AI Trust and Knowledge Management Practices in Enhancing Employee Innovation: Moderating Effect of Career Resilience

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Abstract

This study uses Knowledge Sharing (KSH), Knowledge Documentation (KDC), Knowledge Creation (KCR), and Knowledge Application (KAP) to examine how AI Trust (ATR) affects Employee Innovative Behavior (EIB). The main goal is to examine AI Trust's direct and indirect effects on creativity and Career Resilience (CRL)'s moderating role. The study employed a standardized questionnaire to collect data from IT staff in China, Saudi Arabia, and Pakistan. This study uses quantitative research. Data analysis was done using SMART PLS 4.0 on 678 replies. ATR directly and indirectly affects EIB through knowledge management strategies. CRL moderates ATR and Innovation, strengthening it. The study emphasizes the importance of knowledge management and ATR in organizations to foster innovation. This research could help organizations foster creativity using artificial intelligence. These findings may potentially affect managers and politicians trying to boost employee creativity and responsiveness to technology.

Keywords: knowledge management, artificial intelligence, employee innovative behavior, trust

1. Introduction

AI revolutionizes businesses, transforming workflows and improving performance. However, organizations face challenges building trust, considering workplace, customer, decision-making processes, complexity, and human-AI interaction (Maier et al., 2022). I can sense, analyze, act, learn, and mimic human intelligence (McCartney & McCartney, 2020). It helps companies increase product ranges, speed decision-making, and manage information (Borges et al., 2021). AI enhances business process efficiency, decision-making, and innovation (Bonnaure, 2018). Successful AI projects require trust. It provides ethical behavior and employment rights, so employees must trust the workforce to trust AI's talents and implications (Mariani et al., 2022). Understanding how ATR affects employee innovation is crucial.

Data-centric and digital cultures use AI to innovate business models, improve processes, and gain a competitive edge (Ransbotham et al., 2019). AI-powered machine learning and Big Data analysis improve career paths in human resource management (Chowdhury et al., 2022). ATR is crucial for enterprise adoption, enhancing creativity, productivity, and performance. Ethical AI systems boost innovation, growth, and competitiveness (Choung et al., 2023).

ATR is crucial for enterprise ethics, law, and client satisfaction, enhancing brand image, user trust, and competitiveness through reliable systems (Choung et al., 2023). ATR is technical, real, perceived, and impartial. AI systems must perform well to acquire client trust. Scientific theories explain how ATR affects creativity, decision-making, and business success (Xiang, 2023). Theories reveal that trust significantly impacts organizational behavior, choices, and practices, necessitating effective management of trust and transparency risks to effectively implement disruptive technologies (Liu et al., 2023).

The WEF predicts AI will transform HRM, increasing GDP by 15% by 2030. Technology is transforming the workforce demographics, job relevancy, and customer experience. Global AI spending is expected to rise 24.5% to $204 billion in 2025, while the WEF predicts 133 million employment losses and gains from AI by 2022. Companies must adapt to new technology, harness information, and empower staff to survive in changing global markets (M. H. Lee et al., 2018).

Company career mobility affects AI adaptability, which can boost staff creativity. Knowledge Management Practices technology employ AI to recommend, structure, and share fresh information quickly. Although research is sparse, CRL and ATR affect Knowledge Management Practices and EIB (Odugbesan et al., 2023). This paper addresses the lack of cross-sectional CRL research and how trust influences AI-KM innovation initiatives. This study indicates how firms can purposefully improve ATR, Knowledge Management Practices, and CRL to encourage EIB (Fridgeirsson et al., 2021).

The study analyzes how ATR influences employee innovation in firms. This link is moderated by CRL and mediated by knowledge management approaches like producing, recording, sharing, and using information. The project promotes worker creativity by improving CRL, knowledge management, and ATR. It gives companies concrete ways to use ATR to improve knowledge processes and build resilient, inventive workforces. According to the above objectives, Problems and significance of the study mentioned below research questions are proposed:

Q1: How does ATR impact employee knowledge practices and their innovative behavior in organizational settings?

Q2: How does Knowledge Management Practices (Creation, documentation, Sharing, Application) mediate the relationship between ATR and employee innovation?

Q3: What role does CRL play in the relationship between trust in AI and employees' innovative behavior?

Q4: What strategies can organizations use to boost innovation through trust in AI, knowledge management practices (Creation, documentation, Sharing, Application), and individual’s ability?

2. Literature Review and Hypotheses Development

2.1 AI Trust

ATR means an AI system will perform tasks competently, accurately, and ethically. Users trust the system to execute tasks and communicate openly. Trust in AI depends on talent, kindness, and integrity. AI needs human acceptance and participation (Choung et al., 2023; Elsa et al., 2025).

