FACTORS INFLUENCING ARTIFICIAL INTELLIGENCE TECHNOLOGY USE BEHAVIOR AMONG TEACHERS IN APPLIED UNDERGRADUATE COLLEGES

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Abstract

Purpose: To explore the mechanisms that influence teachers' use of AI technology in application-oriented undergraduate colleges, providing theoretical support and practical guidance to promote the deep integration of AI and higher education.

Study Design/Methodology/Approach: An analytical framework was developed by integrating the Theory of Planned Behavior, the Technology Acceptance Model, and Self-Determination Theory. A questionnaire survey was conducted among 602 teachers across four major regions in China using a revised scale. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the hypotheses.

Findings: Teachers' usage behavior is driven by both intrinsic cognition and the external environment; perceived value is the core antecedent, with usage value having the strongest effect, while perceived risk exerts an inhibitory effect; individual innovativeness plays a positive catalytic role. Social influence and convenient conditions not only directly promote usage behavior but also exert selective indirect effects through perceived value: social influence operates primarily via emotional value, and convenient conditions primarily via use value, whereas the mediating path through functional value is not significant.

Originality/Value: This study constructs a comprehensive "Environment–Cognition–Behavior" framework to systematically reveal the multidimensional mechanism underlying teachers' AI usage behavior in application-oriented undergraduate colleges. It fills a gap in existing research by analyzing specific college types and value-cognition pathways, providing theoretical supplementation and practical reference value.

Keywords: Applied Undergraduate Colleges, Artificial Intelligence Technology, College Teachers, Technology Use Behavior, Technology Acceptance Model

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Introduction

The new generation of intelligent technology represented by generative artificial intelligence is promoting the systematic reform of global higher education, and artificial intelligence technology has become the core engine of digital transformation of education. In 2023, the white paper on Higher Education in the era of artificial intelligence, which was prepared under the leadership of the UNESCO Innovation Center for higher education, marked a new stage in the systematic promotion of global education intelligence. In this context, college teachers, as key actors in education reform, their acceptance and application depth of AI technology directly affect the actual effect of technology-enabled education (Selwyn, 2019). As a key hub connecting the education system and industrial demand, application-oriented undergraduate colleges and universities undertake the important mission of serving regional development and cultivating application-oriented talents (Ministry of Education of the People's Republic of China, 2020). The behavior patterns of teachers in such colleges and universities in the use of AI technology are not only related to the depth of technology application but also have prominent typical significance and practical urgency.

With the rapid penetration of generative AI in higher education, college teachers' AI use behavior has become a research hotspot. It is generally believed that AI is profoundly changing teachers' teaching methods, research paradigms and professional development paths (Lan et al., 2021; Liu, 2019), and discussions have been launched around technology empowerment, role remodeling, ethical risks, and governance (Bao & Wan, 2025; Zhou & Chang, 2023). Existing studies focus on the institutional response and governance framework (Gao & Zhang, 2024; Li & Xue, 2024)., and on teachers' AI literacy, attitude and use behavior (Li et al., 2022; Hu & Cao, 2024). In general, the existing research has formed a multi-level pattern of "whether to use–how to use–how to standardize the use", but empirical research on the specific group of teachers in application-oriented undergraduate colleges is still insufficient. Based on this, this study takes the teachers of application-oriented universities as the research object, integrates the planned behavior theory (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989) and the Self-Determination Theory (Ryan & Deci, 2000), and systematically discusses the key factors and internal mechanisms affecting their AI technology use behavior, in order to provide a theoretical basis and practical reference for the digital transformation of higher education.

Objectives

This study aims to investigate the driving mechanisms behind the adoption of Artificial Intelligence (AI) technologies by college teachers at applied undergraduate colleges. Specifically, the objectives of this study include:

1. To assess the current usage patterns and behavioral characteristics of college teachers at applied undergraduate colleges regarding their adoption of AI technologies.

2. To examine how internal cognitive factors–such as perceived value, perceived risk, and personal innovativeness–as well as external environmental factors influence the AI usage behavior of teachers in application-oriented undergraduate colleges.

3. To identify the primary driving factors underlying AI usage behaviors among college teachers at applied undergraduate colleges, thereby offering strategic recommendations for optimizing institutional support systems.

Literature Review

Analysis of Differences in AI Technology Usage Among Teachers with Varying Characteristics

Individual characteristics serve as key moderating factors in technology acceptance. Within the context of higher education institutions, background factors–such as faculty members' educational qualifications, academic disciplines, and geographic locations–constitute significant antecedents for explaining variations in technology utilization (Hu & Cao, 2024; Luo & Zhou, 2025). Given the inherent complexity and cognitively demanding nature of Artificial Intelligence (AI) technologies, the diverse knowledge reserves, academic paradigms, and resource endowments possessed by faculty members may give rise to systemic ecological challenges regarding their technological cognition, professional judgment, and deep-level application of these tools (Tang & Dai, 2026). Accordingly, it is posited that the AI technology usage behaviors of faculty members at applied undergraduate institutions exhibit significant variations based on their individual characteristics.

