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Article

The Dual Cognitive and Emotional Pathways Linking AI Awareness and Knowledge Sharing Intention: Evidence from Private Higher Education Institutions in China

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Abstract: Purpose: This study seeks to explore how artificial intelligence awareness (AIA) affects the knowledge sharing intention (KSI) of faculty in Chinese private universities via dual cognitive and emotional pathways, while also assessing the moderating role of organisational change adaptability (OCAD) in this relationship, thereby clarifying the dynamics of knowledge behaviour transformation within educational institutions amid technological empowerment. **Design/methodology/approach:** This research utilises a quantitative methodology, gathering data from faculty members of private universities in China using online surveys. A dual-path mechanism model is developed, grounded in the TPB and JD-R frameworks, to examine the influence of AIA on KSI, incorporating OCA as a moderating component. A hierarchical model analysis technique (Model 1–Model 5) is employed, integrating PLS-SEM and OLS regression to validate hypotheses and investigate mediating and moderating effects, therefore systematically elucidating the underlying mechanisms. **Findings:** The results demonstrate that Artificial Intelligence Awareness (AIA) has a significant and beneficial effect on Attitude Towards Knowledge Sharing (ATKS) and Knowledge Sharing Intention (KSI), while also indirectly enhancing KSI by mitigating Emotional Exhaustion (EE). Organisational Change Adaptability (OCA) significantly moderates the association between AIA and ATKS, but does not significantly affect the relationship between AIA and EE. This indicates that educators' understanding of AI influences their desire to share knowledge via cognitive and emotional channels, while their adaptation to organisational change significantly contributes to this dynamic. **Originality/value:** This paper develops a theoretical model that synthesises cognition, attitude, emotion, and organisational regulation at the nexus of AI awareness and information sharing. This study elucidates the impact of AI awareness on knowledge-sharing intentions via cognitive and emotional channels, delineates the moderating effect of organisational change adaptability, and expands the theoretical framework of educational technology adoption and knowledge management. This study offers novel insights into the psychological dynamics of knowledge workers towards rising technology.

Keywords: artificial intelligence awareness; knowledge sharing intention; organizational change adaptability; TPB; JD-R

1. Introdcution

The swift advancement of artificial intelligence (AI) technology is effecting a significant revolution in the

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worldwide education sector [1]. The proliferation of AI has not only revolutionized pedagogical approaches and knowledge management systems but has also significantly influenced the cognitive functions and behavioral patterns of educators, a crucial category of knowledge workers [2]. In higher education, knowledge sharing behavior is considered the fundamental method for enhancing organizational learning, fostering academic innovation, and accumulating knowledge capital [3]. In China's higher education system, the propensity for information sharing among educators in private colleges and universities has historically been somewhat feeble. The "Blue Book on the Development of Private Education in China (2024)" indicates that by the conclusion of 2023, the total number of full-time educators in private colleges and universities in China surpassed 360,000, with more than 60% being young and middle-aged professionals Despite ongoing advocacy for collaboration and resource sharing within organizations, issues such as "closed results", "limited willingness to collaborate", and "inadequate cross-departmental communication" persist, significantly hindering the healthy development of the organizational knowledge ecosystem [4]. In light of the ongoing integration of artificial intelligence into educational and scientific research practices, the cognition and perception of AI by educators are progressively shaping their knowledge-related decision-making [5,6]. Consequently, Artificial Intelligence Awareness (AIA) has emerged as a significant psychological variable that warrants attention.

Contemporary studies on information sharing behavior mostly emphasize external characteristics, including corporate culture, leadership style, and incentive mechanisms [7–9]. Research in education examines the impact of variables such as teachers' professional identity and psychological security on collective intent [10]. Simultaneously, investigations on AI awareness are progressively surfacing, particularly in contexts such as corporate governance and tertiary education. Research indicates that an individual's cognitive characteristics of AI, including usefulness, substitutability, and controllability, and emotional responses such as fear, perceived danger, and exhaustion, can profoundly affect their behavioral intents and work attitudes [11]. C. Li et al. discovered that employees' awareness of AI indirectly influences their work withdrawal behavior via negative rumination and emotional tiredness [12]. Moreover, W. Li et al. discovered that within the teaching demographic, AI teaching expertise and social value cognition positively influence teaching willingness, whereas AI anxiety and perceived role threat impede cognitive engagement [13]. These findings indicate that AI consciousness may serve as a "double-edged sword", capable of fostering positive cognitive intents but also imposing inhibitory consequences via emotional systems. Nevertheless, within the framework of information dissemination, particularly concerning the function of educators in private colleges and universities, the dual trajectory of AI awareness remains inadequately elucidated.

Despite the ongoing expansion of research on information sharing and AI awareness, three substantial research gaps remain. Firstly, regarding theoretical construction, current literature has not integrated AI consciousness into the broader framework of the Theory of Planned Behavior (TPB) to thoroughly elucidate its impact on knowledge sharing intention (KBI) via cognitive attitudes (ATT). Secondly, the explanatory capacity of the emotional trajectory is inadequate. Despite current research associating AI stress with emotional exhaustion (EE) [14], there remains an absence of integration of the JD-R theory to establish a negative pathway of AIA→EE→KBI for emotional exhaustion. Thirdly, regarding context selection, current empirical evidence predominantly examines industry personnel or university researchers [15], with limited studies addressing the function of professors in private universities in China. This group exists in a milieu of significant organizational transformation and intensive resource competition, and their intricate cognitive perspectives on AI may be more polarized. Data from the National Institute of Education Sciences of China (2024) indicates that 67% of educators in private colleges and universities possess ambivalent attitudes towards the implementation of AI, with over 30% expressing concerns that AI may diminish their professional worth. This "cognitive contradiction" requires immediate analysis through rigorous investigation.

This work aims to develop a dual-path mechanism model, with artificial intelligence consciousness (AIA) as the primary independent variable, based on the aforementioned background and identified research needs. The bidirectional influence mechanism on the intention of knowledge sharing (KBI) was elucidated through the cognition-attitude pathway (AIA → ATKS → KBI) in the Theory of Planned Behavior (TPB) and the emotional exhaustion pathway (AIA → EE → KBI) in the Job Demands-Resources (JD-R) theory, thereby uncovering its

"double-edged sword effect." This research presents Organizational Change Adaptability (OCA) as a moderating variable, seeking to examine how individuals' psychological adaptability to organizational change mitigates or exacerbates the influence within the aforementioned connection. Organizational Change Adaptability denotes an individual's capacity for acceptance, flexibility, and reconstruction in response to technological advancements, institutional modifications, and alterations in work methodologies. It is classified as a standard "adaptive psychological resource" [16]. In the context of AI's swift integration into educational environments and the ongoing transformation of teachers' duties, individuals with elevated OCA are more inclined to perceive AI as an opportunity, thereby improving their positive cognitive attitudes and mitigating emotional tiredness. Individuals with a diminished OCA are more prone to feelings of threat, burnout, and behavioral disengagement [17]. Consequently, the incorporation of OCA as a moderating variable not only reflects the moderating mechanism of "resources" on work requirements within the JD-R theory but also offers a novel approach for comprehending how individual differences influence the process of AIA.

