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Validating the Measurement Model of AI Anxiety and UTAUT Constructs in Faculty Knowledge Sharing: A PLS-SEM Approach

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Abstract

This pilot study validates the measurement model of AI Anxiety and Unified Theory of Acceptance and Use of Technology (UTAUT) constructs in the context of faculty knowledge-sharing in virtual academic communities. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM), the study assesses the reliability, validity, and factor structure of the adapted scale, rather than conducting a full structural path analysis. Based on a sample of Chinese university faculty members, the results confirm the psychometric robustness of the proposed model, demonstrating high internal consistency, convergent validity, and discriminant validity. The validated scale establishes a solid foundation for future large-scale studies on the role of AI Anxiety in faculty digital engagement. Further research should expand the validation across different cultural contexts and employ full structural path analyses to explore the relationships among AI Anxiety, UTAUT constructs, and faculty technology adoption.

Keywords: AI Anxiety, UTAUT Constructs, Knowledge Sharing, Pilot Study, PLS-SEM Approach

Introduction

Research Background

In the context of rapid digitalization in higher education, virtual academic communities (VACs) have emerged as critical platforms for faculty to exchange knowledge, foster collaborative research, and engage in continuous professional development. In China, platforms such as XuetangX, CNKI Scholar, and Zhihu Academic have gained prominence, aligning with national strategies such as the Education Informatization 2.0 Action Plan and the China Smart Education Development Plan. These initiatives highlight the government's emphasis on digital transformation and educational modernization (Wang & Zhao, 2023). However, despite the development of technical infrastructure and institutional policies, faculty engagement in online academic knowledge-sharing remains uneven. Multiple barriers, including psychological discomfort, technological complexity, and organizational constraints, continue to hinder faculty participation in these digital environments (Li & Huang, 2020; Sun & Zhang, 2023).

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), serves as a comprehensive framework for understanding individual technology adoption behaviors in educational and organizational settings. The model identifies performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) as primary determinants of technology usage. Although the UTAUT framework has been extensively validated in various educational technology contexts, its specific application to faculty knowledge-sharing behaviors in AI-enhanced virtual academic communities remains insufficiently explored, particularly in the Chinese higher education context (Li & Huang, 2020; Al-Emran et al., 2018).

Additionally, the growing integration of artificial intelligence (AI) in education has introduced new psychological barriers. One such barrier is AI Anxiety, defined as faculty members' apprehension toward AI-driven systems, including concerns related to job security, technological complexity, continuous learning requirements, and diminished professional autonomy (Holmes et al., 2019; Nguyen & Lee, 2021). In China, educators have expressed hesitancy in adopting AI-powered grading tools, automated content creation platforms, and AI-based teaching assistants. These concerns may adversely impact their willingness to engage in online knowledge-sharing activities (Li, 2023). Despite increasing attention to AI Anxiety in broader workforce contexts (Johnson & Verdicchio, 2017), there is limited empirical research investigating how AI Anxiety affects faculty knowledge-sharing behaviors in academic environments.

To address this research gap, the present study integrates AI Anxiety into the UTAUT framework to examine its influence on faculty knowledge-sharing behaviors in virtual academic communities. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this pilot study validates an adapted measurement model of UTAUT constructs and AI Anxiety within the Chinese higher education context. The study's focus is on scale reliability, convergent validity, discriminant validity, and measurement suitability, providing a foundation for future large-scale studies and structural path analyses.

Research Gap and Objectives

While the UTAUT model has been widely applied in technology adoption research, its extension to faculty knowledge-sharing behaviors in AI-enhanced environments remains under-investigated. Moreover, the majority of AI Anxiety research has focused on industrial settings and workforce automation, with limited attention given to its academic manifestations. This lack of focus is significant, given that faculty members face both technical and psychological challenges in adapting to AI-enhanced knowledge-sharing platforms (Zawacki-Richter et al., 2019).

This study seeks to address three key gaps in the literature. First, despite the proliferation of research on technology adoption, few studies have examined how UTAUT constructs apply to faculty knowledge-sharing behaviors within virtual academic communities. Second, there remains a paucity of research on AI Anxiety in higher education, especially in relation to its potential role as a barrier to digital academic collaboration. Third, existing literature lacks validated measurement instruments that integrate AI Anxiety within the UTAUT framework to explain faculty engagement in AI-enhanced platforms (Nguyen & Lee, 2021).