The Impact of College Teachers' Internal Cognition on AI Technology Usage Behavior

Internal cognition refers to the internal representation and cognitive processing of Artificial Intelligence (AI) technology formed by teachers at the psychological level. Existing studies primarily explain usage behavior through the lenses of cognition, attitude, and individual traits. Drawing on the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models, perceived usefulness, perceived ease of use, and attitude toward usage are identified as key antecedents (Fei et al., 2025; Luo & Zhou, 2025). In the context of generative AI, the alignment between technology and teaching tasks, as well as its enhancing effect on professional judgment, offer stronger explanatory power than the mere perception of technological advancement (Tang & Dai, 2026). At the emotional and value levels, positive experiences, self-efficacy and professional identity can promote continued usage (Xu & Xu, 2025). Conversely, techno-anxiety, occupational stress and identity crises exert an inhibitory effect, demonstrating a characteristic coexistence of "empowerment and anxiety" (Bao & Wan, 2025; Zhang, 2020).

Perceived value refers to the overall evaluation of the utility of a technology formed by users based on a trade-off between benefits and costs. There have been researches on the use of AI by college teachers which have expanded from a single "usefulness" to a multi-dimensional construct. Li et al. (2025), Xu and Xu (2025) emphasized the comprehensiveness of their cognitive evaluation; Zhang and Wang (2025)

pointed out that it involves multiple trade-offs, such as time investment, learning burden, ethical risk and teaching control. In this study, perceived value is divided into functional value, use value and emotional value: functional value reflects the role of technology in promoting teaching and research goals; use value reflects ease of use, controllability and process compatibility; emotional value reflects positive experiences such as fun, a sense of achievement and identity. Therefore, we propose the following hypothesis:

H1: Functional value significantly enhances teachers' adoption of AI technologies.

H2: Use value significantly enhances teachers' adoption of AI technologies.

H3: Emotional value significantly enhances teachers' adoption of AI technologies.

Individual innovativeness reflects a stable tendency for teachers to accept and explore new things. According to the diffusion of innovation theory, highly innovative teachers have a more open attitude toward technological change and a higher tolerance for initial uncertainty. Rogers (1995) pointed out that individuals with higher innovativeness are more likely to become early adopters of new technologies and exhibit stronger willingness to try and adaptability under uncertain conditions. In the context of the rapid evolution of artificial intelligence technology, highly innovative teachers are more willing to actively explore application scenarios and accumulate usage experience. This trait can directly stimulate usage willingness and behavior and may also indirectly play a role by enhancing value perception (Fei et al., 2025; Luo & Zhou, 2025). Therefore, we propose the following hypothesis:

H4: Teachers' individual innovativeness significantly enhances their AI technology usage behavior.

Perceived risk refers to teachers' concerns regarding the potential losses that may arise from the use of technology, encompassing aspects such as functional reliability, data privacy, psychological stress, and social interaction. Although Artificial Intelligence (AI) technologies offer support for teaching, research and administration, the challenges they pose–specifically regarding data security and academic ethics (Zhou & Chang, 2023; Zhang & Wang, 2025; Li & Xue, 2024), the relinquishment of pedagogical control (Tang & Dai, 2026), and the resulting professional role crises and psychological stress (Bao & Wan, 2025; Zhang, 2020)–can trigger deep-seated apprehensions among teachers. When teachers perceive risks such as data insecurity or compromised decision-making autonomy, their motivation to adopt AI technologies diminishes significantly; indeed, even when teachers recognize the inherent value of the technology, a high level of perceived risk can still serve as a barrier to its practical implementation (Xu & Xu, 2025). Therefore, it is proposed that:

H5: Perceived risk significantly and negatively influences technology use behavior.

The Impact of the External Environment on College Teachers' Use of AI Technology

In addition to internal cognition, external environments such as social environments and organizational conditions are also important situational variables. College teachers' technology adoption is embedded in the school system, organizational culture, peer interaction and resource support; research shows that school policy orientation, peer demonstration and organizational culture will affect teachers' technology adoption through social norms and social identity (Wei et al., 2025); technical support, training

resources and system guarantees, as well as other conveniences will also directly affect the possibility of AI being embedded in teaching and research (Ge & Liu, 2025; Li, 2025). In application-oriented colleges and universities with strong practicality but relatively limited resources, insufficient conveniences are more likely to raise the use threshold and restrict in-depth application (Wang et al., 2025).

Social impact refers to the expectations, pressures and demonstration effects perceived by teachers from important others or reference groups, which act on decision-making through normative and informational influences. Liu and Yan (2019), Ge and Liu (2025) pointed out that when the use of AI is defined as a professional development trend or institutional expectation by organizational culture, policy orientation or peer practice, teachers are more likely to form a positive attitude toward the use of AI; a positive social atmosphere and successful cases of peers can enhance the willingness to use and provide legitimacy support for behavior. This leads to the following hypothesis:

H6: Social influence significantly and positively influences technology use behavior.

Convenience refers to the completeness of objective support resources perceived by teachers, including hardware facilities, technical training, incentive policies and exploration space. The effective use of AI technology not only depends on personal will, but also needs platforms, tools, training and institutional guarantees. Li et al. (2025) believe that convenience not only directly affects whether teachers try to use AI but also enhances their competence and perceived behavior control, reduces implementation barriers, and promotes the transformation of use intention to stable practice. Therefore, the following hypothesis is proposed:

H7: Convenient conditions significantly enhance teachers' adoption of AI technologies.

The Indirect Influence of the External Environment on the Technology Use Behavior of University Teachers: Shaping the Internal Cognition of University Teachers

The external environment not only directly affects the use behavior, but also has an indirect effect by shaping the internal cognition, in which the perceived value is an important psychological transformation hub. Luo and Zhou (2025) pointed out that when teachers internalize policy advocacy, technical support and social impact into "meaningful" and "worth investing" value cognition, their use intention will be significantly enhanced; Bao and Wan (2025) also believed that even with perfect technical and institutional support, without positive value recognition, the use behavior would still be difficult to sustain.