This paper's primary theoretical contributions are evident in three aspects: By integrating the Theory of Planned Behavior (TPB) with the Job Demands-Resources Model (JD-R), a dual-path mechanism encompassing cognition, attitude/emotion, and behavior has been established, thereby enhancing the theoretical framework of educational behavior research within the realm of artificial intelligence. This framework elucidates the manner in which artificial intelligence consciousness (AIA) exerts both positive and negative cross-influences on the intention to share knowledge through the dual pathways of knowledge-sharing attitude and emotional exhaustion, thereby deepening the comprehension of the "double-edged sword effect." This study examined the moderating role of Organizational Change Adaptability (OCA) for the first time among educators in private colleges and universities in China, validating its moderating mechanism in the technology adoption process and enhancing the theoretical framework of change adaptability within higher education.

2. Literature Review, Research Framework, and Hypotheses

2.1. Theory

2.1.1. Planned Behavior Theory (TPB)

The Theory of Planned Behavior (TPB) is a social psychology framework established by Ajzen, derived on the Theory of Reasoned Action (TRA) [18]. It is utilized to forecast and elucidate an individual's intentions and actual behaviors inside a certain behavioral setting. The Theory of Planned action posits that an individual's intention to behave is the most accurate predictor of actual action, and this intention is shaped by three fundamental variables: Attitude toward the Behavior, Subjective Norm, and Perceived Behavioral Control.

In knowledge sharing research, the Theory of Planned Behavior (TPB) is extensively utilized to elucidate the correlation between individual intentions and behaviors regarding knowledge sharing [19, 20]. This study employs the Theory of Planned Behavior (TPB) as a theoretical framework, concentrating on the variables of "attitude" and "intention" to elucidate how AI Awareness predicts employees' Knowledge Sharing Intention (KBI) and Knowledge Sharing Behavior by affecting their Attitude towards AI (ATT). This pathway illustrates a cognition-driven affirmative process, highlighting how employees' rational comprehension of AI technology influences their behavioral inclinations.

The versatility of the TPB framework allows for its extension into technology acceptance and organizational behavior study. This study expanded the TPB model by integrating the AI context and including "AI consciousness" as the antecedent variable, so establishing an influence pathway of "cognition-attitude-intention".

2.1.2. Job Demands-Resources Model

The Job Demands-Resources Model (JD-R), introduced by Bakker and Demerouti in 2007 [21], seeks to elucidate the relationship between job burnout and employee motivation across various occupational settings. The JD-R paradigm asserts that all job characteristics may be categorized into two groups: Job Demands and Job Resources. Job needs encompass the physical, psychological, social, or organizational attributes of work that necessitate sustained effort, and overly high job demands frequently result in emotional tiredness. Work

resources assist individuals in attaining their professional objectives and mitigate the adverse effects associated with work demands.

In recent years, the swift integration of artificial intelligence technology within enterprises has increasingly become AI-related work pressure a new "job requirement." Research indicates that AI consciousness can induce anxiety, dread, or uncertainty, adversely affecting employees' emotional well-being [14]. This study develops the JD-R model, integrates AI awareness into the job requirements dimension, and investigates its indirect effect on employees' knowledge sharing behavior through emotional tiredness. Simultaneously, "Organizational Change Adaptability (OCA)" is presented as a moderating variable to investigate its mitigating influence on employees experiencing AI pressure, thereby establishing a detrimental pathway of "AI awareness → emotional exhaustion → knowledge sharing behavior".

This study merged the Theory of Planned Behavior (TPB) and the Job Demands-Resources (JD-R) theory to develop a dual-path mechanism model encompassing cognitive and emotional processes. The Theory of Planned Behavior posits that an individual's actions are primarily shaped by their behavioral attitudes, subjective norms, and perceived behavioral control, highlighting that reasonable expectations govern behavioral intents. The JD-R theory examines emotions and resources, highlighting how the supply and demand of resources in the workplace impact an individual's psychological condition (e. g., emotional weariness) and subsequently influence their behavioral outcomes. This study posits that the Theory of Planned Behavior (TPB) and the Job Demands-Resources (JD-R) theories exhibit theoretical complementarity in elucidating the mechanics of individual behavior: the former underscores cognitive motivation, whereas the latter concentrates on behavioral inhibition resulting from emotional weariness. Collectively, they illustrate the cognitive-emotional composite process of educators' knowledge-sharing behavior within the framework of artificial intelligence. The two theories are relatively independent regarding path assumptions. In practice, an individual's emotional state and cognitive disposition may influence one another. Subsequent studies may investigate the interaction mechanism between the two pathways.

2.2. Artificial Intelligence Awareness, AIA

Artificial intelligence awareness pertains to an individual's understanding and perspective about the advancement of AI technology, its implementation inside businesses, and its possible effects [22]. This idea was originally employed to examine employees' adaptation to technological disruption. As AI progressively integrates into educational practices, instructors' understanding of AI will directly influence their teaching confidence and professional identity [17]. Current studies suggest that increased AI awareness can enhance good cognitive outcomes, such as transformative learning motivation, while also inducing feelings of fear, including loss of control and replacement anxiety, hence exerting a bidirectional impact on employee behavior [14]. Nevertheless, the existing method by which AI consciousness affects knowledge-sharing behavior via cognitive or emotional pathways has not been rigorously evaluated.

2.3. Attitude Toward Knowledge Sharing, ATKS

Knowledge sharing attitude denotes an individual's comprehensive assessment and inclination towards the act of disseminating knowledge, experience, or information [23]. The Theory of Planned Behavior posits that attitude is a fundamental antecedent element affecting behavioral intention. Current study indicates that a favorable disposition towards information sharing can substantially forecast the knowledge sharing behaviors of educators, researchers, and corporate employees [24]. Nonetheless, among swift technology advancements and ambiguous job functions, there remains a deficiency of empirical study about the influence of AI-related cognition on an individual's disposition towards knowledge sharing.

2.4. Emotional Exhaustion, EE

Emotional exhaustion denotes the depletion of energy individuals encounter as a result of prolonged exposure to occupational stress and emotional fatigue. This is a fundamental aspect of burnout [25]. Within the

JD-R theoretical framework, emotional weariness is frequently perceived as an adverse consequence of excessive job expectations, consequently impairing employees' exhibition of positive behaviors [21]. The ambiguity of roles and the learning demands imposed by AI technology may establish new "cognitive job requirements", perhaps leading to teachers' emotional tiredness and diminishing their inclination to share information within the business [26]. Currently, there remains an absence of systematic discourse regarding the integration of emotional tiredness within the framework of AI in knowledge sharing research.

2.5. Knowledge Sharing Intention, KSI

Knowledge sharing intention denotes the propensity of individuals to actively disseminate knowledge in forthcoming organizational contexts [27]. This variable, as the immediate precursor of knowledge sharing behavior, has been extensively utilized in TPB-focused empirical studies. KSI is influenced by cognitive elements like attitude and is also readily affected by factors such as organizational climate and emotional condition [27]. In the context of AI propelling educational revolution, the willingness of instructors to share their pedagogical strategies, experiences with AI, and other knowledge has emerged as a crucial determinant of organizational learning efficacy. Nevertheless, existing pertinent research remains inadequate.

