong cross-sample consistency [27].

It is evident that the five-dimensional structure model developed in the present study exhibits ideal external validity and sample consistency. The fitted parameters between the estimation and validation groups show high agreement, demonstrating strong reproducibility of the model's internal structure [27]. The randomized split-cross-validation approach effectively mitigates overfitting risks associated with single-sample analyses. The validation results further confirm the broad applicability of the five-dimensional construct across diverse pre-service teacher populations, providing methodological support for subsequent research on online learning engagement measurement and intervention [27].The cross-validation fit metrics are presented in Table 4.

Table 4: Cross-validation Fit Metrics for the Five-Dimensional Structure Model of Pre-Service Teachers (N=1478)

Model	Sample Book	x^2	*df*	x^2/df	CFI	TLI	RMSEA(90%CI)
Estimation Model	Sample A (n=739)	265.828	125	2.127	0.988	0.982	0.039(0.033-0.046)
Validation Model	Sample B (n=739)	401.199	140	2.866	0.990	0.986	0.036(0.031-0.040)
Variable Quantity	(B-A)	+135.371	+15	+0.739	+0.002	+0.004	-0.003

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4. Discussion

The present study performed path analysis and conditional validation, model fit testing, conceptual structure relationship and reliability validity analysis, as well as cross-group validity testing for the five-dimensional structure model of pre-service teachers' GenAI-based online learning engagement, systematically evaluating the scientific validity and applicability of the model.

The study findings indicate that the five-dimensional structure model of pre-service teachers 'GenAI-based online learning engagement meets the conditions for path analysis, demonstrating strong model fit. The causal relationships between each latent variable and the observed variables are significant and meaningful, with each concept exhibiting unidimensionality. Cross-validation across different groups further confirms the model's consistency across samples. The discussion based on these findings is presented below.

First, during the path analysis validation, the correlation coefficients among all observed variables ranged from 0.780 to 0.831, below the critical threshold of 0.90, indicating no multicollinearity; both the absolute values of skewness and kurtosis fell within the ±2 range, confirming normal data distribution and providing a reliable foundation for structural equation modeling analysis using the maximum likelihood method.

Secondly, in the assessment of model applicability and validity, the initial model demonstrated acceptable values for TLI (0.954), CFI (0.958), and SRMR (0.028), although χ^2/df (7.136) and RMSEA (0.061–0.071) slightly exceeded the critical thresholds. After adjustment using the Modesty Index (MI), all metrics met the criteria for good fit ($\chi^2/df = 4.905$, TLI = 0.971, CFI = 0.975, SRMR = 0.024, RMSEA = 0.048–0.055), confirming that the model serves as an effective measurement framework for assessing pre-service teachers 'online learning engagement in GenAI contexts [28] and further expanding the applicability of Redmond et al.' s five-dimensional engagement framework [24].

Furthermore, in the analysis of conceptual structure relationships and reliability and validity, the standardized factor loadings of each observed variable ranged from 0.780 to 0.831 ($t > 33.455$, $p < 0.001$), with R^2 values between 0.608 and 0.690, indicating significant causal relationships between the latent variables and observed variables. The Cronbach's alpha (CR) ranged from 0.872 to 0.883 (> 0.700), and the Average Validity Explanatory (AVE) ranged from 0.637 to 0.673 (> 0.500), reflecting good internal consistency and convergent validity [27]. Notably, high correlations were observed among social engagement and collaborative engagement ($r = 0.938$), collaborative engagement and cognitive engagement ($r = 0.968$), as well as emotional engagement and behavioral engagement ($r = 0.927$). These findings align with Vygotsky's Zone of Proximal Development theory—where social and collaborative behaviors often occur simultaneously and jointly drive cognitive processing in GenAI learning contexts [12]. The strong correlation between emotions and behavior also corresponds to Pekrun's Theory of Academic Emotion [31], demonstrating that positive emotional engagement and deep engagement behaviors form a mutually reinforcing dynamic cycle. This suggests that the various factors within the five-dimensional structure interpenetrate and collectively constitute the overarching ecosystem of engagement in GenAI scenarios.

Finally, the results of randomized half-cross-validation further confirmed the external validity and cross-sample consistency of the five-dimensional structure model. The total sample (1,478) was randomly divided into an estimation group and a validation group (739) for confirmatory factor analysis. The estimation group yielded fitting indices of $\chi^2/df = 2.127$, CFI = 0.988, TLI = 0.982, and RMSEA = 0.039 (90% CI: 0.033–0.040); the validation group reported $\chi^2/df = 2.866$, CFI = 0.990, TLI = 0.986, and RMSEA = 0.036 (90% CI: 0.031–0.040). The indices showed high concordance, with the validation group performing better in some metrics, indicating that both groups represented the same model and demonstrating strong cross-sample reproducibility of the five-dimensional structure [32], effectively mitigating overfitting risks. These findings suggest the model's universality across diverse pre-service teacher populations, laying a solid foundation for subsequent multigroup measurement invariance analyses. Additionally, according to Bandura's (1977) social cognitive theory, learners 'self-efficacy plays a critical moderating role in learning engagement [33]. In the GenAI-based online learning context, pre-service teachers' perceived usefulness of GenAI tools and their self-efficacy may serve as underlying mechanisms driving the coordinated operation of the five engagement dimensions, providing crucial research directions for exploring the antecedents and influence pathways of five-dimensional engagement.

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5. Conclusion and Recommendations

In summary, while the present study provides empirical evidence for the five-dimensional structure model of pre-service teachers' GenAI-based online learning engagement, several limitations warrant attention and require further investigation. First, the sample primarily originates from domestic universities; whether this five-dimensional framework applies to pre-service teachers across diverse cultural backgrounds and university types necessitates broader cross-cultural validation through expanded sampling. Second, the five latent variables exhibit strong correlations—particularly between collaborative engagement and cognitive engagement ($r = 0.968$)—requiring theoretical clarification of their boundaries and exploration of whether a Second-Order Factor Model could achieve more refined conceptual integration to optimize measurement efficiency and conceptual distinctiveness. Third, the five-dimensional engagement model focuses solely on structural validation; the dynamic evolution of engagement under GenAI contexts and the mechanisms through which each dimension influences learning outcomes demand further longitudinal tracking studies and refined experimental designs.

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