Social influence—exerted through normative pressure and role modeling—can alter teachers' value judgments regarding artificial intelligence technologies (Ajzen, 1991; Liu & Yan, 2019). Specifically, social influence stemming from peers and organizations can prompt teachers to recognize the functional value of AI in enhancing teaching and research performance while simultaneously lowering their expectations regarding technological complexity; this, in turn, strengthens their perceived value-in-use (Luo & Zhou, 2025). Concurrently, a positive organizational climate and a strong sense of identification with one's professional community can effectively alleviate technology-related anxiety, thereby significantly enhancing teachers' perception of the affective value associated with the technology adoption process

(Bao & Wan, 2025; Wei et al., 2025). Therefore, we hypothesize:

H8: Social influence significantly enhances the perception of functional value.

H9: Social influence significantly enhances perceived use value.

H10: Social influence significantly enhances the perception of emotional value.

Ample favorable conditions provide a realistic basis for value perception. Well-equipped facilities, convenient platform tools, and continuous technical training and other teaching support services effectively reduce the operational difficulty and adaptation costs for teachers, helping them to confirm the functional realization of technology in practice (Davis, 1989; Ge & Liu, 2025; Li, 2025). Simultaneously, clear and strict policies and expanded exploration space establish a robust institutional environment, not only alleviating technical pressure (Bao & Wan, 2025) but also satisfying teachers' autonomous psychological needs for exploring new things, prompting them to develop positive emotional experiences such as pleasure and accomplishment (Ryan & Deci, 2000). The sufficiency of external conditions systematically and positively influences teachers' overall value assessment.

H11: Convenient conditions significantly enhance functional value perception.

H12: Convenient conditions significantly enhance perceived use value.

H13: Convenient conditions significantly enhance the perception of emotional value.

The preceding analysis indicates that social influence and convenient conditions not only directly drive usage behavior but also positively influence perceptions of functional, usage, and emotional value; given that these three dimensions of perceived value serve as proximal antecedents to usage behavior, it is highly likely that the external environment indirectly promotes usage behavior through perceived value. Recent studies have provided empirical support for such mediation mechanisms (Jia & Yang, 2025; Fei et al., 2025), demonstrating that external environmental factors can indirectly influence teachers' technology usage behavior via cognitive variables such as perceived usefulness and ease of use. Building on this theoretical and empirical foundation and to examine the "Environment–Cognition–Behavior" transmission pathway, this study further proposes hypotheses (H14-H19) regarding the mediating effects of the three dimensions of perceived value on the relationship between social influence/convenient conditions and teachers' AI usage behavior.

H14: Functional value mediates the relationship between social influence and usage behavior.

H15: Functional value mediates the relationship between convenient conditions and usage behavior.

H16: Usage value mediates the relationship between social influence and usage behavior.

H17: Usage value mediates the relationship between convenient conditions and usage behavior.

H18: Emotional value mediates the relationship between social influence and usage behavior.

H19: Emotional value mediates the relationship between convenient conditions and usage behavior.

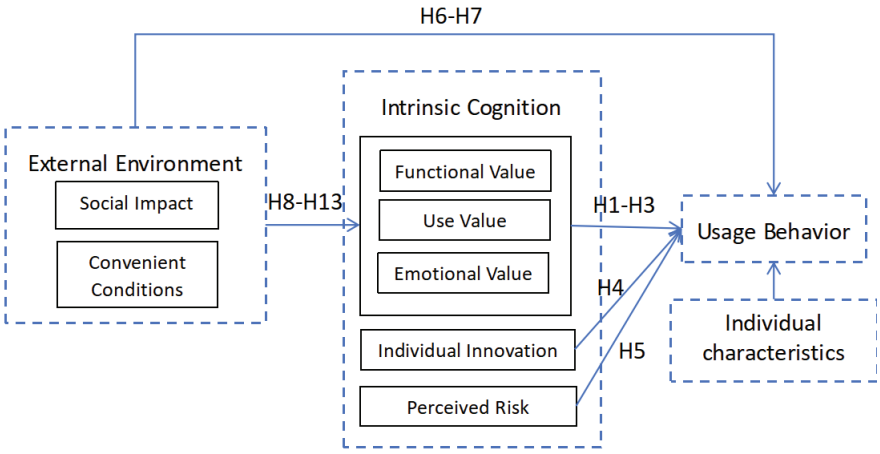


Figure 1 Theoretical Model Diagram

Methodology

1. Data Collection

This study targets the population of full-time college teachers at applied undergraduate colleges nationwide, comprising approximately 402,000 individuals across roughly 670 colleges. Based on the regional classification standards established by the National Bureau of Statistics, these colleges were categorized into four major regions: Northeast, East, Central Region, and West. Within each region, representative colleges were selected for questionnaire distribution using a combination of convenience and purposive sampling methods, weighted according to the proportional distribution of colleges in that region. The survey was conducted from March to April 2025, employing a hybrid methodology that combined targeted online distribution via the "Wenjuanxing" platform with the on-site collection of paper-based questionnaires. To ensure sample independence, the online component utilized IP address restrictions and unique response controls. A total of 680 questionnaires were distributed, with 660 returned, yielding a return rate of 97.1%. Following multiple rounds of data cleaning—during which questionnaires missing key information, exhibiting patterned responses, or containing logical inconsistencies were excluded—A final set of 602 valid samples was obtained, resulting in a valid return rate of 91.2%. The regional distribution of the sample (Northeast: 19.60%; Central: 40.53%; West: 21.43%; East: 18.44%) and its demographic characteristics align closely with statistical trends reported by the Ministry of Education, thereby demonstrating strong national representativeness. Throughout the entire survey process, strict adherence to academic ethics was maintained; informed consent was obtained from all participants, clearly outlining the research objectives as well as the principles of voluntary participation, anonymity, and confidentiality.

