International Journal of Social Science and Education Research Studies
ISSN(print): 2770-2782, ISSN(online): 2770-2790
Volume 06 Issue 08 August 2026
DOI: https://doi.org/10.55677/ijssers/V06I08Y2026-05, Impact Factor: 7.573
Page No : 842-853

Understanding University Teachers' Role Adaptation in the Age of Generative AI: The Roles of Technology Anxiety, Self-Efficacy, and Career Identity

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ABSTRACT

The rapid advancement of generative artificial intelligence (AI) is reshaping teaching practices in higher education, yet how university teachers adapt to these changes remains insufficiently understood. This study examines the relationships among technology anxiety, self-efficacy, and role adaptation, with a particular focus on the mediating role of career identity. Data were collected from 376 university teachers and analyzed using structural equation modeling. The results indicate that both technology anxiety ($\beta = 0.356$, $p < 0.001$) and self-efficacy ($\beta = 0.371$, $p < 0.001$) exert significant positive effects on teachers' role adaptation to generative AI, with self-efficacy demonstrating a slightly stronger influence. Career identity also shows a significant direct effect on role adaptation ($\beta = 0.237$, $p < 0.01$). Furthermore, technology anxiety ($\beta = 0.492$, $p < 0.001$) and self-efficacy ($\beta = 0.391$, $p < 0.001$) significantly predict career identity, which partially mediates these relationships, accounting for approximately 25% and 20% of the total effects, respectively. These findings underscore the importance of not only enhancing teachers' self-efficacy but also constructively addressing technology-related anxiety and strengthening career identity as an integrated pathway to support meaningful role adaptation in AI-integrated teaching contexts. The results offer empirical evidence for integrated professional-development strategies that simultaneously address anxiety, technological competence, and professional identity.

Published Online: August 17, 2026

KEYWORDS:
Generative AI, Technology anxiety, Self-efficacy, Career identity, Role reconstruction, Structural equation modeling

I. INTRODUCTION

The rapid advancement of generative artificial intelligence (AI), particularly tools such as ChatGPT, is transforming teaching and learning practices in higher education. These technologies offer new opportunities for enhancing instructional design, automating routine tasks, and supporting personalized learning. At the same time, the integration of generative AI introduces new challenges for university teachers, including role ambiguity, increased performance expectations, and the need to continuously adapt to evolving technological environments. As a result, understanding how teachers respond to and adapt to AI-driven changes has become an important issue in educational technology research.

Previous studies have highlighted the importance of psychological factors in shaping teachers' responses to educational technologies. In particular, Technology Anxiety (TA) and Self-Efficacy (SE) have been widely examined as key predictors of technology adoption and instructional change. While TA has traditionally been associated with negative outcomes, such as resistance and avoidance (Venkatesh et al., 2003), emerging evidence suggests that moderate levels of anxiety may also motivate individuals to engage more actively with new technologies. In contrast, SE is consistently found to facilitate technology integration by enhancing confidence and perceived capability (Bandura, 1997). However, existing research has largely examined these factors independently and has paid limited attention to the

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****Cite this article: Fan, S., Huisuan, W., Bin Omar, M.K., Shuang, Y. (2026). Understanding University Teachers' Role Adaptation in the Age of Generative AI: The Roles of Technology Anxiety, Self-Efficacy, and Career Identity. International Journal of Social Science and Education Research Studies, 6(8), 842-853***

underlying psychological mechanisms that connect them to teachers' professional adaptation.

Career identity (CI) provides a useful lens for understanding how teachers role and respond to technological change. CI reflects individuals' sense of professional self and their alignment with evolving role expectations. In the context of generative AI, teachers may need to renegotiate their professional identities as knowledge transmitters, facilitators, and designers of learning experiences. Despite its relevance, CI has received limited attention in studies of technology integration, particularly as a mediating mechanism linking psychological factors to teachers' Role reconstruction(RR).

To address these gaps, this study aims to examine how TA and SE influence university teachers' role adaptation to generative AI, with a particular focus on the mediating role of CI. By integrating these constructs within a unified model and providing empirical evidence from higher education, this study seeks to extend existing research on technology adoption and offer practical insights for supporting teachers in AI-enhanced learning environments.

II. LITERATURE REVIEW

2.1 Technology Anxiety

Technology anxiety (TA) has its conceptual roots in computer anxiety (Brosnan, 1998) and technostress research (Tarafdar et al., 2007), broadly denoting apprehension toward engaging with new technological systems. Within educational technology, a deficit framing has dominated: TA is consistently positioned as an impediment to adoption intentions, associated with avoidance behaviours and reduced instructional effectiveness (Chiu & Churchill, 2016; Venkatesh et al., 2003). This negativity bias, however, reflects an incomplete theoretical account. The transactional stress-coping model (Lazarus & Folkman, 1984) distinguishes distress—anxiety that depletes psychological resources—from eustress—anxiety that mobilises adaptive energy and motivates growth-oriented behaviour (Edwards, 2007). Crucially, this distinction has rarely been applied in educational technology research, leaving open the possibility that moderate TA in high-disruption contexts may stimulate reflective professional engagement rather than avoidance.