Users usually measure ATR. Dependability, proficiency, openness, and equity are scaled. Modern research has produced self-assessment instruments for these dimensions. With AI, user behavior better evaluates trust. A recent study demonstrated that transparency and feedback affect consumers' trust in practical AI (Choung et al., 2023; Omrani, 2022).

2.2 Knowledge Management Practices

Knowledge Management Practices create, acquire, transfer, and use knowledge to boost a firm's value and competitiveness (Hendriks, 2005). The organizational knowledge economy necessitates effective management, with AI and machine learning gaining prominence in this field (Dwivedi et al., 2021). For organizational knowledge improvement, knowledge management (KM) includes explicit knowledge storage and internal knowledge (Nonaka & von Krogh, 2009). Knowledge repositories and collaboration platforms enable content development and sharing, promoting organizational knowledge management (Alavi & Leidner, 2001). To properly transfer and evaluate tacit knowledge, organizations need leadership commitment, supporting culture, change resistance, and information overload (De Spiegelaere et al., 2014).

2.3 Knowledge Creation and Acquisition

Knowledge management practices include socialization, externalization, combination, and internalization. Knowledge is a strategic asset for competitive advantage, according to the Knowledge-Based View (KBV). The organizational learning theory promotes learning and creativity through knowledge acquisition, encoding, storage, and dissemination (Chowdhury et al., 2022). Course-of-Professionals (CoP) mentorship and coaching programs frame knowledge transfer (Wenger, 1998). AI, ML, and knowledge bases promote knowledge development and acquisition (Chowdhury et al., 2022; Manzoor & Jahangir, 2024). Integrating technology into practices fosters innovation and competitive advantage through knowledge growth and updating through documentation and collaboration in IT (Abbas & Sağsan, 2019).

2.4 Knowledge Documentation and Storage

Knowledge Management (KM) involves documenting and storing important information for future access. This is crucial for organizations to maintain continuity and organization memory, especially in sectors like healthcare, finance, and pharmaceuticals. Trust in AI technology is essential for proper documentation and fostering organizational learning (Dwivedi et al., 2021). Decision-making and innovation, especially in remote and distributed work situations, require knowledge retention, legal compliance, and documentation to avoid mistakes (Chowdhury et al., 2022). Knowledge Management Systems (KMS), cloud solutions, and collaboration tools safeguard knowledge between locations. AI, Blockchain, and mobile apps improve knowledge retention, security, and efficiency (Mohammed & Kamalanabhan, 2020).

2.5 Knowledge Sharing

A company's knowledge management practices foster deliberate knowledge transmission, which impacts organizational learning, innovation, and performance. KSH requires leadership, culture, trust, and technology (Song et al., 2020). Open and honest communication, reliable authority, simplified secure tools like Knowledge Management Systems (KMS), and social media platforms like Twitter, Facebook, Teams, and Slack can break geographical barriers and increase KSH in diverse and dispersed organizations (Glikson & Woolley, 2020).

However, departmentalization, distrust, perceived rivalry, and job insecurity may hamper information exchange. For these issues, organizations may encourage information exchange in their culture and structures (Witherspoon et al., 2013). AI-powered KMSs encourage trust and best practices. Top management provides resources, support, and awards for KSH. SNA identifies areas of organizational information flow for intervention and improvement (Hansen, 1999).

2.6 Knowledge Application

Innovation uses knowledge to solve problems, make decisions, and create goods (Grant, 1996). This process creates new ideas and skills by synthesizing and rearranging knowledge (Bresciani et al., 2018). AI inspires creativity by analyzing massive amounts of data and finding patterns humans cannot (Jarrahi, 2018). Trust matters. Information integration and use can help organizations adapt to environmental changes and grow (Li Sa et al., 2020). Continuous learning with ATR boosts creativity, problem-solving, and organizational asset development (Dwivedi et al., 2021).

Trust influences the success of intranets and collaborative platforms by allowing KSH to be applied across corporate sectors (Glikson & Woolley, 2020). Effective leaders encourage learning and application, which builds trust and innovation (Avolio et al., 2009). AI automates processes, analyzes large data sets, and discovers proactive replies, increasing KAP (Balakrishnan & Dwivedi, 2021; Dwivedi et al., 2021). This helps organizations grow by generating and maintaining goods and services.

2.7 Employee Innovative Behavior

Innovation has method and product categories. To expand, compete, and achieve strategic goals, modern firms need innovations. Understanding how ATR, knowledge management, and CRL effect employee creativity and organisational outcomes is vital (Alshebami, 2021).