2.6. Organizational Change Adaptability, OCA

Organizational change adaptability denotes an individual's capacity to adjust and psychological resilience in response to institutional, procedural, or technical transformations at the organizational level [28]. Employees exhibiting great adaptability are more inclined to remain actively engaged in transitions and to accept new technology and responsibilities. Research indicates that OCA can predict employees' engagement in change behavior and may mitigate emotional tiredness resulting from change [29]. This work considers OCA a crucial moderating element in the AI awareness influence pathway to investigate its buffering mechanism in cognitive and affective pathways.

2.7. Research Framework

Based on the above two theoretical frameworks, this study constructs an integrated model from a dual-path perspective (as shown in Figure 1):

Cognitive Pathway (TPB): AI Awareness → Attitude (ATKS) → Knowledge Sharing Intention (KBI)

Emotional Pathway (JD-R): AI Awareness → Emotional Exhaustion (EE) → Knowledge Sharing Intent (KBI)

This study identified Organizational Change Adaptability (OCA) as a moderating variable to examine its influence on the "AI awareness-attitude" and "AI awareness-emotional exhaustion" pathways, respectively.

This "double-edged sword" effect approach facilitates a thorough understanding of the cognitive and emotional processes employees undergo while interacting with AI technology, while also elucidating its facilitative and obstructive mechanisms on knowledge-sharing behavior.

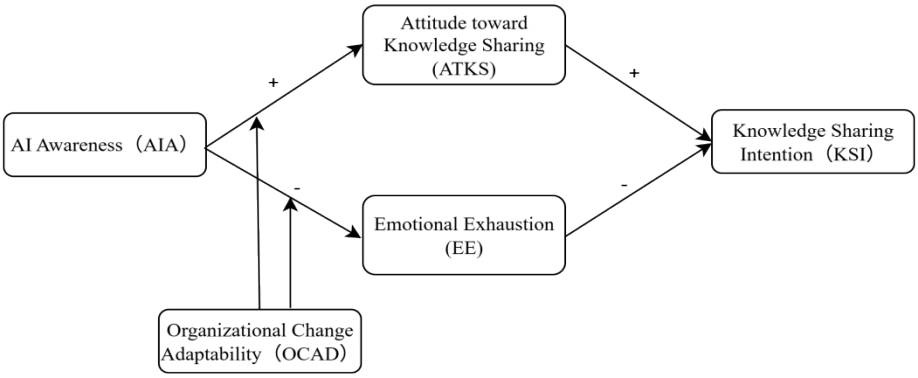

Figure 1. Research Framework.

2.8. Hypotheses

This research is grounded in the Theory of Planned Behavior (TPB) and the Job Demands-Resources Model (JD-R). A dual-way model illustrating the impact of AI Awareness (AIA) on Knowledge Sharing Behavior (KSB) was developed: the TPB path highlights the cognitive motivation mechanism, while the JD-R path elucidates the risk mechanism associated with emotional weariness. Additionally, this study incorporated Organizational Change Adaptability (OCA) as a moderating variable to assess its moderating effect on the two pathways. The particular assumptions are as follows:

2.8.1. Forward Assumptions of the TPB Path

The Theory of Planned conduct (TPB) posits that an individual's cognitive comprehension of a certain conduct might affect the development of their attitude [18]. Prior research indicates that a more extensive technical understanding correlates with a greater propensity among personnel to have a positive attitude towards adaptability [30]. Employees possessing a robust understanding of AI may see that by engaging in information sharing, they can not only adapt to technological transition but also enhance their own skill development and facilitate organizational integration [31]. Consequently, AI awareness will augment employees' acknowledgment and favorable assessment of the significance of knowledge sharing. In conclusion, the subsequent hypotheses are posited:

H1: *There is a positive relationship between artificial intelligence awareness and attitudes toward knowledge sharing.*

Attitude is a fundamental anagen variable in the Theory of Planned conduct (TPB) model, representing an individual's emotional and cognitive assessment of conduct, which directly affects the development of behavioral intention [18]. In knowledge management, researchers typically identify a positive disposition towards knowledge sharing as a significant predictor of the intention to share knowledge [32]. Employees who exhibit a positive disposition towards sharing are typically more inclined to broaden their perspectives and provide assistance proactively in their work, thereby augmenting their desire to share information in the future. In conclusion, the subsequent hypotheses are put forth:

H2: *There is a positive relationship between attitudes toward knowledge sharing and knowledge sharing intention.*

The integration of the Theory of Planned Behavior indicates that awareness of artificial intelligence impacts employees' attitudes towards information sharing, therefore influencing their intentions to share knowledge. Prior research indicates that the augmentation of technology cognition initially affects behavioral intentions by fostering positive attitudes, including self-efficacy and value recognition [33]. In the realm of knowledge sharing, if employees perceive AI as beneficial for organizational learning and collaboration, they will cultivate a more favorable disposition towards sharing, hence increasing their intention to share. Consequently, the disposition towards knowledge sharing may serve as a mediating factor between AI awareness and the intention to share knowledge. In conclusion, the subsequent hypotheses are posited:

H3: *Attitudes toward knowledge sharing serve as a mediating mechanism between artificial intelligence awareness and knowledge sharing intention.*

2.8.2. Negative Assumptions of the JD-R Path

According to the JD-R hypothesis, Job Resources are beneficial elements that can mitigate work-related stress, facilitate goal attainment, and foster personal development. Job Demands: Elements that deplete an individual's energy, resulting in tension and emotional fatigue. Resources can mitigate strain and diminish depletion. Insufficient resources facilitate the experience of Emotional Exhaustion (EE). This article asserts that artificial intelligence consciousness is a resource capable of alleviating stress. The cognitive proficiency of employees about artificial intelligence might be considered a form of cognitive resource. As employees gain comprehension of AI principles, developmental trends, and organizational applications, their psychological stress regarding ambiguity and potential disruptions diminishes, therefore lowering the danger of emotional tiredness. Consequently, AI consciousness exhibits a detrimental predictive influence on emotional weariness. In

conclusion, the subsequent hypotheses are put forth:

H4: *There is a negative relationship between artificial intelligence awareness and employees' emotional exhaustion.*

The JD-R theory posits that emotional weariness in employees leads to a decrease in their job motivation, prompting a tendency towards task reduction and energy conservation [34]. Knowledge sharing is an inherently voluntary and selfless act. When employees' emotional resources are significantly exhausted, sustaining enthusiasm for open collaboration becomes challenging. Empirical research has demonstrated a significant correlation between emotional weariness and knowledge concealment, as well as adverse collaborative behaviors [35]. Consequently, emotional tiredness might considerably diminish employees' willingness to share expertise. In conclusion, the subsequent hypotheses are put forth:

H5: *There is a negative relationship between emotional exhaustion and the intention to share knowledge.*

While artificial intelligence consciousness motivates adaptive behavior, it may also induce technical worry and discomfort, resulting in emotional fatigue. Prior research indicates that employees who feel a lack of control over technological changes are susceptible to emotional reactions, including cognitive overload and work-related anxiety, which subsequently diminishes their inclination to engage in organizational behavior [22]. This study posits that emotional tiredness, characterized as a detrimental condition of psychological resource depletion, may moderate the adverse impact of AI consciousness on the will to share information. In conclusion, the subsequent hypotheses are put forth:

H6: *Emotional exhaustion serves as a mediating mechanism between artificial intelligence awareness and knowledge sharing intention.*

2.8.3. Hypothesis of Moderating Effects

Organizational Change Adaptability (OCAD) is typically characterized as the psychological flexibility, cognitive adjustment capacity, and behavioral coping skills exhibited by an individual in response to change scenarios, such as technological advancements or structural modifications within an organization [28]. In the context of escalating technological innovation, particularly with the emergence of disruptive technologies like artificial intelligence infiltrating organizational operations and job structures, employees' adaptability to change is considered a crucial moderating variable for managing stressors such as technical job demands and role ambiguity [36].