A further limitation concerns cultural specificity. Dominant TA models derive from Western individualist contexts, where autonomous competence and individual mastery are the primary adaptive resources (Mishra & Koehler, 2006). In collectivist educational ecologies such as Chinese higher education, role-based obligations and institutional belonging may transform anxiety into motivated identity renegotiation rather than passive resistance (Kim, 2024). Eren et al. (2025), publishing in this journal, corroborate this nuanced view by demonstrating that individual innovativeness significantly shapes how AI anxiety translates into outcomes among university students—a finding that underscores the context-dependence of anxiety's functional role and motivates the present study's examination of TA as a potential eustress catalyst in a Chinese institutional context.

2.2 Self-Efficacy

Bandura's (1977) self-efficacy theory positions perceived capability as the cornerstone of motivational regulation, linking beliefs about competence to enacted behaviour. In educational technology research, this framework has yielded consistent predictive validity: SE positively predicts technology adoption, instructional innovation, and professional development (Compeau & Higgins, 1995; Tondeur et al., 2017). Bossman and Agyei (2022) further demonstrate that SE-centred professional development cultivates cross-boundary competencies in technologically disrupted environments, reinforcing its practical relevance.

However, SE's explanatory power has important boundary conditions that the field has insufficiently examined. Hassan (2026), using longitudinal data from a UK university, found that AI access alone did not improve academic outcomes—structured pedagogical framing was required for competence confidence to translate into performance gains. This suggests that task-specific SE may be necessary but insufficient for deeper professional adaptation: SE provides motivational fuel, but an identity-level integrative mechanism is needed to organise that motivation into coherent role transformation. Prior research has predominantly modelled SE's direct effects on adoption intentions, largely neglecting the psychological pathways through which SE shapes more fundamental changes in how teachers understand and enact their professional roles (Smith et al., 2023).

2.3 Career Identity

Career identity (CI)—the dynamic self-concept individuals construct around professional roles, values, and trajectories (Ibarra, 1999)—has received surprisingly limited attention in educational technology research. Where professional identity appears at all in technology acceptance studies, it typically functions as a control variable rather than as an active mediating mechanism (Admiraal et al., 2016). This marginalisation is theoretically consequential: social identity theory (Hogg, 2016) establishes that identity threats can mobilise adaptive responses rather than simply producing avoidance, suggesting CI may be precisely the construct needed to explain why TA and SE yield qualitatively different outcomes across individuals and contexts.

The marginalisation of CI is especially problematic in collectivist settings. Wang and Zhao (2021) document how Chinese university teachers' professional adaptation is shaped by role-based social obligations—a dimension CI explicitly encompasses but that cognitive adoption models do not capture. Qualitative evidence from Tipple et al. (2026), published in this journal, further indicates that teachers with stronger identity integration around AI-augmented roles displayed richer critical engagement with generative AI's risks and affordances—consistent with CI functioning as an interpretive filter rather than a mere background variable. The present study addresses this gap by positioning CI as the pivotal mediating mechanism through which TA and SE are organised into enacted professional transformation.

2.4 Role Reconstruction

Role reconstruction (RR) refers to the substantive reorganisation of professional activities and self-understanding in response to disruptive environmental demands (Ibarra, 1999)—distinct from surface-level adaptation in that it involves fundamental revision of the professional self rather than mere behavioural adjustment. The emergence of generative AI has intensified the urgency of understanding RR because, unlike prior educational technologies, it challenges teachers' epistemic authority as knowledge intermediaries rather than simply augmenting their technical repertoire (Rudolph et al., 2023). Holstein and Aleven (2022) identify three converging pressures: displacement of knowledge transmission functions, intensified role ambiguity, and accelerated boundary erosion between teacher and AI responsibilities. These pressures collectively demand reconstruction rather than incremental adaptation.

Despite this urgency, the psychological mechanisms driving RR in AI-integrated higher education remain empirically underspecified. Most existing studies treat role-related outcomes as attitudinal (willingness to adopt new roles) rather than enacted, and few have examined how TA, SE, and CI interact as antecedents. This study addresses these gaps within the Chinese higher education context, where Ministry of Education (2025) policy mandates for AI integration create institutional pressures that may interact with individual psychological factors in distinctive ways.

2.5 Hypothesis Development

Building on the critical review above, this study proposes the AI-Identity Resilience Framework (AIRF), integrating self-efficacy theory, social identity theory, and the eustress-distress distinction. The AIRF challenges the deficit model by proposing that moderate TA in collectivist institutional contexts may catalyse identity renegotiation, motivating RR rather than impeding it. Both TA and SE are proposed to influence RR directly and indirectly through CI as the pivotal mediating mechanism—a proposition that yields more actionable implications for professional development design than either direct-effect or moderator models (Figure 1).

H1: TA positively predicts RR (eustress-driven professional mobilisation).

H2: CI positively predicts RR (professional identity as adaptive anchor).

H3: SE positively predicts RR (competence confidence enabling role enactment).