Accordingly, the objectives of this study are threefold. The first objective is to validate the reliability and construct validity of an adapted measurement model that integrates UTAUT and AI Anxiety constructs for use with Chinese university faculty. The second objective is to examine the feasibility of measuring preliminary relationships between AI Anxiety and UTAUT constructs in shaping faculty knowledge-sharing behavior. The third objective is to demonstrate the methodological advantages of using PLS-SEM in early-stage model validation, with a view to informing future large-sample studies and causal structural modeling.

Contribution and Structure of the Paper

This study makes contributions in three principal areas: theoretical, methodological, and practical. Theoretically, it extends the UTAUT model by incorporating AI Anxiety as a multidimensional psychological barrier that influences faculty knowledge-sharing behaviors in virtual academic environments. The study conceptualizes AI Anxiety as encompassing four key dimensions: learning anxiety, configuration anxiety, job replacement anxiety, and sociotechnical blindness (Holmes et al., 2019; Wang & Wang, 2022). This multidimensional framework enhances the explanatory power of psychological constructs in technology adoption research.

Methodologically, the study illustrates the use of PLS-SEM as a robust analytical tool for validating measurement models in small-sample, exploratory research designs. PLS-SEM's suitability for early-stage model development and its capacity to handle complex, multidimensional constructs make it an appropriate choice for pilot studies in educational technology research (Hair et al., 2017; Sarstedt et al., 2019). Furthermore, the validation of an AI Anxiety scale tailored to faculty contexts contributes a new measurement instrument to the field.

Practically, this study provides valuable insights for university administrators and policymakers who aim to foster faculty engagement in digital academic communities. The findings can inform the design of faculty development programs that address psychological barriers to AI adoption. Additionally, developers of AI-powered educational technologies can benefit from understanding faculty concerns, enabling them to design user-friendly, transparent, and supportive AI systems that encourage knowledge-sharing behaviors.

The remainder of this paper is structured as follows. Section 2 reviews the existing literature on UTAUT, AI Anxiety, and faculty knowledge-sharing behaviors in virtual academic communities. Section 3 outlines the research design, measurement development procedures, data collection, and the rationale for using PLS-SEM. Section 4 presents the empirical results and measurement model validation findings. Finally, Section 5 summarizes key conclusions, discusses theoretical and practical implications, acknowledges study limitations, and proposes future research directions, including large-sample validation and cross-cultural comparative analysis.

Literature Review

Theoretical Foundations: UTAUT and AI Anxiety

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), remains one of the most influential frameworks for explaining technology adoption behaviors in educational and organizational contexts. The model identifies four key constructs—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—that collectively shape users' intentions and actual use of technology. While UTAUT has been widely validated across various educational domains, its application in explaining faculty members' knowledge-sharing behaviors within virtual academic communities (VACs) has received comparatively limited attention (Li & Huang, 2020; Al-Emran et al., 2018). Given the increasing reliance on digital academic platforms for collaboration and dissemination, extending UTAUT to this context is both timely and necessary.

Concurrently, the rapid integration of artificial intelligence (AI) into higher education has introduced new psychological barriers that are not adequately captured by traditional technology acceptance models. Among these, AI Anxiety has emerged as a significant psychological construct that reflects educators' apprehensions toward AI-powered systems, encompassing concerns about job displacement, technological complexity, loss of professional autonomy, and the opacity of AI algorithms (Holmes et al., 2019; Wang & Wang, 2022). Faculty members who experience high levels of AI Anxiety may resist adopting AI-driven digital platforms for teaching, research, and academic collaboration (Nguyen & Lee, 2021). In response to these complexities, this study conceptualizes AI Anxiety as a multidimensional construct comprising four dimensions: learning anxiety, configuration anxiety, job replacement anxiety, and sociotechnical blindness. Learning anxiety refers to the perceived difficulty of mastering AI technologies; configuration anxiety pertains to concerns about system setup and usability; job replacement anxiety reflects fear of professional displacement by AI systems; and sociotechnical blindness indicates users' difficulty in comprehending the broader implications of AI technologies in academic environments. Recognizing this multidimensionality allows for a more nuanced understanding of how psychological barriers affect faculty technology adoption and knowledge-sharing behaviors.