Prior research indicates that employees exhibiting greater adaptability are more likely to perceive organizational change as a growth opportunity, viewing it as a chance for skill enhancement and career advancement rather than a source of threat [37]. When faced with work redistribution or process automation changes initiated by artificial intelligence, individuals are more inclined to develop a positive cognitive response, hence enhancing psychological resources such as self-efficacy and technological confidence. Consequently, employees who exhibit high adaptability to change are more inclined to concentrate on the prospective advantages, such as enhanced efficiency and collaborative ease, associated with artificial intelligence-related content, thereby fostering a more positive disposition towards knowledge-sharing behavior. In contrast, employees exhibiting weaker adaptability may perceive a threat stemming from cognitive rigidity and resistance to change, hence diminishing the likelihood of fostering a positive attitude towards AI consciousness [38].

In conclusion, adaptability to organizational change not only signifies employees' regulatory resources in response to environmental uncertainties but may also affect their processing patterns during the transformation of technical cognitive variables, such as AI awareness, into behavioral attitudes. Consequently, this study proposes the following theories:

H7: *Organizational change adaptability enhances the effect of artificial intelligence awareness on attitudes toward knowledge sharing.*

In the context of the extensive implementation of artificial intelligence and the consequent restructuring of employment, employees may perceive AI as a threat, experience role ambiguity, and encounter task complexity,

leading to emotional weariness [14]. Employees exhibiting strong adaptability to change often perceive AI as a chance for skill enhancement and efficiency optimization, embracing "challenging re-cognition", which mitigates their unfavorable perceptions of AI and diminishes the likelihood of burnout [39]. Conversely, personnel with low adaptability tend to perceive AI as an uncontrollable menace and lack adequate regulatory resources, resulting in heightened emotional tiredness [34].

In conclusion, adaptation to organizational change may modulate the extent of AI awareness's effect on emotional weariness by shaping employees' subjective assessment of the technological transformations associated with AI. Consequently, the subsequent theories are proposed:

H8: *Organizational change adaptability weakens the relationship between low artificial intelligence awareness and increased emotional exhaustion.*

3. Methodology

3.1. Research Design

This study employs a quantitative research methodology and gathers data via a cross-sectional questionnaire survey, with the objective of examining the joint influence of AI Awareness (AIA) on teachers' knowledge sharing intention (KSI) through both the cognitive pathway (Knowledge Sharing Attitude, ATKS) and the emotional pathway (Emotional Exhaustion, EE). Additionally, investigate the moderating function of Organizational Change Adaptability (OCA).

3.2. Sample and Data Collection

This study aims to investigate the impact of Artificial Intelligence Awareness (AIA) on the Knowledge Sharing Intention (KSI) of knowledge workers via cognitive and emotional pathways, focusing on a representative sample of teachers from private undergraduate institutions in mainland China.

This research employed the simple random sampling technique. The questionnaires were delivered anonymously via the web platform. The poll encompassed fundamental characteristics including awareness of artificial intelligence, attitudes towards information sharing, emotional weariness, intentions toward knowledge sharing, and adaptation to organizational change. This study integrates many control variables into the structural model to improve its explanatory power and estimation accuracy.

This study specifically accounted for the following demographic variables: Gender (1 = male, 2 = female), age (1 = 21–30 years, 2 = 31–40 years, 3 = 41–50 years, 4 = 51–60 years, 5 = over 60 years), educational attainment (1 = bachelor's degree, 2 = master's degree, 3 = doctorate), occupation type (1 = administrative staff, 2 = full-time educators), and years of professional experience (1 = 5 years or less, 2 = 6–10 years, 3 = 11–15 years, 4 = 16–20 years, 5 = more than 20 years). The aforementioned variables may influence employees' views towards AI, emotional tiredness, and service innovation behaviors, and will therefore be controlled in following analyses. This study also accounted for variations in organizational contexts regarding the application of artificial intelligence, as these may influence employees' cognitive and behavioral responses. It controlled for the extent of AI involvement in roles (1 = minimal AI application, 5 = heavily reliant on AI support) to more precisely illustrate the impact of AI awareness on employees' cognitive and behavioral mechanisms.

Data gathering occurred from May to June 2025. A total of 473 questionnaires were disseminated, and 391 valid responses were obtained, resulting in an effective recovery rate of 82.6%. To uphold research ethics and data confidentiality, all questionnaires include an explanation of the research purpose, a statement of voluntary participation, and a promise to data anonymity at the outset. All participants engaged in this study with informed consent to guarantee the legality and scientific integrity of the data sources. The participants are encapsulated in Table 1.

Table 1. Demographic Information.

Feature	Category	Quantity	Percentage
Gender	Male	191	48.80%
	Female	200	51.20%
Age	21–30	81	20.30%
	31–40	79	19.80%
	41–50	77	19.30%
	51–60	87	21.80%
	Over 60	67	16.80%
Position	Administrative staff	195	49.40%
	Full-time teacher	196	49.60%
Working life	5 years or less	74	18.60%
	6–10 years	83	20.90%
	11–15 years	77	19.40%
	16–20 years	75	18.90%
	More than 20 years	82	20.60%
Educational level	Bachelor	132	33.30%
	Master	144	36.40%
	PhD	115	29.20%
AI Involvement	Never used	77	19.69%
	Try using it occasionally (once a month or less)	86	21.99%
	Sometimes used (1–2 times a week)	65	16.62%
	Frequently used (almost every day)	83	21.23%
	Used very frequently (multiple times a day and integrated into the teaching/ research process)	80	20.46%

3.3. Measurement Instruments

This study's primary measuring variables are: Artificial Intelligence Awareness (AIA), Attitude toward Knowledge Sharing (ATKS), Emotional Exhaustion (EE), Organizational Change Adaptability (OCAD), and Knowledge Sharing Intention (KSI). All scales originate from widely acknowledged mature measurement instruments, possessing a robust theoretical framework and assured reliability and validity. To guarantee measurement compatibility and semantic equivalency, the study team conducted multilingual translation, expert review, and pre-testing processes in the initial phase.

This study utilized the condensed variant of the Artificial Intelligence Literacy Questionnaire (AILQ) created by Ng [40] to assess teachers' cognitive understanding of artificial intelligence. This scale was initially published in the British Journal of Educational Technology. It possesses a straightforward structure and a robust theoretical foundation, and has been extensively utilized in the research contexts of educational technology and AI cognition. This study implemented slight linguistic modifications to several items in accordance with the context of university educators. Ultimately, the subsequent five questions were preserved to assess the degree of AI consciousness as a cognitive resource.

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artificial intelligence cognition. This study implemented slight linguistic modifications to several items in accordance with the context of university educators. Ultimately, the subsequent five questions were preserved to assess the degree of AI consciousness as a cognitive resource.

All characteristics were assessed on a five-point Likert scale (1 = "strongly disagree", 5 = "strongly agree"). Table 2 will present the metrics, including factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE), of the scale.