H4: TA positively predicts CI (anxiety catalysing identity renegotiation in collectivist contexts).

H5: CI partially mediates the TA→RR and SE→RR relationships (identity as integrative mechanism).

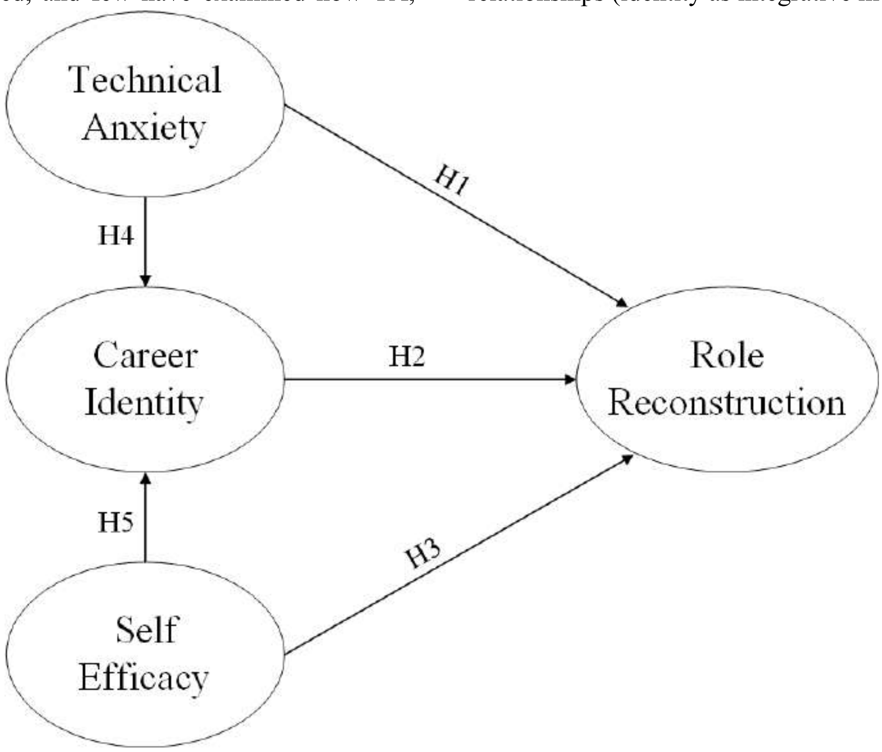

Figure 1. Hypothetical Model

III. METHOD

3.1 Research Design

This study adopts a quantitative research design to examine the relationships among TA, SE, CI, and university teachers' RR in the context of generative AI. A survey-based approach was employed to collect data, and structural equation modeling (SEM) was used to test the proposed research model and hypotheses.

3.2 Participants and Context

Purposive sampling constitutes the core sampling strategy. Wu (2014) demonstrates that purposive sampling proceeds after researchers verify target population feasibility, enabling deliberate informant selection that facilitates theoretical framework construction. The study surveyed full-time faculty from 12 universities distributed across China's regional strata: 4 institutions in eastern provinces, 4 in central territories, 4 in western zones. Each institution maintains approximately 1,500 instructors on average. Sample size determination followed criteria established by Krejcie and Morgan (1970) (Figure 2).

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	900	269	3000	341
20	19	120	92	300	169	950	269	3500	346
25	24	130	97	320	175	1000	274	4000	351
30	28	140	103	340	181	1100	278	4500	354
35	32	150	108	360	186	1200	285	5000	357
40	36	160	113	380	191	1300	290	6000	361
45	40	170	118	400	196	1400	297	7000	364
50	44	180	123	420	201	1500	302	8000	367
55	48	190	127	440	205	1600	307	9000	368
60	52	200	132	460	210	1700	310	10000	370
65	56	210	136	480	214	1800	313	15000	375
70	59	220	140	500	217	1900	317	20000	377
75	63	230	144	550	226	1900	320	30000	379
80	66	240	148	600	234	2000	327	40000	380
85	70	250	152	650	240	2200	330	50000	381
90	73	260	155	700	248	2400	331	75000	382
95	76	270	159	750	254	2600	335	1000000	384

Figure 2. Krejcie And Morgan (1970) Sampling Ratio

Online survey recruitment proceeded through professional questionnaire platforms. Sample diversity was ensured through coverage spanning disciplinary fields and geographic regions representing varied AI adoption ecologies. Following exclusion of incomplete or invalid responses, 376 questionnaires constituted the final analytic sample. Demographic composition: 48.1% male, 51.9% female; mean age 42.3 years (SD = 8.7, range = 25–60 years). Average teaching experience registered 15.2 years (SD = 7.4). Disciplinary distribution proved heterogeneous: 35% humanities and social sciences, 22% natural sciences, 15% engineering. Educational credentials: 62% held doctoral degrees, 31% master's degrees, 7% bachelor's degrees.

Participation proceeded voluntarily, with informed consent obtained digitally at survey commencement. Ethical approval was secured from the Institutional Review Board of China Three Gorges University (Approval No. SD20251018). Post hoc power analysis via SPSS 26.0 confirmed the sample furnished adequate statistical power (>0.95) for structural equation modeling with four latent variables and moderate effect magnitudes (Cohen's $f^2 = 0.15$, $\alpha = 0.05$).