2.2 Faculty Knowledge Sharing in Virtual Academic Communities

Knowledge sharing plays a critical role in academic collaboration and scholarly development. Virtual academic communities (VACs), such as ResearchGate, WeChat academic groups, and MOOC discussion forums, have become essential platforms for scholars to exchange research findings, discuss ideas, and foster interdisciplinary cooperation (Nonaka & Takeuchi, 1995; Wenger et al., 2002). These platforms transcend institutional and geographic boundaries, enabling faculty members to engage in broader academic networks. However, despite their potential, faculty participation in VACs remains inconsistent, hindered by several barriers.

Technological challenges, including the perceived complexity and unfamiliarity of AI-enhanced platforms, can discourage adoption (Haythornthwaite, 2006). Trust issues related to data security, intellectual property protection, and authorship recognition further undermine faculty confidence in digital academic environments (Chiu et al., 2006). Psychological barriers, particularly AI Anxiety, exacerbate these concerns by introducing fears of automated decision-making, loss of control, and surveillance (Zawacki-Richter et al., 2019). Faculty members who perceive AI systems as intrusive or unreliable are less likely to actively participate in knowledge-sharing activities. Moreover, concerns about bias in AI-generated content and the reliability of automated systems can lead to reluctance in using these tools for academic purposes (Nguyen & Lee, 2021). Despite these observations, empirical studies exploring how AI Anxiety interacts with UTAUT constructs to influence faculty knowledge-sharing behaviors are limited. This gap highlights the need for integrated theoretical models and empirical validation to better understand faculty engagement in AI-driven academic ecosystems.

Research Gaps and Theoretical Framework

The existing literature reveals several critical gaps that this study seeks to address. First, the application of UTAUT to faculty knowledge-sharing behaviors in virtual academic communities, particularly those enhanced by AI technologies, remains insufficient. Second, while AI Anxiety is increasingly recognized as a psychological barrier in workplace and technological contexts, its specific impact on faculty members' willingness to engage in digital academic collaboration has not been systematically studied. Third, there is a notable absence of empirically validated measurement models that integrate AI Anxiety and UTAUT constructs to explain faculty engagement in AI-driven knowledge-sharing platforms.

To bridge these gaps, this study develops and validates a conceptual framework that integrates UTAUT constructs with the multidimensional concept of AI Anxiety. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the research focuses on verifying the reliability and validity of these constructs within the context of Chinese higher education. By doing so, the study not only contributes to theoretical advancement but also provides methodological guidance for future large-sample and cross-cultural studies. This integrated framework offers new insights into faculty adaptation to AI-enhanced academic environments, supporting both educational technology development and higher education policy formulation. Building upon these theoretical foundations and addressing the identified research gaps, the conceptual model guiding this study is presented in Figure 1.