Table 2. Constructs, items, and reliability.

Constructs	Items	Statements	Item Loading	Cronbach Alpha	AVE	CR	CA
Knowledge Sharing Intention, KSI				0.864	0.711	0.865	0.908
(Marimuthu) [3]	KSI1	1. I intend to share knowledge with my colleagues more frequently in the future.	0.838				
	KSI2	2. I will try to share knowledge with my colleagues.	0.847				
	KSI3	3. I will always make an effort to share knowledge with my colleagues.	0.832				
	KSI4	4. I intend to share knowledge with colleagues who ask.	0.855				
Artificial Intelligence Awareness, AIA				0.854	0.696	0.858	0.902
(Ng) [40]	AIA1	I understand the main functions of AI and its potential uses in education.	0.867				
	AIA2	I can identify actual use cases of AI in teaching, research, or administration.	0.8				
	AIA3	I believe I have the ability to learn and use AI tools to enhance my work efficiency.	0.832				
	AIA4	I am familiar with some mainstream AI tools or platforms and am willing to try them.	0.838				
Attitude toward Knowledge Sharing, ATKS				0.888	0.691	0.889	0.918
(Bock et al.) [23]	ATKS1	1. My knowledge sharing with other organizational members is good.	0.845				
	ATKS2	2. My knowledge sharing with other organizational members is harmful.	0.81				
	ATKS3	3. My knowledge sharing with other organizational members is an enjoyable experience.	0.828				
	ATKS4	4. My knowledge sharing with other organizational members is valuable to me.	0.846				
	ATKS5	5. My knowledge sharing with other organizational members is a wise move.	0.825				
Emotional Exhaustion, EE				0.781	0.695	0.783	0.873
(Watkins et al.) [41]	EE1	1. I feel emotionally drained from my work.	0.765				
	EE2	2. I feel burned out from my work.	0.816				
	EE3	3. I feel exhausted when I think about having to face another day on the job.	0.81				
	EE4	4. I feel mentally fatigued after a long day of work.	0.534				
Organizational Change Adaptability, OCAD				0.842	0.678	0.844	0.894
(Oreg) [28]	OCAD1	1. I'll be better off after the move, in comparison with my situation before.	0.825				

Table 2. Cont.

Constructs	Items	Statements	Item Loading	Cronbach Alpha	AVE	CR	CA
	OCAD2	2.I think it is good that we're going through this move.	0.799				
	OCAD3	3.The move will do us all good.	0.848				
	OCAD4	4. I don't really think the move was necessary.	0.82				

3.4. Data Analysis Strategy

This work utilizes diverse statistical analysis methodologies to enhance the robustness of model estimate and the depth of result interpretation. Integrating Partial Least Squares Structural Equation Modeling (PLS-SEM), Ordinary Least Squares Regression (OLS), and Bootstrapping The system analyzes the direct impacts, mediating mechanisms, and moderating effects among different factors.

Initially, during the PLS-SEM analysis phase, the research evaluated the measurement model and the structural model utilizing SmartPLS 4.0 software. The assessment of the measuring model includes internal consistency reliability (Cronbach's α, composite reliability CR), convergent validity (standardized factor loading, average variance extracted AVE), and discriminant validity (Fornell-Larcker criterion and HTMT value). The assessment of the structural model encompasses the path coefficient (β), coefficient of determination (R^2), effect size (f^2), and predictive relevance index (Q^2). The importance of the path coefficient is determined using the Bootstrapping method with 5000 resamples.

Secondly, to augment the rigor and external comparability of the findings, the study utilized OLS multiple linear regression analysis to validate the critical path relationships (e.g., AIA → ATKS → KSI) and moderating effects (e.g., AIA × OCAD → ATKS), subsequently cross-verifying them with the PLS results. The marginal impacts and statistical significance of moderating variables are thoroughly examined by hierarchical regression and interaction term analysis.

Additionally, to mitigate potential Common Method Bias (CMB), the study implemented anonymous responses and a semantic interval design during data collection, and employed the Harman single-factor test in the statistical analysis phase to perform principal component analysis on all measurement items. The analysis indicates that the primary factor accounts for less than 40% of the overall variation, suggesting the absence of a significant common technique bias issue in this study.

This study thoroughly investigated the mechanism of AI consciousness on knowledge sharing intention by integrating PLS-SEM, the bootstrapping method, and OLS regression, considering both cognitive and emotional pathways, along with the moderating effect of organizational change adaptability, thereby augmenting the rigor and theoretical explanatory power of model estimation.

4. Results

4.1. Descriptive Statistics

This study collected 391 valid questionnaires from teachers and administrative personnel of various genders, ages, positions, teaching experiences, educational credentials, and levels of artificial intelligence utilization in private colleges and universities. The sample's distribution is fairly balanced and possesses a degree of representativeness.

The gender distribution comprised 48.80% (n = 191) male and 51.20% (n = 200) female, with proportions staying approximately equal. The age distribution of the samples is predominantly between 21 and 60 years. The age groups 51–60 years (21.80%) and 21–30 years (20.30%) exhibit the highest proportions, succeeded by 31–40 years (19.80%) and 41–50 years (19.30%). The percentage of individuals aged over 60 is 16.80%.

The ratio of administrative staff to full-time teachers is nearly identical, at 49.40% and 49.60%, respectively. The percentage of those with 6 to 10 years of experience (20.90%) and those with over 20 years (20.60%) is marginally greater, indicating a rather balanced distribution of experience. The highest proportion of educational

attainment is among master's degree holders at 36.40%, followed by bachelor's degree holders at 33.30%, and doctoral degree holders at 29.20%, indicating a significantly elevated overall educational level of the sample.

Regarding AI utilization, 20.46% of respondents indicated they employed AI tools (such as ChatGPT and intelligent teaching systems) "very frequently", while 21.23% reported using them "often." Over 40% of the participants exhibit a significant reliance on AI technology in their regular tasks. Conversely, the percentage of "never used" was 19.69%, suggesting that despite a generally elevated application level, considerable individual disparities remained.

The study's samples exhibit commendable demographic representation regarding gender, age, position, and technology utilization, so establishing a robust basis for further investigation.

4.2. Measurement Model

This study employed the partial least squares structural equation model (PLS-SEM) to assess the measurement model, focusing on three aspects: internal consistency reliability, convergence validity, and discriminant validity.

Table 2 displays the Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE) for all latent variables. The findings indicated that the Cronbach's α for each construct exceeded 0.70, and the composite reliability values surpassed 0.80, signifying that each variable exhibited strong internal consistency [42]. The α values for Knowledge Sharing Intention (KSI) was 0.864, AI awareness was 0.854, Knowledge Sharing Attitude (ATKS) was 0.888, emotional fatigue (EE) was 0.781, and organizational change adaptability (OCAD) was 0.842, all satisfying the reliability standards.

All variable factor loadings exceeded 0.7 and were statistically significant ($p < 0.001$). The loadings of the majority of measurement items for ATKS, KSI, AIA, and OCAD ranged from 0.80 to 0.86, signifying that each index possesses substantial explanatory ability for latent variables. The Average Variance Extracted (AVE) for all variables surpassed the 0.50 threshold, with KSI at 0.711, AIA at 0.696, ATKS at 0.691, EE at 0.695, and OCAD at 0.678. This signifies that the model possesses strong convergent validity.