2. Measuring Tools

All core variables were adapted from established scales and contextualized for the specific setting; a uniform 5-point Likert scale was employed for scoring. The sources and item counts for each scale are presented in the table below. In accordance with the recommendations of Nunnally (1978),

each latent variable was assigned a minimum of three items; prior to administration, all scales underwent optimization through expert review and pilot testing.

Table 1 Sources and Number of Items for Each Variable

Variable	Number of Items	Item Source
Function Value	4	Sheth et al. (1991); Sweeney and Soutar (2001)
Use Value	4	Sheth et al. (1991); Sweeney and Soutar (2001)
Emotional Value	3	Sweeney and Soutar (2001); Mathwick et al. (2001)
Individual Innovativeness	5	Agarwal and Prasad (1998); Yi et al. (2006)
Perceived Risk	4	Bauer (1960); Jacoby and Kaplan (1972)
Convenient Conditions	4	Venkatesh (2003); Venkatesh et al. (2003)
Social Influence	4	Venkatesh and Davis (2000);Venkatesh et al. (2003)
Behavioral Usage	3	Davis (1989); Venkatesh et al. (2003)

3. Data Analysis

SPSS 26.0 was used to conduct descriptive statistics, Common Method Bias testing (Harman's single-factor test), correlation analysis, and preliminary reliability assessment. Data normality was examined using the Jarque–Bera test and the robust Jarque–Bera test; in cases of non-normal distribution, hypothesis testing was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a method robust to non-normal data. WarpPLS 8.0 software was employed to sequentially evaluate the measurement and structural models, assessing internal consistency reliability (Cronbach's α and Composite Reliability [CR]), convergent validity (Average Variance Extracted [AVE]), and discriminant validity (Fornell-Larcker criterion and Heterotrait-Monotrait ratio [HTMT]). Direct effects were tested via path coefficients, *p-values*, and effect sizes, while mediation effects were examined using the bias-corrected bootstrapping method (5,000 resamples).

Results

1. Data Distribution and Method Justification

The descriptive statistics indicate that the data are not strictly normal. Both the Jarque-Bera (Normal-JB) and Robust Jarque-Bera (Normal-RJ) tests returned "No" across all constructs. This non-normality strongly justifies the use of Partial Least Squares Structural Equation Modeling (PLS-SEM), as it is a variance-based, non-parametric method well-suited for such data distributions.

2. Measurement Model Assessment (Reliability and Convergent Validity)

The measurement model demonstrates excellent internal consistency and convergent validity across all constructs (Table 2).

Indicator Reliability: All outer loadings exceed the recommended threshold of 0.708 (ranging from 0.796 to 0.876), indicating that the constructs explain more than 50% of the variance in their respective indicators.

Internal Consistency: Both Composite Reliability (CR) and Cronbach's Alpha (CA) values are well above the 0.70 threshold, establishing strong construct reliability.

Convergent Validity: The Average Variance Extracted (AVE) for all constructs ranges from 0.668 to 0.755, safely exceeding the 0.50 minimum requirement.

Collinearity: All Variance Inflation Factor (VIF) values are below 3.3 (max 1.659), confirming that collinearity is not a concern at the measurement level.

Table 2 Reliability and Convergent Validity of the Constructs (n = 602)

Construct	Loadings Range	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE	VIF (Block)
Usage Behavior	0.862-0.876	0.838	0.902	0.755	1.659
Functional Value	0.818-0.831	0.843	0.895	0.680	1.507
Use Value	0.810-0.842	0.851	0.900	0.691	1.655
Emotional Value	0.826-0.867	0.805	0.885	0.720	1.483
Individual Innovativeness	0.796-0.843	0.876	0.910	0.668	1.499
Perceived Risk	0.825-0.843	0.856	0.902	0.698	1.508
Social Influence	0.826-0.848	0.858	0.904	0.701	1.653
Convenient Conditions	0.830-0.860	0.869	0.911	0.719	1.592

3. Discriminant Validity

Discriminant validity was established using both the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. In the table below, the square root of the AVE is presented on the diagonal, demonstrating that each construct shares more variance with its own indicators than with other constructs. Furthermore, all HTMT values (in the lower triangle) are well below the conservative threshold of 0.85, confirming that the constructs are empirically distinct.