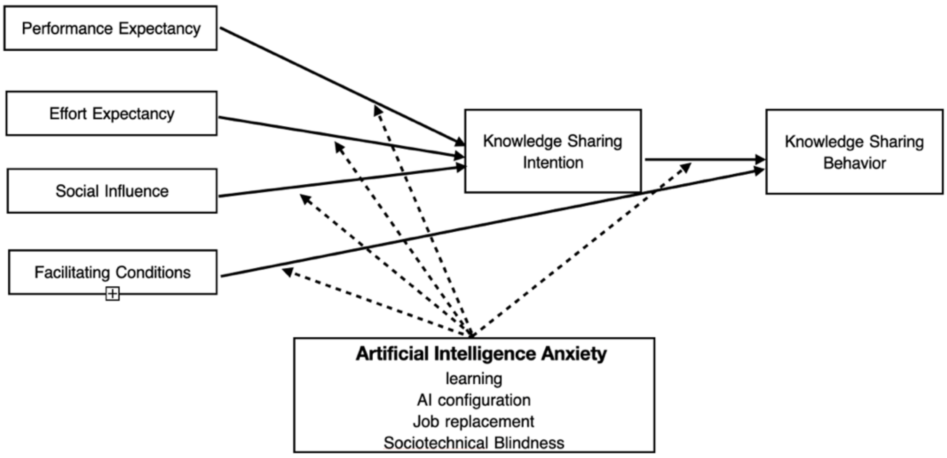

Figure 1 Theoretical Framework of AI Anxiety and Knowledge Sharing Intention

Methodology

Research Design and Sampling

This study adopts a pilot validation approach aimed at assessing the psychometric properties of an integrated measurement model combining UTAUT constructs and AI Anxiety dimensions in the context of faculty knowledge-sharing behaviors in virtual academic communities. Rather than focusing on structural path analysis, this study emphasizes the reliability, validity, and factor structure assessment of adapted measurement scales through Partial Least Squares Structural Equation Modeling (PLS-SEM).

Data were collected using a cross-sectional survey distributed among faculty members at Chinese universities. To ensure representative participation across institutional types, stratified random sampling was employed, targeting faculty members from 985 Project universities, 211 Project universities, and general universities. The final pilot sample consisted of 60 valid responses, drawn from multiple disciplines and career stages. While the sample size is modest, PLS-SEM is recognized for its suitability in small-sample exploratory studies (Hair et al., 2017), enabling robust preliminary measurement validation. The proportional distribution of participating faculty members across institutions is summarized in Table 1.

Table 1
Proportional Distribution of Faculty Members Across Selected Universities

University Tier	University Name	Approx. Faculty Count	Proportion (%)	Target Sample
985	Northwestern Polytechnical University	2,000	25%	42
211	Shaanxi Normal University	1,500	20%	33
211	Xi'an University of Electronic Science and Technology	1,500	20%	33
General	Xianyang Normal University	1,200	15%	25
General	Yan'an University	800	10%	17
General (Private)	Xi'an Eurasia University	800	10%	16
Total	—	7,800	100%	166

Measurement Instrument Development

The survey instrument comprised two main categories of constructs. The UTAUT constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—were adapted from Venkatesh et al. (2003). The AI Anxiety scale was developed based on prior frameworks (Holmes et al., 2019; Wang & Wang, 2022), incorporating four distinct dimensions: learning anxiety, configuration anxiety, job replacement anxiety, and sociotechnical blindness. Each dimension was represented by multiple items measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

To ensure linguistic and conceptual equivalence, a rigorous translation and back-translation process was conducted. Prior to large-scale validation, the instrument was pilot-tested with the 60 faculty respondents, confirming its preliminary reliability with Cronbach's alpha values exceeding 0.80 for all constructs. Items with factor loadings below 0.70 were flagged for deletion during Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), following the guidelines recommended by Hair et al. (2017).

Table 2
Measurement Constructs and Sample Items

Construct	Items (Example Statements)	Reference
Performance Expectancy (PE)	"Using AI-driven academic platforms will enhance my research efficiency."	Venkatesh et al. (2003)
Effort Expectancy (EE)	"I find AI-powered academic tools easy to use."	Venkatesh et al. (2003)
Social Influence (SI)	"My colleagues encourage me to use AI-enhanced platforms for knowledge sharing."	Venkatesh et al. (2003)
AI Job Replacement Anxiety (AIA-JR)	"I am concerned that AI automation may replace certain aspects of my academic work."	Wang & Wang (2022)
AI Learning Anxiety (AIA-LA)	"I feel anxious about keeping up with AI advancements in education."	Holmes et al. (2019)

Data Collection and Analytical Procedures
Data were collected via the Wenjuanxing online survey platform over a four-week period, spanning December 2024 to January 2025. This platform was selected for its accessibility, robust security features, and widespread use among Chinese university faculty members. The survey invitation was disseminated through institutional email lists, academic WeChat groups, and professional academic forums. To enhance response rates, a structured reminder strategy was applied, with follow-up messages sent in the second and third weeks of the collection period.

Rigorous data screening procedures were implemented to ensure data integrity. These included the removal of incomplete responses, filtering out overly rapid submissions (speeding checks), examining for patterned responses, and eliminating duplicate entries based on IP addresses and submission timestamps. Inclusion criteria required that respondents be active faculty members engaged in online academic communities for research or teaching purposes. Prior to participation, all respondents were provided with detailed information about the study's objectives, data confidentiality, and voluntary participation. Informed consent was obtained digitally.