In the Emotional Exhaustion (EE) scale, the initial fourth factor loading was merely 0.534, falling short of the suggested threshold of 0.70. Consequently, this item was excluded in the subsequent analysis to enhance the measurement quality and overall validity of the model.

4.3. Structural Equation Modeling

This study employed SmartPLS 4.0 software for partial least squares structural equation modeling (PLS-SEM) to examine the causal relationships among latent variables in the theoretical model, utilizing the Bootstrap method (n = 5000) to estimate path coefficients and their significance levels.

Initially, the comprehensive fit of the model was assessed. The results indicated that the SRMR (Standardized Root Mean Square Residual) value was 0.057, below the suggested threshold of 0.08, signifying a strong model fit. The variance inflation factor (VIF) for each variable varied between 1.03 and 2.17, indicating the absence of significant multicollinearity issues [42].

This research additionally evaluated discriminant validity using the Fornell-Larcker criterion and the HTMT (Heterotrait-Monotrait) ratio.

The Fornell-Larcker test (Table 3) demonstrates that the square roots of the Average Variance Extracted (AVE) for all latent variables, shown by the diagonal values, exceed their correlation coefficients with other variables, indicated by the non-diagonal values, so confirming the model's robust discriminant validity. The square root of the AVE for KSI is 0.843, surpassing its correlation coefficients with AIA (0.525), ATKS (0.593), EE (-0.484), and OCAD (0.511).

Moreover, according to Table 4, the HTMT values were significantly below the discriminant threshold of 0.85, hence reinforcing the robust discriminant validity among the latent variables. The HTMT values are as follows: AIA and KSI at 0.61, ATKS and KSI at 0.676, and OCAD and KSI at 0.597, all falling within an acceptable range. The HTMT of OCAD × AIA and other variables reached 0.179 (in comparison to AIA), much below any threshold of concern.

Table 3. Fornell-Larker criterion.

	AIA	ATKS	EE	KSI	OCAD
AIA	0.834				
ATKS	0.51	0.831			
EE	−0.525	−0.466	0.834		
KSI	0.525	0.593	−0.484	0.843	
OCAD	0.504	0.504	−0.484	0.511	0.823

Table 4. Heterotrait-monotrait (HTMT) ratios.

	AIA	ATKS	EE	KSI	OCAD	OCAD × AIA
AIA						
ATKS	0.584					
EE	0.64	0.559				
KSI	0.61	0.676	0.589			
OCAD	0.592	0.58	0.596	0.597		
OCAD × AIA	0.179	0.038	0.066	0.026	0.164	

4.4. Model Fit Assessment

4.4.1. Model 1

Model 1 (Table 5) examines the direct impact of AI awareness (AIA) on attitudes towards knowledge sharing (ATKS), emotional exhaustion (EE), and knowledge skills (KSI), as well as the indirect effects of attitudes towards knowledge sharing and emotional fatigue on knowledge skills. The results demonstrate that AI awareness markedly affects attitudes towards knowledge sharing ($\beta = 0.510$, $p < 0.01$), emotional fatigue ($\beta = -0.526$, $p < 0.01$), and knowledge competencies ($\beta = 0.228$, $p < 0.01$). The influence of knowledge sharing attitude ($\beta = 0.387$, $p < 0.01$) and emotional exhaustion ($\beta = -0.178$, $p < 0.01$) on knowledge skills was substantial. The educational degree shows a strong negative influence on knowledge and talents ($\beta = -0.077$, $p = 0.046$). The model fitting index reveals $R^2 = 0.453$, modified $R^2 = 0.44$, a maximum VIF of 2.275, and an SRMR of 0.038, indicating a satisfactory model fit. The findings corroborate the hypothesis that AI awareness directly effects attitudes towards knowledge sharing and emotional tiredness, while indirectly influencing knowledge skills through these mediating variables.

4.4.2. Model 2

Model 2 verified the mediating role of emotional fatigue and knowledge-sharing attitudes between AI awareness and knowledge skills. AI awareness strongly influences attitudes toward information sharing ($\beta = 0.510$, $p < 0.001$) and emotional exhaustion ($\beta = -0.526$, $p < 0.001$). Furthermore, the indirect influence of AI consciousness on knowledge and skills is significant, as evidenced by emotional fatigue ($\beta = 0.138$, $p < 0.01$) and a propensity for knowledge sharing ($\beta = 0.238$, $p < 0.01$). The direct impact of AI awareness on knowledge and abilities is not substantial, as indicated by direct route analysis ($\beta = 0.059$, $p = 0.134$). The maximum VIF is 2.275, the adjusted R^2 is 0.409, the SRMR is 0.038, and the model fit index is $R^2 = 0.421$. These findings support the notion that emotional fatigue and attitudes toward information sharing serve as mediators between AI awareness and knowledge skills.

4.4.3. Model 3

Model 3 looked at how organizational culture fitness (OCAD) affects the link between knowledge-sharing attitudes and AI awareness. The results confirmed the presence of a moderating impact, as the interaction term

AIA × OCAD significantly influenced the attitude toward information sharing (β = 0.117, p = 0.016). The model fitting index exhibits R^2 = 0.354, adjusted R^2 = 0.349, a maximum VIF of 2.26, and an SRMR of 0.053. These findings underscore the significance of organizational culture alignment in the relationship between knowledge-sharing attitudes and AI awareness.

4.4.4. Model 4

Model 4 examined the impact of organizational culture alignment on the relationship between emotional exhaustion and AI awareness. The findings refuted the possibility of a moderating effect and demonstrated that the interaction term AIA × OCAD had no discernible impact on emotional weariness (β = −0.055, p = 0.219). The maximal VIF is 2.243, the adjusted R^2 is 0.388, the SRMR is 0.061, and the model fit index is R^2 = 0.343. The results indicate that the relationship between emotional fatigue and AI awareness is not much influenced by the compatibility of company culture.

4.4.5. Model 5

Model 5 concurrently examines the primary effect, mediating effect, and moderating effect as it is a comprehensive pathway model. The research reveals substantial direct impacts of emotional tiredness (EE) (β = −0.383, p < 0.001), knowledge sharing intention (KSI) (β = 0.228, p < 0.001), and AI awareness (AIA) on knowledge sharing attitude (ATKS) (β = 0.356, p < 0.001). ATKS exhibited a considerable positive predictive influence on KSI (β = 0.387, p < 0.001), whereas EE demonstrated a notable negative predictive influence (β = −0.178, p = 0.001). AIA's influence on KSI is mediated by both ATKS and EE.

The indirect impacts in the "AI awareness → ATKS → KSI" pathway are considerably enhanced by Organizational Change Adaptability (OCAD) (β = 0.046, p = 0.025). This indicates that when educators are more adept at adjusting to changes, awareness of AI is more likely to augment the intention to share information by enhancing attitudes toward sharing. However, OCAD's regulatory influence on the "AI consciousness → EE → KSI" pathway was negligible (β = 0.010, p = 0.303), indicating minimal impact on the emotional trajectory.

The explanatory variance of KSI, as indicated by model fitting metrics, was R^2 = 0.453, and after modification, R^2 = 0.441. The structural equation model demonstrated an excellent fit, evidenced by a root mean square residual (SRMR) of 0.039, much below the recommended criterion of 0.08. Multicollinearity is addressed when the variance inflation factor (VIF) for each path attains a maximum value of 2.275.