Table 3 Discriminant Validity (Fornell-Larcker & HTMT)

Construct	Usage Behavior	Functional Value	Use Value	Emotional Value	Individual Innovativeness	Perceived Risk	Social Influence	Convenient Conditions
Usage Behavior	**(0.869)**	0.427	0.461	0.425	0.431	-0.435	0.461	0.448
Functional Value	0.509	**(0.825)**	0.450	0.340	0.357	-0.400	0.414	0.423
Use Value	0.546	0.531	**(0.831)**	0.422	0.410	-0.429	0.415	0.453
Emotional Value	0.517	0.413	0.509	**(0.849)**	0.416	-0.357	0.450	0.367
Individual Innovativeness	0.503	0.415	0.475	0.496	**(0.818)**	-0.370	0.438	0.385
Perceived Risk	0.514	0.471	0.503	0.431	0.428	**(0.835)**	-0.419	-0.421
Social Influence	0.543	0.487	0.486	0.540	0.505	0.489	**(0.838)**	0.445
Convenient Conditions	0.525	0.494	0.526	0.439	0.442	0.488	0.515	**(0.848)**

Remarks: Bolded values indicate the loadings of the principal factor to which the item belongs.

4. Model Fit and Quality Indices

The structural model demonstrates a robust fit with the data. The primary fit indices all meet or exceed established criteria:

Average Path Coefficient (APC): 0.162 ($p < 0.001$)

Average R-squared (ARS): 0.301 ($p < 0.001$)

Average Adjusted R-squared (AARS): 0.297 ($p < 0.001$)

Tenenhaus GoF (GoF): 0.492 (Large effect size, \ge 0.36)

Standardized Root Mean Square Residual (SRMR): 0.064 (Acceptable fit, \le 0.08)

Collinearity: Both AVIF (1.429) and AFVIF (2.019) are \le 3.3, verifying an absence of widespread collinearity in the model.

Paradox & Causality: SPR, RSCR and SSR are all perfect at 1.000, and the NLBCDR is 0.912 (all exceeding their respective thresholds of 0.7 or 0.9), ensuring causality directions are logical and free of Simpson's paradox issues.

5. Direct Effects Testing (H1-H13)

The structural model was assessed to test the direct hypotheses (H1-H13). The significance of the relationships was determined using the path coefficients (Beta) and their corresponding *p*-values. As shown in the table below, all thirteen direct effect hypotheses were supported by the data.

Notably, Individual Innovativeness had the strongest direct positive effect on Usage Behavior (Beta = 0.146, $p < 0.001$), while Perceived Risk had a significant negative effect (Beta = -0.119, $p = 0.002$), supporting H5. Furthermore, both Social Influence and Convenient Conditions demonstrated strong positive impacts on the perceptions of functional, use and emotional values (Beta ranges from 0.249 to 0.334, all $p < 0.001$).

Table 4 Results of Direct Effect Hypothesis Testing for the Structural Model (H1-H13)

Hypothesis	Path / Relationship	Beta	SE	*p*-value	Effect Size (ES)	Decision
H1	Functional Value → Usage Behavior	0.107	0.040	0.004	0.047	Supported
H2	Use Value → Usage Behavior	0.118	0.040	0.002	0.056	Supported
H3	Emotional Value → Usage Behavior	0.120	0.040	0.001	0.052	Supported
H4	Individual Innovativeness → Usage Behavior	0.146	0.040	<0.001	0.065	Supported
H5	Perceived Risk → Usage Behavior	-0.119	0.040	0.002	0.053	Supported
H6	Social Influence → Usage Behavior	0.142	0.040	<0.001	0.068	Supported
H7	Convenient Conditions → Usage Behavior	0.119	0.040	0.002	0.054	Supported
H8	Social Influence → Functional Value	0.297	0.039	<0.001	0.132	Supported
H9	Social Influence → Use Value	0.295	0.039	<0.001	0.134	Supported
H10	Social Influence → Emotional Value	0.334	0.039	<0.001	0.151	Supported
H11	Convenient Conditions → Functional Value	0.297	0.039	<0.001	0.131	Supported
H12	Convenient Conditions → Use Value	0.325	0.039	<0.001	0.153	Supported
H13	Convenient Conditions → Emotional Value	0.249	0.040	<0.001	0.102	Supported

Remarks: Demographic control variables (Gender, Age, Education, and Experience) were included in the model but showed no significant effect on Usage Behavior (all *p*-values > 0.05).

6. Mediation Effect Testing

Structural Equation Modeling (SEM) combined with the bias-corrected bootstrap method (with 95% confidence intervals) was employed to test the mediation hypotheses (H14-H19). The presence of mediation effects was comprehensively evaluated based on the significance of path coefficients, whether the confidence intervals included zero, and the corresponding *p*-values. As presented in Table 5, of the six mediation hypotheses, three were supported by the data, while the remaining three did not reach statistical significance.

The results indicate that the indirect effects of social influence and convenient conditions on usage behavior through usage value (H16, H17) and emotional value (H18) were significant. Specifically, the mediating path of convenient conditions on usage behavior via usage value (H17) exhibited the largest effect size (Beta = 0.052, $p = 0.035$); the mediating path of social influence on usage behavior via emotional value (H18) was also significant (Beta = 0.049, $p = 0.044$). In addition, the indirect path of social influence on usage behavior through functional value (H14, Beta = 0.042, $p = 0.071$) and the indirect paths of convenience conditions on usage behavior through functional value (H15, Beta = 0.042, $p = 0.071$) and through emotional value (H19, Beta = 0.037, $p = 0.101$) did not reach statistical significance; accordingly, hypotheses H14, H15 and H19 were not supported. These findings suggest that usage value and emotional value play a more critical mediating role between external environmental factors (social influence and convenient conditions) and usage behavior, whereas the mediating role of functional value is not significant in the current model.