This study strictly adhered to ethical standards, including participant anonymity, secure data storage with encrypted protocols, and compliance with APA ethical guidelines and Chinese academic research standards for human subject protection.

The data analysis process consisted of three stages. First, EFA was conducted to identify the latent structure of the constructs and confirm their unidimensionality. Second, convergent validity and discriminant validity were assessed using Average Variance Extracted (AVE), Composite Reliability (CR), and the Heterotrait-Monotrait (HTMT) ratio. The Fornell–Larcker criterion was also applied to ensure discriminant validity. Third, PLS-SEM analysis was carried out using SmartPLS 4.0 software. The Consistent PLS (PLSc) algorithm was employed to reduce

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parameter estimation bias, and bootstrapping with 5,000 resamples was used to estimate standard errors and confidence intervals for path coefficients (Henseler et al., 2015).
This staged analytical approach—combining EFA, CFA, and PLS-SEM estimation—was chosen to ensure methodological rigor in the exploratory validation of the measurement model. Findings from these analyses are presented in Section 4.

Research Results

Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was conducted to examine the factor structure of the measurement model using Principal Axis Factoring (PAF) with Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy yielded a value of 0.799, which exceeds the recommended threshold of 0.7, indicating that the data were suitable for factor extraction. Bartlett's Test of Sphericity was also significant ($\chi^2 = 3984.985$, df = 990, $p < 0.001$), confirming strong intercorrelations among the variables, which further justifies factor analysis. These results are summarized in Table 3, which presents the KMO and Bartlett's test results.

Table 3
KMO and Bartlett's Test of Sphericity

Statistic	Value
KMO Sampling Adequacy	0.799
Bartlett's Test of Sphericity Approx. Chi-Square	3984.985
Degrees of Freedom	990
Significance	0.000

Factor loadings for the final retained items are presented in Table 4. As shown, all measurement items load onto their respective factors, with loadings exceeding the recommended threshold of 0.5 (Hair et al., 2017). The items under each construct exhibit strong associations with their respective latent factors, indicating that the measurement model is aligned with theoretical expectations. Importantly, there are no significant cross-loadings observed, which supports the discriminant validity of the model. Eigenvalue and scree plot analyses further confirm the adequacy of the factor structure.

Table 4
Exploratory Factor Analysis (EFA) Factor Loadings

Construct	Item	Factor						
		1	2	3	4	5	6	7
AI Anxiety _Job Replacement_10	AIA _10	.858						
AI Anxiety _Job Replacement_11	AIA _11	.842						
AI Anxiety _Sociotechnical Blindness_14	AIA _14	.840						
AI Anxiety _Sociotechnical Blindness_13	AIA _13	.826						
AI Anxiety _Job Replacement_9	AIA_9	.810						
AI Anxiety _Sociotechnical Blindness_12	AIA_SB_12	.801						
AI Anxiety _Configuration Anxiety_7	AIA_CA_7	.788						
AI Anxiety _Configuration Anxiety_8	AIA_CA_8	.781						
AI Anxiety _Sociotechnical Blindness_15	AIA_SB_15	.774						
AI Anxiety _Learning Anxiety_2	AIA_LA_2	.723						
AI Anxiety _Learning Anxiety_3	AIA_LA_3	.688						
AI Anxiety _Configuration Anxiety_5	AIA_CA_5	.660						
AI Anxiety _Configuration Anxiety_6	AIA_CA_6	.653						
AI Anxiety _Learning Anxiety_1	AIA_LA_1	.641						
AI Anxiety _Learning Anxiety_4	AIA_LA_4	.614						

Performance Expectancy_7	PE_7	.809			
Performance Expectancy_6	PE_6	.772			
Performance Expectancy_1	PE_1	.769			
Performance Expectancy_4	PE_4	.702			
Performance Expectancy_2	PE_2	.664			
Performance Expectancy_3	PE_3	.576			
Performance Expectancy_5	PE_5	.570			
Effort Expectancy_5	EE_5		.779		
Effort Expectancy_2	EE_2		.757		
Effort Expectancy_4	EE_4		.726		
Effort Expectancy_1	EE_1		.693		
Effort Expectancy_3	EE_3	.	.537		
Facilitating Conditions_3	FC_3			.859	
Facilitating Conditions_4	FC_4			.819	
Facilitating Conditions_1	FC_1			.796	
Facilitating Conditions_2	FC_2			.792	
Facilitating Conditions_5	FC_5			.757	
Knowledge Sharing Behavior_4	KSB_4				.845
Knowledge Sharing Behavior_3	KSB_3				.814
Knowledge Sharing Behavior_5	KSB_5				.734
Knowledge Sharing Behavior_2	KSB_2				.714