In the context of this study, generative AI tools are increasingly used by university teachers to support various instructional activities, including lesson planning, content generation, assessment design, and student support. These tools enable teachers to automate routine tasks and enhance teaching efficiency, while also requiring them to adapt to new pedagogical roles and technological environments.

Participants in this study had varying levels of experience with generative AI, but all were exposed to its growing presence in higher education. Therefore, their perceptions of TA, SE, and CI were examined within this emerging AI-integrated teaching context.

3.3 Instrument development

All measurement instruments derived from established psychometric scales, undergoing translation into Chinese via back-translation protocols ensuring linguistic fidelity (Brislin, 1980). Two bilingual experts independently translated items, reconciled discrepancies through consensus negotiation, and piloted the questionnaire with 30 instructors to verify clarity and cultural appropriateness. A 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) operationalized all constructs. Demographic variables (age, gender, teaching tenure, disciplinary affiliation) served as statistical controls.

Technology Anxiety : Four items adapted from Venkatesh et al. (2003) assessed apprehension toward generative AI (exemplar: "I feel anxious about using AI tools like ChatGPT in teaching"). Preliminary Cronbach's $\alpha = 0.85$.

Self-Efficacy : Six items from Smith (2023) and Compeau and Higgins (1995) gauged confidence in AI integration (exemplar: "I am confident in using generative AI to enhance my pedagogical practices"). Preliminary $\alpha = 0.89$.

Career Identity : Five items drawn from Ashforth (2001) and cognate identity scales evaluated professional self-concept alignment (exemplar: "My career identity as a teacher aligns with the changes brought by AI"). Preliminary α = 0.87.

Role Reconstruction : Five items adapted from Ibarra (1999) captured adaptive transformations (exemplar: "Generative AI has helped me reconstruct my teaching role positively"). Preliminary α = 0.88.

3.4 Data analysis

Data underwent analysis via SPSS 26.0 for preliminary statistics and AMOS 26.0 for structural equation modeling (SEM), following a two-phase protocol (Anderson & Gerbing, 1988).

Phase One: Confirmatory factor analysis (CFA) validated the measurement model, scrutinizing convergent and discriminant validity. Acceptance criteria included factor loadings exceeding 0.70, composite reliability (CR) surpassing 0.70, average variance extracted (AVE) above 0.50, and AVE square root values exceeding inter-construct correlations (Fornell & Larcker, 1981). Model fit evaluation deployed multiple indices: chi-square (χ^2), comparative fit index (CFI > 0.95), Tucker-Lewis index (TLI > 0.95), root mean square error of approximation (RMSEA < 0.08), and standardized root mean square residual (SRMR < 0.08) (Hu & Bentler, 1999). Diagnostic checks verified normality, linearity, and multicollinearity assumptions (VIF < 3.0). Missing data (<5% of cases) underwent treatment via full information maximum likelihood (FIML).

Phase Two: The structural model tested hypothesized relationships, estimating direct and indirect effects. Mediation pathway robustness was assessed through 5000 bootstrapped samples (Preacher & Hayes, 2008). Demographic variables operated as covariates on endogenous constructs to mitigate confounding effects. All analytic procedures adhered to ethical protocols, with data anonymized and stored under secure conditions.

3.5 Instrument Validation

Confirmatory factor analysis (CFA) excluded items with standardized factor loadings below 0.60, following criteria established by Lomax and Schumacker (2004). All retained items demonstrated loadings exceeding this threshold, spanning 0.779 to 1.000. Cronbach's α coefficients for Technology Anxiety, Self-Efficacy, Career Identity, and Role Reconstruction registered 0.907, 0.897, 0.879, and 0.903 respectively, evidencing robust internal consistency. See Table 1.

TABLE I: MEASUREMENT MODEL RESULTS: FACTOR LOADINGS, RELIABILITY, AND VALIDITY

	ITEMS	Factor loading	Cronbach's alpha	Composite reliability（CR）	Average variance extracted (AVE)
TA	TA1	1.000	0.907	0.908	0.663
	TA2	0.858			
	TA3	0.935			
	TA4	0.963			
	TA5	0.835			
CI	CI1	1.000	0.897	0.901	0.646
	CI2	0.799			
	CI3	0.834			
	CI4	0.974			
	CI5	0.834			
SE	SE1	1.000	0.879	0.882	0.652
	SE2	0.847			
	SE3	0.784			
	SE4	0.779			
RR	RR1	1.000	0.903	0.906	0.707
	RR2	0.864			
	RR3	0.864			
	RR4	0.970			

IV. RESULTS

4.1 Measurement Model and Overall Fit

Adhering to the two-phase SEM protocol, this investigation first validated the measurement model through confirmatory factor analysis (CFA), subsequently testing the structural model. All analyses proceeded via AMOS 26.0 software, deploying maximum likelihood estimation with bootstrapping (5000 resamples) for indirect effect assessment. Diagnostic assumptions were satisfied: normality, linearity, and multicollinearity (VIF < 3). Demographic controls were incorporated but yielded non-significant effects ($p > 0.05$), thus omitted from detailed reporting for parsimony. Model fit indices demonstrated acceptable performance: $\chi^2/df = 3.12$, CFI = 0.97, TLI = 0.96, RMSEA = 0.06, SRMR = 0.05, satisfying established thresholds (Hu & Bentler, 1999). Global goodness-of-fit (GOF) registered 0.723 , surpassing the large effect criterion of 0.36 and confirming robust overall model quality (Tenenhaus et al., 2005).