Organizational change adaptability, as a significant individual characteristic variable in the cognitive-attitude framework, exerts a moderating influence on the intent of information sharing, as evidenced by the aforementioned results, which also corroborate the direct and indirect pathways of AI awareness.

After a meticulous analysis of the five distinct models, a complete model was constructed that integrated the critical pathways—the main effect, mediating effect, and moderating effect—identified in the preceding models. Partial Least Squares (PLS) is employed to evaluate this comprehensive model to determine its overall fit and robustness, while also providing a more nuanced perspective on the relationships among various variables. The results of the comprehensive model further substantiate the impact of AI consciousness on knowledge and skills through attitudes towards information sharing and emotional fatigue. These conclusions are fundamentally consistent with the analytical outcomes of the prior five models. The correlation between AI awareness and attitudes toward information sharing is notably influenced by the compatibility of company culture, emphasizing the importance of considering organizational culture fitness when implementing AI technologies (Figure 2).

Additionally, this model's fitting index displays R^2 = 0.421 and modified R^2 = 0.410, suggesting that it can account for almost 41% of the variability in knowledge and skill, which is in line with earlier models' explanatory power. The model fit well and there was no significant multicollinearity issue, as evidenced by the maximum variance inflation factor (VIF) of 2.275 and the standardized root mean square residual (SRMR) of 0.056.

Table 5. Structural model and model fit.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
AIA ATKS	0.51 (0.039) **	0.51 (0.039) **	0.356 (0.357) **		0.356 (0.051) **
ATSK-KSI	0.387 (0.052) **	0.466 (0.046) **			0.387 (0.052) **
AIA-KSI	0.228 (0.055) **	0.059 (0.04) *			0.228 (0.055) **
AIA-EE	−0.526 (0.039) **	−0.526 (0.039) **		−0.384 (0.052) **	−0.383 (0.052) **
EE-KSI	−0.178 (0.052) **	−0.263 (0.045) **			−0.178 (0.052) **
AIA-ATKS-KSI		0.238 (0.032) **			0.138 (0.025) **
AIA-EE-KSI		0.138 (0.026) **			0.068 (0.020) **
AIA × OCAD-ATKS			0.117 (0.049) *		0.046 (0.02) *
AIA × OCAD → EE				−0.055 (0.045) ns	0.01 (0.009) ns
Gender	−0.016 ns	−0.007 ns			−0.016 ns
Age	−0.051 ns	−0.063 ns			0.051 ns
Position	0.021 ns	−0.005 ns			0.021 ns
Working life	0.021 ns	0.027 ns			0.021 ns
Educational	−0.077 *	−0.07 ns			−0.077 *
AI_Involvement	0.054 ns	0.059 ns			0.054 ns
R^2 (KSI)	0.453	0.421	0.354	0.343	0.453
Adj. R^2	0.44	0.409	0.349	0.388	0.441
VIF (Max)	2.275	2.275	2.26	2.243	2.275
SRMR	0.038	0.038	0.053	0.061	0.039

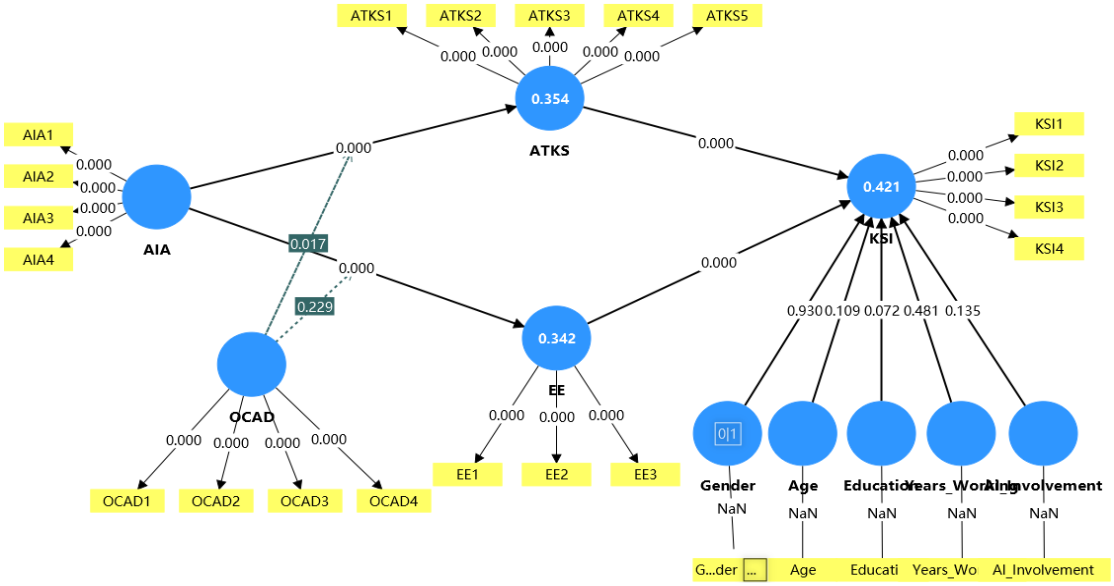

Figure 2. Structural Model Results of the Integrated Model.

5. Discussion & Conclusion

5.1. Discussion

This article primarily examines the mechanism via which university professors disseminate knowledge inside an artificial intelligence context. To comprehensively investigate the impact of artificial intelligence consciousness (AIA) on knowledge sharing intention (KSI) via knowledge sharing attitude (ATKS) and emotional exhaustion (EE), five structural models were constructed and validated utilizing PLS-SEM. Furthermore, organizational change adaptability (OCAD) exerts a moderating effect within this system. The

subsequent are the principal research findings:

First, KSI is significantly positively predicted by AIA (β = 0.228, $p < 0.001$), suggesting that instructors' favorable perceptions of AI technology encourage them to share their knowledge. This finding emphasizes how important AI awareness is as a psychological prepositional variable in fostering the flow of teachers' knowledge as education undergoes a digital transition.

The study established that AIA exerts two indirect effects on KSI: firstly, it enhances KSI by augmenting ATKS (AIA → ATKS: β = 0.354; ATKS → KSI: β = 0.387, both $p < 0.001$); secondly, it further elevates KSI by diminishing EE (AIA → EE: β = −0.342; EE → KSI: β = −0.178, $p = 0.001$). The results of the previously indicated mediating pathway indicate that awareness of AI can enhance cognitive attitudes and diminish emotional fatigue, subsequently affecting the intention to exchange knowledge reciprocally.

Thirdly, the study of moderating effects demonstrates that OCAD has a substantial positive moderating function in the "AIA → ATKS" path (β = 0.046, $p = 0.025$). The beneficial impact of AI awareness on instructors' attitudes toward information sharing is amplified when they exhibit high adaptability. This research indicates that an individual's psychological flexibility in response to organizational change significantly enhances the conversion of their technological knowledge into a willingness to share.

OCAD exhibits a rather modest intervention effect on the emotional pathway, evidenced by its non-significant regulatory impact on the "AIA → EE" pathway (β = 0.010, $p = 0.303$). This study suggests that whereas shift adaptation has a limited impact on emotion regulation, it significantly affects the attitude pathway.