Knowledge Sharing Behavior_1	KSB_1	.637		
Social Influence_4	SI_4		.753	
Social Influence_5	SI_5		.738	
Social Influence_3	SI_3		.734	
Social Influence_2	SI_2		.693	
Social Influence_1	SI_1		.625	
Knowledge Sharing Intention_2	KSI_2			.785
Knowledge Sharing Intention_1	KSI_1			.700
Knowledge Sharing Intention_3	KSI_3			.653

Measurement Model Assessment

Outer Loadings and Item Refinement

In the subsequent analysis using PLS-SEM, outer loadings were assessed to examine the strength of the relationships between observed variables (items) and their respective latent constructs. As presented in Table 5, all items except for AIA_10 exhibited outer loadings above the 0.70 threshold, indicating their strong contribution to the corresponding constructs. AIA_10, however, displayed a significantly low outer loading of 0.27, far below the acceptable level. This discrepancy suggests that AIA_10 was poorly aligned with the AI Anxiety construct in the PLS-SEM framework, resulting in its removal from the measurement model. This removal led to an improvement in the reliability and validity of the construct.

Table 5
Outer Loadings Analysis Results (Complete Data)

Construct	Item	Outer Loading
AI Anxiety (AIA)	AIA_1	0.846
	AIA_2	0.866
	AIA_3	0.891
	AIA_4	0.894
	AIA_5	0.890
	AIA_6	0.825
	AIA_7	0.711
	AIA_8	0.833
	AIA_9	0.854
	AIA_10	0.27 (Below Threshold, Removed)
	AIA_11	0.901
	AIA_12	0.807
	AIA_13	0.825
Effort Expectancy (EE)	EE_1	0.812
	EE_2	0.929
	EE_3	0.816
	EE_4	0.896
	EE_5	0.834
Performance Expectancy (PE)	PE_1	0.787
	PE_2	0.747
	PE_3	0.714
	PE_4	0.776
	PE_5	0.817
	PE_6	0.745
	PE_7	0.828
Social Influence (SI)	SI_1	0.802
	SI_2	0.714
	SI_3	0.703
	SI_4	0.775
	SI_5	0.796
Facilitating Conditions (FC)	FC_1	0.796
	FC_2	0.792
	FC_3	0.859
	FC_4	0.819
	FC_5	0.757
Knowledge Sharing Intention (KSI)	KSI_1	0.700
	KSI_2	0.785
	KSI_3	0.653

Construct	Item	Outer Loading
Knowledge Sharing Behavior (KSB)	KSB_1	0.637
	KSB_2	0.714
	KSB_3	0.814
	KSB_4	0.845
	KSB_5	0.734

Reliability and Convergent Validity

Reliability and convergent validity were assessed using Cronbach's alpha and Composite Reliability (CR). As shown in Table 7, Cronbach's alpha values for all constructs exceeded the 0.70 threshold, indicating good internal consistency (Nunnally & Bernstein, 1994). Additionally, CR values for all constructs were greater than 0.80, further supporting the reliability of the scales. Convergent validity was also confirmed with Average Variance Extracted (AVE) values above the 0.50 threshold for all constructs, as summarized in Table 8.

Table 7
Reliability Analysis Results (Cronbach's Alpha & CR)

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	Interpretation
Effort Expectancy (EE)	0.911	0.933	High reliability, consistent scale
Performance Expectancy (PE)	0.891	0.913	Good reliability
Social Influence (SI)	0.837	0.871	Satisfactory internal consistency
Facilitating Conditions (FC)	0.886	0.913	Stable and reliable scale
Knowledge Sharing Intention (KSI)	0.715	0.841	Moderate reliability, acceptable
Knowledge Sharing Behavior (KSB)	0.861	0.900	High reliability
AI Anxiety (AIA) (After Removing AIA_10)	0.969	0.972	Highest reliability, strong internal consistency