4.2 Descriptive Statistics and Correlations

TABLE II: DESCRIPTIVE STATISTICS AND CORRELATIONS

	TA	CI	SE	RR
TA	0.814			
CI	0.760	0.803		
SE	0.701	0.743	0.807	
RR	0.755	0.760	0.759	0.841

Note: *p < 0.05, **p < 0.01, ***p < 0.001. TA = Technology Anxiety; SE = Self-Efficacy; CI = Career Identity; RR = Role Reconstruction.

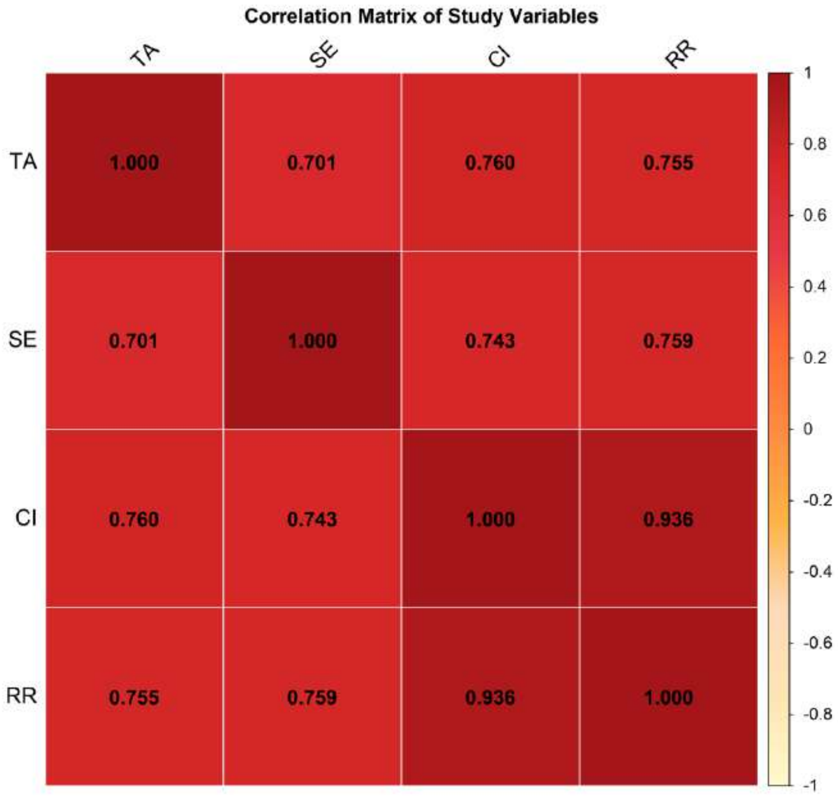

Figure 3. Correlation Matrix Of Study Variables

4.3 Hypothesis Testing and Structural Paths

The structural model was tested using structural equation modeling. The results indicate that TA, SE, and CI all have significant effects on RR ($p < 0.01$). In addition, TA and SE significantly influence CI ($p < 0.001$). Mediation analysis using bootstrapping (5000 resamples) shows that CI partially mediates the relationships between TA and RR, as well as between SE and RR. The indirect effects are statistically significant ($p < 0.01$). Furthermore, the model explains a substantial proportion of variance in RR ($R^2 = 0.779$) and CI ($R^2 = 0.789$).See Tables 3–5.

The structural model accounted for substantial variance across endogenous variables. Table 3 documents standardized path coefficients. Direct effects achieved statistical significance for all hypotheses, though H1 and H4 exhibited positive directions contrary to predictions.

TA positively predicted role reconstruction (RR; β = 0.356, SE = 0.077, t = 4.648, $p < 0.001$), supporting H1 albeit with reversed directionality. CI exerted a significant positive direct effect on RR (β = 0.237, SE = 0.090, t = 2.629, p = 0.009), corroborating H2. SE positively influenced RR (β = 0.371, SE = 0.070, t = 5.286, $p < 0.001$), validating H3. Concerning mediating pathways, TA positively affected CI (β = 0.492, SE = 0.063, t = 7.869, $p < 0.001$), supporting H4 with reversed directionality. SE positively impacted CI (β = 0.391, SE = 0.059, t = 6.645, $p < 0.001$), affirming H5.