Table 5 Mediation Effects Testing (H14-H19) with 95% CI

Hypothesis	Mediation Path	Beta	SE	95% CI (Calculated)	*p*-value	Effect Size	Decision
H14	Social Influence → Functional Value → Usage Behavior	0.042	0.029	[-0.015, 0.099]	0.071	0.020	Not Supported
H15	Convenient Conditions → Functional Value → Usage Behavior	0.042	0.029	[-0.015, 0.099]	0.071	0.019	Not Supported
H16	Social Influence → Use Value → Usage Behavior	0.047	0.029	[-0.010, 0.104]	0.050	0.023	Supported
H17	Convenient Conditions → Use Value → Usage Behavior	0.052	0.029	[-0.005, 0.109]	0.035	0.024	Supported
H18	Social Influence → Emotional Value → Usage Behavior	0.049	0.029	[-0.008, 0.106]	0.044	0.024	Supported
H19	Convenient Conditions → Emotional Value → Usage Behavior	0.037	0.029	[-0.020, 0.094]	0.101	0.017	Not Supported

Discussion

Drawing on an integrated "Environment–Cognition–Behavior" perspective, this study empirically reveals the multiple driving mechanisms of AI usage behavior among teachers in application-oriented undergraduate colleges. The findings indicate that internal cognitive and external environmental factors do not operate in isolation; rather, they synergistically influence teachers' technology adoption through both direct and indirect pathways, thereby offering new empirical insights into the patterns of technology acceptance within specific institutional contexts.

With respect to Research Objective 1, the structural model shows that the paths from demographic control variables such as gender and age to usage behavior are all nonsignificant ($p > 0.05$), suggesting that static background factors are not direct determinants of behavior; their influences are more likely to be indirectly realized through psychological cognition and environmental perception.

Regarding Research Objective 2, all three dimensions of perceived value significantly drive usage behavior (H1-H3 supported). Among them, emotional value ($\beta = 0.120$, $p = 0.001$) and usage value ($\beta = 0.118$, $p = 0.002$) exhibit comparable direct effect sizes, indicating that for highly interactive technologies such as AI, the driving role of emotional experiences, e.g., (enjoyment and identification), is no less important than rational judgments of ease of use. Personal innovativeness demonstrates the strongest direct positive predictive power ($\beta = 0.146$, $p < 0.001$), whereas perceived risk is the only significant negative barrier ($\beta = -0.119$, $p = 0.002$), quantitatively confirming a cognitive profile characterized by the coexistence of empowerment and anxiety.

Regarding Research Objective 3, social influence and convenient conditions not only directly drive behavior but also exert indirect effects by shaping perceived value, with distinct differences observed in the mediating pathways. Social influence primarily promotes usage behavior indirectly through emotional value (H18 supported), indicating that the core functions of peer modeling and organizational climate are to internalize technology usage into a professional identity at the emotional level. Convenient conditions meanwhile, primarily exert a mediating effect through use value (H17 supported; indirect effect $\beta = 0.052$, the highest among the paths), demonstrating that the primary function of resource support is to lower operational barriers, thereby enabling teachers to perceive the technology as easy to use and controllable. The mediating effects of functional value were not significant in either pathway (H14 and H15 were not supported), a finding consistent with a core tenet of the Technology Acceptance Model: The formation of perceived usefulness relies more on an individual's direct assessment of task-technology fit (Venkatesh & Davis, 2000) than on the simple transmission of external influences or convenient conditions. In applied undergraduate institutions, signals regarding social influence and the general support provided by convenient conditions require deep contextualization within specialized teaching environments to foster a perception of usefulness; the indirect and context-dependent nature of this cognitive construction diminishes their significance as mediating pathways. In contrast, use value and emotional value can be more readily enhanced through observational learning and resource provision, making them more efficient mediators in the translation of external factors into actual behavior.

Conclusions

This study constructed and validated an integrated "Environment–Cognition–Behavior" model, systematically revealing the driving mechanisms of AI usage behavior among teachers in application-oriented undergraduate colleges. The main conclusions are as follows:

1. Teachers' AI usage behavior is synergistically driven by internal cognition and the external environment. All three dimensions of perceived value significantly and positively predict usage behavior, with emotional value and usage value demonstrating comparable driving forces, indicating that in the adoption of highly interactive technologies such as AI, positive emotional experiences are as critical as perceived ease of use. Personal innovativeness is the strongest positive predictor, while perceived risk is the only significant negative barrier, revealing a behavioral profile characterized by the coexistence of empowerment and anxiety.

2. The external environment exerts an indirect influence on usage behavior through perceived value, and the mediating pathways show clear differentiation. Social influence drives behavior indirectly primarily through emotional value, suggesting that the core roles of peer demonstration and organizational climate lie in internalizing technology use into professional identity and positive emotional experiences. Convenient conditions exert their mediating effect mainly through usage value, indicating that the primary function of resource provision is to reduce operational barriers and enhance perceived ease of use. Notably,

the mediating effect of functional value is nonsignificant in both pathways, which implies that the key to transforming external support into behavioral drive is not reinforcing perceived usefulness but rather leveraging the dual forces of ease-of-use experience and emotional identification. This finding deepens the understanding of the "Environment–Cognition–Behavior" transmission pathway.