Corporate productivity, adaptability, and competitiveness are all improved by innovation in internal procedures and resource utilization. AI and automation improve resource allocation, decision-making, and employee innovation (Chaturvedi, 2023). Product, logistics, and delivery innovations boost efficiency, savings, and performance (Si et al., 2020). Lean manufacturing and digital technologies remove redundancy and focus on key tasks to improve quality and customer satisfaction (Womack & Jones, 1997).

Innovative products attract customers, helping companies prosper in competitive markets. Creating or improving consumer goods increases value and markets (Aloulou, 2019; Manzoor & Jahangir, 2023). Machine learning, predictive modeling, and analytics improve product development and identify market gaps. Companies that use AI to meet consumer expectations have happier, more loyal customers (Trajtenberg, 2018). Technology and AI innovate, but strategic organization and cross-departmental collaboration produce goods (Dougherty, 1992).

2.8 Career Resilience

Technology and economic unpredictability make CRL vital in today's fast-changing workplace (Coetzee & Potgieter, 2019). Career issues and change. AI/IT workers switch jobs. New talent helps EIB. CRL improves engagement, turnover, and adaptability. When professional resilience turns mistakes into accomplishments, job satisfaction and engagement rise. Innovation grows. Goal-setting, career management, and feedback improve skill-organizational fit (Jo et al., 2024). CRL advances technology. CRL groups assist changing circumstances boost EIB and organizational success.

Think positively, be emotionally intelligent, and adapt career-wise. Overcoming challenges and learning from failures builds resilience (Bandura et al., 1999). Stress management and work adaptations involve self-awareness, empathy, and emotional control (Mayer et al., 1995). Growing from problems makes resilient people joyful (Karhu et al., 2022). Business AI enhances CRL, flexibility, learning, and technological integration (Balakrishnan & Dwivedi, 2021). Organizational culture, growth, and social support increase resilience (Masten et al., 2021; Iqbal et al., 2025).

Awareness, emotional security, and change-oriented professionals improve CRL (L. Zhao et al., 2022). Job satisfaction, engagement, and dedication improve CRL and company/individual performance (Hafeez, 2023; Tajdar, 2023; G. Zhao, 2021). CRL helps organizations adapt, create, and flourish despite changing labor markets and technology.

3. Conceptual Framework and Hypothesis

3.1 Theoretical Framework of Research Model

The case of Artificial Intelligence (AI) integration into organizations is indeed, redesigning how EIB is obtained. The issues of ATR – trust in artificial intelligence systems – remain crucial for creating incentives for more developments. This relationship is also expected to be mediated through Knowledge Management Practices and moderated by CR. Thus, the rationale for development of this framework stems from such theoretical underpinnings as the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Social Exchange Theory (SET).

3.2 Technology Acceptance Model (TAM)

IT adoption and utilization in the workplace are often analyzed using the Davis, Jr. (1986) Technology Acceptance Model. PU and PEOU affect tech use. User-friendly job-performance technology is more likely to be used. Extended testing demonstrates TAM predicts technology-wide user acceptability (Davis, Jr., 1986; Venkatesh et al., 2012). AI systems' usability depends on employee belief in their efficacy and reliability. Trust increases AI system exploration by employees (Filieri et al., 2021). ATR lets companies share and utilize knowledge. KM with AI can help companies innovate, find trends, and make smarter decisions (Omrani et al., 2022). CRL manages ATR, KM, and employee innovation. AI and technology can help high-CR professionals improve KM and innovation (Xiang et al., 2023). To maximise AI benefits, organisations must trust AI systems, train people, and build CRL. AI will boost firm innovation and success (Dwivedi et al., 2021). Thus, ATR, KM practices, and CRL create a dynamic, imaginative, and sustainable workplace, giving a competitive edge in today's fast-changing corporate landscape.

3.3 Resource-Based View (RBV)

Resource-Based View (RBV) (Barney et al., 2001) emphasizes competitive advantage through distinctive resources and talents. VRIO claims rare, unique, and coordinated resources provide companies an edge. AI-trusted KM enhances innovation-related KSH and application, making it strategic. AI-powered data analysis, prediction, and process automation promote KM employee innovation. Business gains from AI-trusting workers. Trust makes AI competitive and efficient. AI helps companies improve operations, cut costs, improve customer experiences, and create new products (Dwivedi et al., 2021). AI's predictive analytics and natural language processing are hard to copy due to company culture and proprietary data (Jarrahi et al., 2022).

Career resilience (CR) aids AI and Knowledge Management adoption, suggest Coetzee & Potgieter (2019). AI can help high-CR workers adopt tech. CR promotes organizational learning and competitive advantage through information exchange, cooperation, and innovation. ATR, KM, and CRL are necessary for EIB. Change resilience and AI-based KM can help firms succeed. A dynamic, innovative, and adaptive organisation needs AI and KM for competitive advantage, according to the RBV paradigm (Barney, 1991; Barney et al., 2001).