TABLE III: STANDARDIZED PATH COEFFICIENTS AND HYPOTHESIS TESTING

Hypothesis	Path	β	SE	t-value	P value	Result
H1	TA->RR	0.356	0.077	4.648	0.000	0.349（Supported）
H2	CI->RR	0.237	0.090	2.629	0.009	0.223（Supported）
H3	SE->RR	0.371	0.070	5.286	0.000	0.378（Supported）
H4	TA->CI	0.492	0.063	7.869	0.000	0.513（Supported）
H5	SE->CI	0.391	0.059	6.645	0.000	0.423（Supported）

4.4 Indirect Effects

Bootstrapped mediation analysis disclosed significant partial indirect effects operating through CI (Table 4). The indirect pathway from TA to RR via CI proved positive and statistically significant [indirect effect = 0.131, Boot SE = 0.038, z = 4.449, p = 0.001, 95% CI (0.057, 0.202)], constituting 29.0% of the total effect (total effect = 0.451, direct effect = 0.320). The indirect pathway from SE to RR via CI likewise achieved positive significance [indirect effect = 0.118, Boot SE = 0.032, z = 3.722, $p < 0.001$, 95% CI (0.052, 0.175)], representing 24.9% of the total effect (total effect = 0.474, direct effect = 0.356).

TABLE IV: BOOTSTRAPPED INDIRECT EFFECTS

Path	c	a	b	a*b	a*b	a*b	a*b	a*b	c	Mediation Type	Proportion Mediated
Path	**Total Effect**	**a**	**b**	**Indirect Effect**	**Boot SE**	**z-value**	**p-value**	**95% BootCI**	**Direct Effect**	**Mediation Type**	**Proportion Mediated**
ZTA=>ZCI=>ZRR	0.451**	0.437**	0.298**	0.131	0.038	3.449	0.001	0.057 ~ 0.202	0.320**	Partial	29.0%
ZSE=>ZCI=>ZRR	0.474**	0.395**	0.298**	0.118	0.032	3.722	0.000	0.052 ~ 0.175	0.356**	Partial	24.9%

Note: **$p < 0.01$.

4.5 Model Explanatory Power and Representation

TABLE V: DIRECT, INDIRECT, AND TOTAL EFFECTS OF THE STRUCTURAL MODEL

The model also demonstrates strong explanatory power, accounting for 77.9% of the variance in role reconstruction and 78.9% of the variance in career identity.

Dependent Variable	Independent Variable	Direct Effect	Indirect Effect	Total Effect	Proportion Mediated	R^2
RR	TA	0.356	0.117	0.473	25%	0.779
RR	SE	0.371	0.093	0.464	20%	0.779
RR	CI	0.237	-	0.237	-	0.779
CI	TA	0.492	-	0.492	-	0.789
CI	SE	0.391	-	0.391	-	0.789

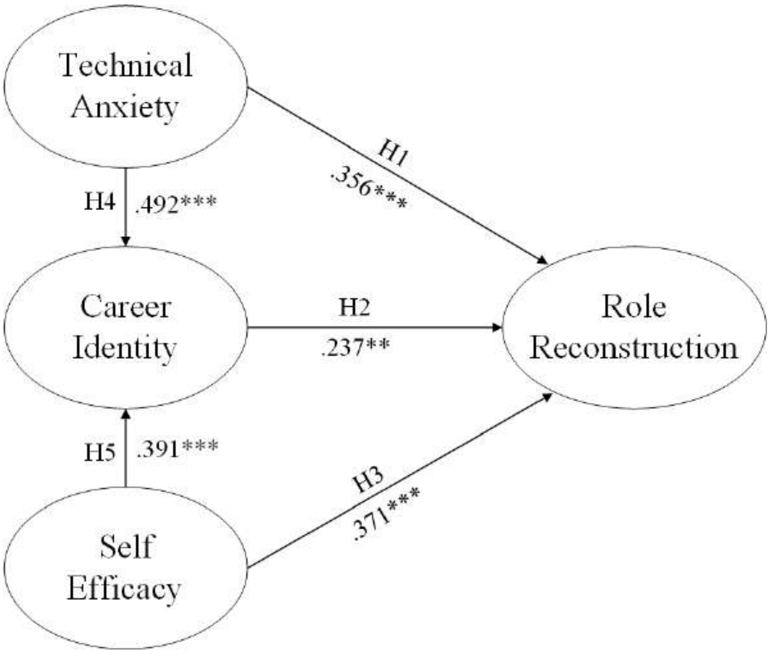

Figure 4. Standardized Path Coefficients for the Structural Model

V. DISCUSSION

5.1 Summary of Key Findings

This study examined the relationships among TA, SE, CI, and RR in the context of generative AI use in higher education. The results reveal several key findings. First, TA, SE, and CI all have significant positive effects on RR, indicating that both psychological pressure and perceived capability contribute to teachers' role adaptation. Notably, TA shows a positive association with RR, suggesting that technology-related anxiety may function differently in AI-integrated teaching contexts. Second, both TA and SE significantly influence CI, highlighting the role of psychological and cognitive factors in shaping teachers' professional identity. Finally, CI partially mediates the relationships between TA and RR as well as between SE and RR, indicating that career identity serves as an important mechanism linking individual perceptions to role transformation.