3. Teachers' AI adoption decisions follow a contextual logic of "emotion-driven priority, resource-supported foundation". This study demonstrates that in the professional and organizational context of application-oriented undergraduate colleges, teachers' technology use is not merely a rational utility calculation but a dynamic process integrating value trade-offs, emotional identification, and contextual adaptation. Effective promotion strategies must achieve synergy between soft and hard measures: hard convenient conditions such as training, platforms and policies should lower usage thresholds, while soft social influences such as peer leadership and institutional expectations should stimulate emotional identification. Only by advancing along these dual pathways can a sustainable institutional support system be constructed.

Recommendations

Based on the research findings, the following suggestions are proposed to effectively enhance the depth and effectiveness of artificial intelligence technology application among teachers in applied undergraduate institutions:

1. Strengthen policy guidance and ecological construction. The government should strengthen top-level design and resource investment and promote the integrated development of digital transformation of higher education and the artificial intelligence industry chain. For example, the government or the competent department of education can set up a "special fund for AI education base" to fund colleges and universities to build campus privatization "Intelligent Computing Center" or introduce an exclusive education model to provide free and stable computing power guarantee for teachers' daily use of AI tools.

2. Focusing on teachers' digital literacy and identity transformation, the program systematically implements the "Digital New Teacher" training initiative. Through training, practical communities, and incentive mechanisms, it helps teachers overcome technological anxiety and cognitive limitations, achieving a shift in mindset and enhancing their capabilities from tool application to teaching innovation.

3. Deepen the integration of production and education and scene co-construction. Guide AI enterprises to specialize in educational application scenarios, improve the effectiveness and adaptability of technology supply, and promote the joint research and development of professional customized intelligent teaching systems by colleges and enterprises, such as the "intelligent fiscal and taxation training platform" jointly developed by colleges of finance and economics and technology enterprises, which uses AI to simulate real customer conversations and automatically evaluate students' practical steps.

4. Strengthen the use specification and risk control. Establish AI usage norms to clarify the boundaries, combine case guidance to improve teachers' rational judgment and avoid formal application.

Colleges and universities should issue a detailed guide to the use of teacher-generated AI, which clearly stipulates that in high-risk areas such as student achievement evaluation and academic paper writing, the dual review mechanism of "AI preliminary research+manual review" must be implemented, and the scope of AI participation should be clearly marked in the results.

Research Limitations and Prospects

Although this study employs a systematic analytical framework, it is subject to several limitations. First, regarding the research methodology: the reliance on cross-sectional survey data, while capable of substantiating correlations and predictive relationships among variables, makes it difficult to reveal the dynamic evolutionary trajectories of usage behaviors. Furthermore, subjective self-reports may introduce social desirability bias. Future research could adopt a longitudinal design—incorporating objective data such as platform logs or qualitative interviews—to validate the dynamic effects of the model. Second, regarding the sample and technological context: The sample encompasses 602 faculty members from applied undergraduate institutions across China's four major regions; however, it did not conduct a granular comparison of specific AI tool types. Future research could expand the sample size to facilitate contextualized empirical analyses tailored to specific AI-assisted educational scenarios. Third, regarding the theoretical model: While the study integrates the "Environment–Cognition–Behavior" framework, it does not incorporate cutting-edge variables such as human-AI collaborative trust, technostress, or the institutional ethical governance climate. Future studies could extend the theoretical boundaries to explore the complex mechanisms involving the interplay of multiple factors, thereby enriching the theoretical landscape concerning faculty acceptance of intelligent technologies.

References

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), 204-215. https://doi.org/10.1287/isre.9.2.204

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Bao, W., & Wan, Y. (2025). The complex tension of digital intelligence empowerment: The impact of generative AI usage on the professional ecology of Chinese university teachers. *China Electric Education,* (12), 98-107. https://zdjy.cbpt.cnki.net/portal/journal/portal/client/paper/25442f9f5c8cf810ea282cc824cafea0

Bauer, R. A. (1960). Consumer behavior as risk taking. In R. S. Hancock (Ed.), *Dynamic marketing for a changing world* (pp. 389-398). American Marketing Association. https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1409819

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Fei, J., Liu, B., & Dang, T. (2025). Embracing the future: A study on college teachers' adoption intention of teaching AI technologies. *Modern Educational Technology, 35*(5), 32-41.

Gao, H., & Zhang, Y. (2024). Generative AI policies in renowned UK and US universities and their implications. *Modern Educational Technology, 34*(7), 42-50. https://www.researchgate.net/publication/384190700_Generative_Artificial_Intelligence_Policies_of_Famous_Universities_in_Britain_and_the_United_States_and_Their_Implicationsyingmeizheming gaoxiaodeshengchengshirengongzhinengzhengcejiqiqishi

Ge, F., & Liu, Q. (2025). Artificial intelligence empowering university teaching support services: Connotation, dilemma, model and path. *China Electric Education,* (10), 46-54. https://zdjy.cbpt.cnki.net/portal/journal/portal/client/paper/ab52aea341f0539e7687b85260c2c880

Hu, H., & Cao, R. (2024). The connotation interpretation and practical patterns of intelligent education literacy among university teachers: An empirical study based on faculty in Jiangsu and Zhejiang provinces. *Journal of Educational Academic Monthly,* (6), 79-86. https://doi.org/10.16477/j.cnki.issn1674-2311.2024.06.008

Jacoby, J., & Kaplan, L. B. (1972). The components of perceived risk. In M. Venkatesan (Ed.), *Proceedings of the Third Annual Conference of the Association for Consumer Research* (pp. 382-393). Association for Consumer Research. https://www.scirp.org/reference/referencespapers?referenceid=1471959

Jia, L., & Yang, J. (2025). The impact and mechanism of Artificial Intelligence literacy on creative teaching among higher vocational teachers: An empirical analysis based on the Technology Acceptance Model. *Vocational Education Forum, 41*(11), 59-68.