Furthermore, only "educational level" exhibited a significant negative predictive association with KSI (β = −0.109, $p < 0.05$), as per the analysis of control variables. This indicates potential structural disparities in instructors' desire to disseminate knowledge across educational tiers, which educational administrators should consider.

In conclusion, a robust model delineating the "cognitive-attitude/emotion-behavior-regulation" pathway has been formulated and validated through research, emphasizing the dual psychological mechanisms by which AI consciousness influences knowledge-sharing intentions and the significant role of organizational adaptability in enhancing these mechanisms. This conclusion not only broadens the multidisciplinary perspective of research on artificial intelligence and educational behavior but also provides theoretical foundations and valuable motivation for behavioral incentives and psychological interventions in the advancement of educational technology.

5.2. Theoretical Contributions

The theoretical model that synthesized cognition, attitude, emotion, and organizational regulating processes yielded three notable theoretical advances in the interdisciplinary examination of artificial intelligence awareness and knowledge sharing behavior.

This study expands the behavioral consequence framework of artificial intelligence awareness inside the realms of behavioral research and educational management. In contrast to prior studies that focused on the performance or functionality of AI technologies [43, 44]. This study elucidated the mechanism of the "AI cognition-behavioral intention" pathway within educational human resource management, employing university educators as research subjects to systematically examine how their subjective cognition of AI (AIA) affects their knowledge sharing intention (KSI). This discovery enhances the theoretical framework of AI awareness as a psychological construct and provides empirical data for examining the behavioral implications of technology cognition in educational contexts.

This study developed and validated a "dual-path mediation model" by integrating the "cognitive-emotion-behavior" (JD-R path) and the "cognitive-attitude-behavior" (TPB path) into a unified framework, elucidating the mechanism-level positive and negative bidirectional influence of AI consciousness on behavioral intention. Research indicates that understanding of AI might mitigate emotional fatigue and foster a positive disposition towards information sharing, collectively influencing the intention to disseminate knowledge. This mechanism integration fosters the cohesive advancement of cognitive psychology and information technology theory within education by expanding the applicability of Ajzen's planned behavior theory emotion regulation model, while also enhancing the theoretical comprehension of emotional and attitudinal variables in the context of AI technology [18].

Thirdly, our work established that flexibility to organizational change serves a critical moderating function within the context of AI. The study's findings indicate that, by regulating the mediating pathway, OCAD not only positively moderates the influence of AI awareness on attitudes but also enhances the overall effect of AI consciousness on the intention to disseminate knowledge. This discovery provides new evidence for the amalgamation of occupational adaptability and technology adoption theories within transformational organizations by clarifying how an individual's psychological preparedness for organizational change influences their behavioral performance and reaction to emerging technologies.

This study has established a four-layer path model of "cognition-attitude/emotion-behavior-regulation" and has created a systematic theoretical framework connecting AI awareness, information-sharing behavior, and organizational psychological regulatory mechanisms. It provides a novel academic perspective for understanding the psychological mechanisms of knowledge workers affected by advancing technologies, while also augmenting the theoretical framework of educational technology adoption and knowledge management.

5.3. Practical Implications

In order to give colleges and universities empirical support and useful avenues for fostering the digital transformation of teachers and the development of organizational knowledge ecosystems, this paper makes the following four specific and operational management recommendations based on a methodical analysis of the knowledge sharing behavior mechanism of teachers in private colleges and universities in China against the backdrop of artificial intelligence:

(1) Enhance instructors' understanding of AI and promote knowledge sharing and creative awareness.

Research indicates that educators knowledgeable about artificial intelligence (AIA) exhibit a much greater intention to disseminate knowledge (KSI) and are indirectly influenced by it via a dual mechanism of emotional alleviation and an affirmative disposition. To meet the genuine teaching, research, and development requirements of educators, private colleges and universities ought to establish a cognitive empowerment framework for AI grounded in "task-oriented + value guidance" and develop modular training programs encompassing "AI teaching design training", "research tool empowerment", and "industry case guidance." Enhancing teachers' genuine understanding of AI's effectiveness can effectively foster their faith in technology and willingness to collaborate and share.

(2) Precisely ascertain the psychological condition of educators and implement a technique for emotional regulation and attitude guidance.

Research indicates that attitudes towards knowledge sharing (ATKS) and emotional tiredness (EE) significantly mediate the relationship between AIA and KSI. Given that certain educators experience role anxiety, challenges in technology adaptation, or insufficient recognition of their contributions in the promotion of AI, educational institutions ought to implement a layered support system tailored to the generational traits and developmental phases of instructors. It is proposed that a "AI Application Peer Mutual Assistance Group" and a "Teacher Emotional Health Support Platform" be created, alongside regular psychological adjustment services, to assist teachers in alleviating anxiety and restoring a pleasant professional demeanor.

(3) Augment the adaptability of organizational change and improve the efficacy of behavioral transformation regarding AI awareness.

Empirical findings indicate that organizational change adaptability (OCAD) considerably moderates the influence of AIA on ATKS and amplifies instructors' propensity to convert AI cognition into collective attitudes. Private schools and universities can leverage their flexible structures to improve organizational adaptation in terms of culture, processes, and resources. Proposed strategies encompass the creation of a "AI Teaching Innovation Fund", the implementation of a teacher-driven "trial and error pilot mechanism", and the reformation of the performance evaluation system to encourage educators to proactively investigate and autonomously adapt to technological advancements, thus fostering a supportive and growth-oriented

organizational environment.

(4) Implement a "AI+ teacher co-creation" framework to mitigate technology apprehension and identity dilemmas.

Control variable analysis indicated that highly educated teachers had reduced information sharing intentions, implying they harbor implicit reservations regarding the "blurring of professional boundaries" induced by AI. To mitigate teachers' identity concern, private colleges and universities should integrate the principle of co-creation in the implementation of AI systems and promote instructors' active involvement in the design of AI scenarios and evaluation feedback. A mechanism for co-creating an AI application pilot, a mutual aid group for cross-age technology adaptation, and a participatory feedback mechanism for teachers can be established to enhance teachers' sense of agency and belonging, thereby fostering a symbiotic relationship between AI empowerment and teachers' professional development.

5.4. Limitations and Future Research

This study possesses certain limitations that can be addressed in future research.

The research sample was confined to select university instructors in China. The regional and professional attributes of the sample may influence external validity. Future study may be expanded to encompass additional countries and educational tiers (including elementary and secondary school educators or vocational training cohorts) to ascertain the model's universality.

Secondly, the research used cross-sectional data, which complicates the elucidation of the causal relationship between the variables. Consequently, longitudinal studies or experimental design methodologies may be employed to further examine the dynamic progression of AI awareness and its pathways of effect.

Thirdly, the measuring of variables depends on self-reported questionnaires, which may result in social desirability bias. Subsequent study may use objective metrics, such as behavioral logs and AI platform utilization data, to augment the diversity and reliability of the data.

In conclusion, the ongoing integration of AI technology in higher education underscores the importance of comprehending how educators cultivate knowledge-sharing behaviors, which possesses considerable theoretical and practical significance. This study has developed a preliminary path mechanism model of "AI consciousness-cognition and emotion-shared behavior", aiming to furnish innovative insights for research on the integration of educational technology and to serve as a foundation for universities to enhance teachers' knowledge collaboration and organizational learning.

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Conflicts of Interest

The authors declare no conflict of interest.

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