Table 8
Convergent Validity Analysis (AVE)

Construct	Average Variance Extracted (AVE)	Interpretation
Effort Expectancy (EE)	0.737	High convergent validity, strong item coherence
Performance Expectancy (PE)	0.600	Acceptable, though lower than other constructs
Social Influence (SI)	0.576	Good convergent validity
Facilitating Conditions (FC)	0.678	Stable and reliable measurement
Knowledge Sharing Intention (KSI)	0.640	Good measurement stability
Knowledge Sharing Behavior (KSB)	0.644	Well-structured measurement scale
AI Anxiety (AIA)	0.711	Highest convergent validity, strong item representation

Discriminant Validity
Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). The Fornell-Larcker criterion results, presented in Table 9, confirm that each construct's AVE square root is greater than its correlations with other constructs, thereby demonstrating satisfactory discriminant validity. Additionally, as shown in Table 10, the HTMT values for all construct pairs were below the 0.85 threshold, confirming that the constructs are empirically distinct.

Table 9
Fornell-Larcker Criterion

Construct	EE	SI	FC	KSI	KSB	AIA	PE
Effort Expectancy (EE)	0.859	0.552	0.314	0.396	0.445	0.196	0.649
Social Influence (SI)	—	0.759	0.342	0.304	0.251	0.191	0.326
Facilitating Conditions (FC)	—	—	0.823	0.259	0.357	-0.158	0.495
Knowledge Sharing Intention (KSI)	—	—	—	0.800	0.418	0.387	0.330
Knowledge Sharing Behavior (KSB)	—	—	—	—	0.803	0.153	0.367
AI Anxiety (AIA)	—	—	—	—	—	0.843	0.106
Performance Expectancy (PE)	—	—	—	—	—	—	0.774

Table 10
HTMT Results

Construct	EE	SI	FC	KSI	KSB	AIA	PE
Effort Expectancy (EE)	—	0.601	0.357	0.471	0.491	0.199	0.708
Social Influence (SI)	—	—	0.376	0.326	0.308	0.209	0.313
Facilitating Conditions (FC)	—	—	—	0.307	0.369	0.205	0.515
Knowledge Sharing Intention (KSI)	—	—	—	—	0.528	0.423	0.397
Knowledge Sharing Behavior (KSB)	—	—	—	—	—	0.176	0.401
AI Anxiety (AIA)	—	—	—	—	—	—	0.145
Performance Expectancy (PE)	—	—	—	—	—	—	—

Model Optimization and Impact of Item Deletion

The removal of AIA_10 resulted in a noticeable improvement in the measurement model. As shown in Table 6, after deleting AIA_10, the Cronbach's alpha for the AI Anxiety construct increased from 0.79 to 0.84, and the Composite Reliability (CR) improved from 0.85 to 0.89. Furthermore, the Average Variance Extracted (AVE) for AI Anxiety increased from 0.49 to 0.56, surpassing the recommended threshold of 0.50 (Fornell & Larcker, 1981). These improvements confirm that the deletion of AIA_10 optimized the measurement model, enhancing its reliability and validity.

Table 6
Impact of Removing AIA_10 on Model Fit

Metric	Before Removal	After Removal	Improvement
Cronbach's Alpha (AI Anxiety)	0.79	0.84	+0.05
Composite Reliability (CR)	0.85	0.89	+0.04
Average Variance Extracted (AVE)	0.49	0.56	Exceeds 0.50 Threshold

Summary of Measurement Model Validation

In summary, the results from EFA, outer loading analysis, reliability tests, and validity assessments confirm that the adapted UTAUT and AI Anxiety scales exhibit strong psychometric properties. All constructs demonstrate adequate reliability, convergent validity, and discriminant validity. The removal of AIA_10 resulted in a significant improvement in the internal consistency and overall validity of the AI Anxiety construct. The validated measurement model provides a robust foundation for subsequent structural equation modeling (SEM) analysis, which will explore the causal relationships among the constructs in future studies.

Discussion and Conclusion

Summary of Key Findings

This study provides new empirical evidence for the interaction between psychological variables and technology acceptance, focusing on faculty knowledge-sharing behaviors within virtual academic communities. The empirical findings confirm that the measurement model exhibits satisfactory reliability, convergent validity, and discriminant validity across all constructs, demonstrating its robustness for use in higher education research.