5.2 Interpreting the Role of Technology Anxiety

A notable finding of this study is the positive relationship between TA and RR, which contrasts with the traditional assumption that anxiety generally hinders technology adoption and performance (Venkatesh et al., 2003; Thatcher & Perrewe, 2002). This result suggests that, in the context of generative AI, technology anxiety may not function solely as a negative psychological barrier but can also act as a catalyst for change. See Figure 5.

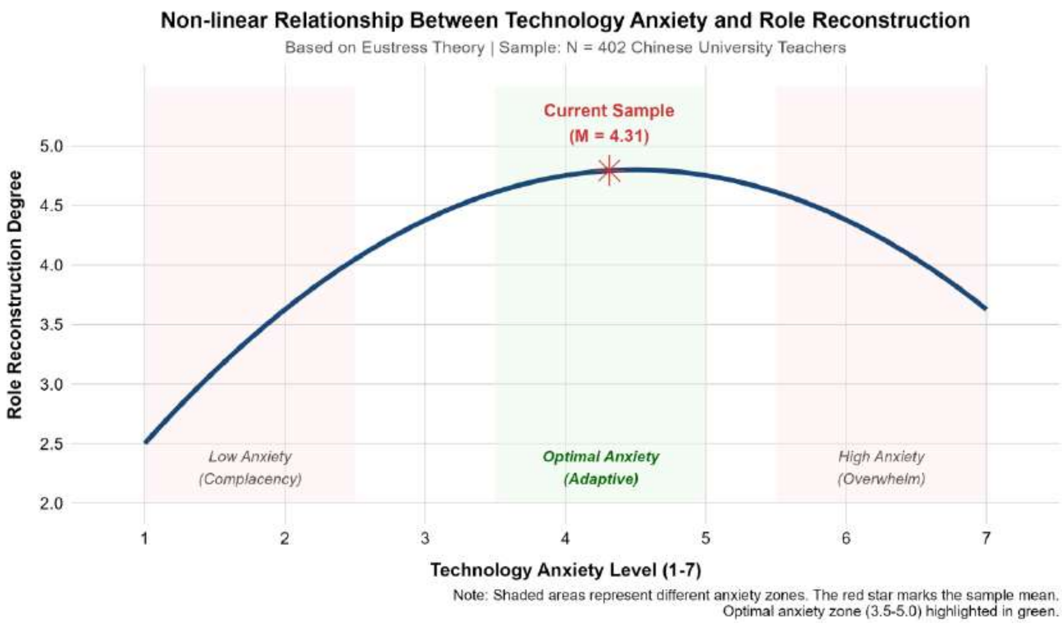

Figure 5. Nonlinear Relationship Between Technology Anxiety and Role Reconstruction

One possible explanation is that generative AI introduces a high level of uncertainty and disruption to established teaching practices, thereby creating a form of "productive tension" that motivates teachers to actively adjust their roles. Rather than withdrawing from technological engagement, teachers experiencing moderate levels of anxiety may be more inclined to explore new tools, experiment with pedagogical strategies, and redefine their professional responsibilities. This interpretation aligns with emerging perspectives that view certain types of anxiety as a stimulus for adaptive behavior under conditions of rapid technological change (Beaudry & Pinsonneault, 2010).

Furthermore, the increasing integration of generative AI into higher education may shift the nature of technology anxiety itself. Instead of reflecting a lack of competence, anxiety in this context may be associated with concerns about professional relevance, role displacement, and changing expectations of teaching practice (Dwivedi et al., 2023). These concerns may prompt teachers to engage more deeply with AI technologies in order to maintain their professional identity and instructional effectiveness.

However, this finding does not imply that technology anxiety is universally beneficial. Excessive anxiety may still lead to resistance or avoidance, particularly in contexts where institutional support is limited. Therefore, the relationship between TA and RR may be contingent on contextual factors such as training opportunities, organizational support, and individual coping strategies.

5.3 The Role of Self-Efficacy

The findings of this study also highlight the significant role of SE in shaping teachers' RR in AI-integrated educational contexts. Consistent with prior research, SE demonstrates a positive influence on both RR and CI, suggesting that teachers who perceive themselves as capable of using technology are more likely to engage in adaptive teaching practices (Compeau & Higgins, 1995).

In the context of generative AI, self-efficacy may play a particularly important role in enabling teachers to navigate new pedagogical demands and technological complexities. Teachers with higher levels of SE are more likely to experiment with AI tools, integrate them into instructional design, and respond proactively to evolving educational expectations. This finding aligns with studies in educational technology that emphasize the importance of perceived competence in facilitating technology adoption and instructional innovation (Teo, 2011).

Moreover, the positive relationship between SE and CI suggests that confidence in technological capabilities contributes not only to behavioral adaptation but also to the reinforcement of professional identity. As teachers gain mastery over AI tools, they may develop a stronger sense of competence and relevance within changing educational environments. Compared to technology anxiety, which may act as a form of motivational pressure, self-efficacy represents a more stable and enabling psychological resource. Together, these findings suggest that both affective and cognitive factors jointly shape teachers' responses to generative AI, albeit through different mechanisms.