Lan, G., Wei, J., Zhang, Y., Guo, Q., Zhang, W., Kong, X., & Wang, Z. (2021). Future higher education teaching: Macro trends, key technology practices, and future development scenarios–Key points and reflections from the 2021 horizon report (teaching edition). *Open Education Research, 27*(3), 15-28. https://doi.org/10.13966/j.cnki.kfjyyj.2021.03.002

Li, H., & Xue, L. (2024). Strengthening risk management of generative AI in higher education: Basic framework and key initiatives. *Higher Education Research, 45*(2), 31-38. https://xueshu.baidu.com/usercenter/paper/show?paperid=171j04a0mn150v408y6e0js0d7162607

Li, J. (2025). Research on the pathways to enhance digital literacy of university teachers based on Artificial Intelligence applications. *China Higher Education,* (Z3), 48-51.

Li, Y., Sun, L., Jiang, Q., Chen, L., Yang, Y., & Wu, F. (2025). AI literacy and enhancement strategies for university teachers. *Open Education Research,* (1), 23-33.

Li, Y., Zhu, Y., & Zhai, X. (2022). Trends and implications of technology empowering higher education transformation under the impact of the pandemic: A comparative study based on the horizon report 2020-2022. *Modern Educational Technology, 32*(8), 14-25. https://xueshu.baidu.com/usercenter/paper/show?paperid=1r240m20s54u0pg0421g0jg0r2238499

Liu, D. (2019). A review of research on AI-enabled transformation in higher education talent cultivation. *Research on Electro-education, 40*(11), 106-113. https://doi.org/10.13811/j.cnki.eer.2019.11.015

Liu, H., & Yan, M. (2019). Survey and analysis of the intention to use smart teaching tools based on the integrated Technology Acceptance Model. *Higher Education Forum,* (12), 54-59.

Luo, Y., & Zhou, G. (2025). Factors influencing the adoption of generative AI by university teachers: A study based on PLS-SEM and fsQCA methods. *Fudan Education Forum, 23*(4), 58-65. https://doi.org/10.13397/j.cnki.fef.2025.04.016

Mathwick, C., Malhotra, N., & Rigdon, E. (2001). Experiential value: Conceptualization, measurement and application in the catalog and internet shopping environment. *Journal of Retailing, 78*(1), 39-56. https://doi.org/10.1016/S0022-4359(00)00045-2

Ministry of Education of the People's Republic of China. (2020). *A reply to the proposal no. 3961 of the third session of the 13th national people's congress (document no. Jiaogaojianyi [2020] no. 357).* https://www.moe.gov.cn/jyb_xxgk/xxgk_jyta/jyta_gaojiaosi/202011/t20201110_499203.html

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). McGraw-Hill.

Rogers, E. M. (1995). *Diffusion of innovations* (4th ed.). Free Press.

Ryan, R. M., & Deci, E. L. (2000). Self-Determination Theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68-78. https://doi.org/10.1037/0003-066X.55.1.68

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research, 22*(2), 159-170. https://doi.org/10.1016/0148-2963(91)90050-8

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing, 77*(2), 203-220. https://doi.org/10.1016/S0022-4359(01)00041-0

Tang, J., & Dai, L. (2026). The boundaries of AI-assisted teaching: Professional judgment and value commitment of university teachers. *Heilongjiang Higher Education Research, 44*(1), 13-18. https://doi.org/10.19903/j.cnki.CN23-1074/G.2026.01.003

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Wang, L., Wu, Y., & Wang, S. (2025). Research on the training model of university teachers under the background of educational digital transformation. *Educational Theory and Practice, 45*(21), 31-36.

Wei, Z., Hu, X., Lin, D., Liu, Y., & Guo, K. (2025). Action research on university teachers building a TPACK sustainable development community: A path based on practice and reflection. *Research on Electro-education, 46*(3), 102-113. https://doi.org/10.13811/j.cnki.eer.2025.03.014

Xu, Z., & Xu, X. (2025). The dual-effect of generative AI on teaching innovation behaviors of university teachers: The role of efficacy-pressure and cognitive restructuring. *Higher Education Management,* (4), 72-85. https://doi.org/10.13316/j.cnki.jhem.20250606.008

Yi, M. Y., Fiedler, K. D., & Park, J. S. (2006). Understanding the role of individual innovativeness in the acceptance of IT-based innovations: Comparative analyses of models and measures. *Decision Sciences, 37*(3), 393-426. https://doi.org/10.1111/j.1540-5414.2006.00132.x

Zhang, M., & Wang, F. (2025). Applications, risks, challenges, and recommendations of generative AI in higher education. *Contemporary Education Forum,* (5), 23-30. https://doi.org/10.13694/j.cnki.ddjylt.20250707.001

Zhang, X. (2020). Identity crisis and its reconstruction of college teachers in the intelligent era. *Modern Educational Technology, 30*(11), 5-11.

Zhou, H., & Chang, S. (2023). The future landscape, potential risks, and governance of generative AI in higher education. *Modern Educational Management,* (11), 1-12. https://doi.org/10.16697/j.1674-5485.2023.11.001



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