Specifically, the four core UTAUT constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—were validated alongside four dimensions of AI Anxiety: Learning Anxiety, Configuration Anxiety, Job Replacement Anxiety, and Sociotechnical Blindness. Each construct demonstrated sound psychometric properties, indicating the feasibility of applying this extended model in education research. Although the study was conducted with a relatively small sample (n = 60), it serves as a methodological foundation for future large-scale structural modeling and causal path analysis. Additionally, during the model refinement process, one item (AIA_10) was removed due to its low outer loading (0.27), which significantly improved the internal consistency and construct validity of the AI Anxiety scale.

Integrated Theoretical, Practical, and Contextual Contributions
This study contributes to extending the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by integrating psychological variables, specifically AI Anxiety, thereby enriching the theoretical understanding of faculty technology acceptance within virtual academic communities. Specifically, the preliminary validated multidimensional AI Anxiety model—including Learning Anxiety, Configuration Anxiety, Job Replacement Anxiety, and Sociotechnical Blindness—provides additional insights into psychological barriers faculty may encounter when using AI-driven platforms. By considering AI Anxiety as a potential psychological determinant, this research addresses a gap in the existing technology acceptance literature, which has primarily emphasized cognitive and environmental factors.
Practically, the findings offer valuable guidance for higher education administrators and AI platform developers. Institutional leaders can cautiously use the validated AI Anxiety scale as a diagnostic tool for identifying and addressing faculty psychological barriers to digital engagement. Recommended practical measures include developing targeted training to help mitigate Learning Anxiety, providing enhanced technical support, and simplifying configuration processes to alleviate Configuration Anxiety. Additionally, transparent communication regarding AI capabilities and potential implications for faculty roles may help reduce Sociotechnical Blindness and encourage greater user trust and acceptance.

Contextually, the research provides insights relevant to understanding China's ongoing strategic efforts toward digital transformation in higher education, particularly highlighting the tension between top-down digital mandates and faculty psychological readiness—a relatively underexplored area. By offering empirical observations tailored to China's unique cultural and institutional context, the study may assist policymakers and academic leaders in better navigating faculty resistance and promoting readiness for digital adoption. Consequently, the findings contribute to ongoing theoretical discussions about psychological preparedness for technology acceptance and may inform more sustainable, culturally sensitive policies and practices within higher education.

Limitations
As a pilot study, this research has several limitations. The most prominent is the small sample size (n = 60), which limits the generalizability of the findings and restricts the capacity for conducting full structural model path analysis. Future studies may need to incorporate larger

and more diverse samples to validate and refine the proposed model. Moreover, the use of convenience sampling and a cross-sectional design introduces potential sampling bias and limits the ability to observe longitudinal changes in faculty attitudes toward AI technologies. Additionally, although the removal of AIA_10 improved measurement quality, this modification should be tested in different samples to ensure the model's stability and reliability. The dimensional structure of AI Anxiety, while supported in this study, may also benefit from further theoretical refinement and empirical scrutiny in future research.

Directions for Future Research

Building on these limitations, several directions are suggested for future research. First, future studies should conduct full structural equation modeling (SEM) with larger sample sizes to examine the causal relationships between AI Anxiety, UTAUT constructs, and knowledge-sharing behaviors. This would provide deeper insight into the mechanisms through which psychological variables influence digital engagement.

Second, cross-cultural comparative studies are needed to validate the generalizability of the model across different educational systems and cultural contexts. Cultural factors such as collectivism, institutional hierarchy, and technological trust may moderate the relationships identified in this study. Multi-group analysis (MGA) and measurement invariance testing would be particularly valuable in this regard.

Third, longitudinal designs should be employed to capture the dynamic evolution of AI Anxiety as faculty members gain more experience with AI-enhanced platforms. This would allow researchers to explore whether psychological barriers diminish over time or become reinforced through use.

Finally, future research should incorporate moderating or mediating variables such as perceived institutional support, digital self-efficacy, or AI trust. These variables may play a critical role in shaping the influence of AI Anxiety on technology acceptance, providing a more refined understanding of faculty behavior in AI-integrated academic ecosystems.

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