5.4 Career Identity as a Mediating Mechanism

The results of this study underscore the pivotal role of CI as a mediating mechanism linking individual psychological factors to RR in AI-integrated educational contexts. Specifically, CI partially mediates the relationships between both TA and RR, as well as SE and RR, suggesting that teachers' professional identity serves as a critical pathway through which internal states are translated into adaptive behaviors.

This finding is particularly relevant in the context of generative AI, which is increasingly recognized as a transformative force reshaping educational practices and professional roles (Lim et al., 2023; Kim, 2024). As teachers encounter AI-driven changes, they are required to reinterpret their roles, shifting from traditional knowledge transmitters to facilitators, designers, and collaborators in technology-enhanced learning environments. In this process, career identity functions as a cognitive and affective filter through which teachers make sense of technological change and align it with their professional self-concept (Ashforth, 2001; Ibarra, 1999).

The mediating role of CI also helps explain how different psychological factors exert their influence on role adaptation. While technology anxiety may generate a sense of urgency or pressure to respond to emerging technologies, and self-efficacy provides the confidence to engage with them, it is the reconstruction of career identity that enables sustained and meaningful role transformation. This interpretation is consistent with prior research emphasizing the importance of identity processes in professional adaptation and role transition (Hogg, 2016).

Therefore, this study extends existing research by highlighting career identity as a key mechanism that integrates affective and cognitive factors in the process of adapting to generative AI. Rather than viewing technology adoption solely as a function of skills or attitudes, the findings suggest that identity-related processes play a central role in shaping how teachers navigate and internalize technological change.

5.5 Practical Implications

The findings of this study offer several practical implications for higher education institutions, policymakers, and educators in the context of generative AI integration. The positive role of TA indicates that institutions should not necessarily seek to eliminate anxiety altogether, but rather create conditions in which it can be constructively managed. In AI-integrated environments, a certain level of tension may encourage teachers to engage more actively with emerging technologies and reconsider their instructional approaches.

Providing supportive environments, including opportunities for collaboration and access to pedagogical resources, may help teachers channel these concerns into adaptive practices (Admiraal et al., 2016).

The findings also highlight the importance of SE in shaping teachers' engagement with generative AI. Strengthening teachers' confidence in using new technologies appears essential for promoting effective integration. Professional development initiatives may therefore benefit from focusing not only on technical skills but also on enhancing teachers' sense of competence and autonomy in technology use, as emphasized in prior research (Bandura, 1977; Scherer et al., 2019).

Another important implication relates to the role of CI. The results suggest that adapting to generative AI involves more than acquiring new skills; it also requires a reconfiguration of how teachers perceive their professional roles. Creating spaces for reflection, dialogue, and professional learning may support teachers in reconstructing their career identity in response to ongoing technological change. As generative AI continues to reshape educational practices (Lim et al., 2023; Kim, 2024), fostering an adaptive sense of professional identity may be critical for sustaining meaningful transformation.

Taken together, these implications point to the need for a more integrated approach to AI implementation in education, one that simultaneously addresses emotional responses, perceived competence, and professional identity.

5.6 Limitations and Future Research

This study is subject to several limitations that should be acknowledged. The use of cross-sectional data limits the ability to draw causal inferences regarding the relationships among technology anxiety, self-efficacy, career identity, and role adaptation. Future research may benefit from longitudinal designs to capture how these relationships evolve over time. In addition, the data were collected through self-reported measures, which may introduce common method bias despite procedural remedies (Podsakoff et al., 2003). Incorporating multiple data sources or behavioral measures could enhance the robustness of future studies. The sample was drawn from a specific higher education context, which may limit the generalizability of the findings. Further research across diverse institutional settings and cultural contexts would help to validate and extend the present results. Finally, as generative AI continues to develop rapidly, future studies could explore how different types of AI tools and levels of integration influence teachers' psychological responses and role transformation processes.

VI. CONCLUSION

This study examined the relationships among technology anxiety, self-efficacy, career identity, and role adaptation in the context of generative AI in higher education. The findings demonstrate that both affective and cognitive factors play significant roles in shaping how teachers respond to AI-driven changes. Notably, the results suggest that technology anxiety may function not only as a barrier but also as a potential driver of adaptive behavior in rapidly evolving technological environments. In addition, career identity emerges as a key mechanism through which individual perceptions are translated into meaningful role transformation. By integrating these perspectives, this study provides a more comprehensive understanding of teachers' adaptation to generative AI, highlighting the importance of emotional responses, perceived competence, and professional identity. The findings offer both theoretical insights and practical guidance for supporting teachers in navigating ongoing digital transformation in education.

ACKNOWLEDGMENTS

The authors acknowledge financial support from the National Social Science Fund Project (Grant No. 23TY013).

DISCLOSURE

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

The de-identified data supporting the findings of this study are available from the corresponding author upon reasonable request and subject to applicable ethics and data-sharing restrictions.

ETHICS STATEMENT

Ethical approval was obtained from the Institutional Review Board of China Three Gorges University (Approval No. SD20251018). All participants provided electronic informed consent before participation.

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