3.4 Behavioral Theory of Firm

The Behavioural Theory of the Firm (BTF) explains organisational behaviour and decision-making as limited rationality, routines, and satisficing (Gavetti et al., 2012 Better data analysis and decision-making can help AI overcome cognitive limits in information processing (Raisch & Krakowski, 2021). AI streamlines administrative processes, regulates repetitious work (Jarrahi, 2018; Pentland & Feldman, 2005), and speeds up "good enough" responses by evaluating many options instantly. AI detects performance gaps and predicts remedies to boost problemistic discovery and creation (Duan et al., 2019). AI promotes ethical decision-making and worker engagement through impartial suggestions and customized learning (Gawer & Phillips, 2013). Companies adapt swiftly to market changes with AI (Shrestha et al., 2019). Ethics, data privacy, and job automation must be addressed to maximise AI's potential (Agrawal et al., 2019). AI helps BTF improve organizational behavior, decision-making, and agility while connecting ethics with business advantage.

3.5 Proposed Framework

Employees' willingness to use AI technologies decreases risk-taking and integrates innovative ideas into business procedures (Dwivedi et al., 2021). Knowledge Management Practices (KMP) are crucial to ATR and EIB. High-touch trust in AI improves knowledge production, storage, and processing for innovation and better outcomes (Jarrahi et al., 2023). A key mediator in this relationship is CRL. (Dwivedi et al., 2021) highlight resilient employees' proactive KMP optimization for innovative results. This paradigm shows that ATR affects KMP-driven performance originality based on CRL. A sustainable innovation culture requires the synergy of frameworks like the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Social Exchange Theory (SET).

3.6 Relationship of AI Trust and Employee Innovative Behavior

ATR drives EIB, which drives innovation and creativity (Choung et al., 2023; Omrani, 2022). ATR boosts organisational cooperation and knowledge exchange, boosting innovation (Choung et al., 2023; Shin, 2021). ATR boosts data analytics, strategic decision-making, and innovation (Chidera Victoria Ibeh et al., 2024). Supportive leaders foster AI innovation (Odugbesan et al., 2023). ATR boosts SCM, education, healthcare, and finance creativity, adaptability, and efficiency.

A study found that ATR has several uses in inventive civilizations. It reduces change aversion, trains people for new technologies, and optimizes AI for data processing, problem-solving, and product/service innovation (Borges et al., 2021). AI-trusting early development organizations are more likely to use its advanced capabilities for competitive advantage (Ashish Tripathi et al., 2022). The study showed that ATR boosts EIB experimentation, collaboration, and strategic innovation. Organizations must trust AI to maximize innovation. Literature hypothesis:

Hypothesis 1: ATR has a direct positive effect on EIB

3.7 Relationship Between AI Trust and Knowledge Management Practices

Organizational adoption and effectiveness of Knowledge Management (KM) solutions depend on trust in the AI system. Trust is affected by reliability, openness, data security, and fairness (Jarrahi, 2023). Transparent, dependable, and ethical AI systems are trusted by employees for knowledge development, sharing, and decision-making (Jarrahi et al., 2023). Leadership support, training, and a creative organizational culture build trust in AI tools, making KM processes smooth (Odugbesan et al., 2023). Updates, user feedback, and evaluations make these systems reliable (Olan et al., 2022).

AI's adaptability, user-friendliness, and ability to enhance human experience boost its KM position (Taherdoost & Madanchian, 2023). Human-AI collaborations build trust and efficiency, while ethical and regulatory compliance ensures fairness and security (Habbal et al., 2024). ATR enhances information sharing, decision-making, and strategy alignment, facilitating KM and organizational growth (Borges et al., 2021). Trust is needed for AI to change KM systems.

Hypothesis 2: ATR has a positive effect on KCR

Hypothesis 3: ATR has a positive effect on KDC

Hypothesis 4: ATR has a positive effect on KSH

Hypothesis 5: ATR has a positive effect on KAP

3.8 Knowledge Management Practices and Employee Innovative Behavior

KMP utilizes EIB to harness corporate knowledge for innovative problem-solving and competitiveness, fostering a culture of knowledge acquisition, sharing, and utilization (Khawaldeh & Alzghoul, 2024). AI enhances KMP efficiency by automating procedures, analyzing data, and facilitating knowledge exchange, fostering innovation and adaptability within organizational practices (Zamiri & Esmaeili, 2024).

AI, cloud computing, and knowledge networks enhance KMP and EIB (Habbal et al., 2024). Open innovation and knowledge networks assist high-tech firms and SMEs innovate by facilitating external and internal knowledge flows (Franco et al., 2024). Leadership support, cultural resistance, and technology constraints must be overcome to optimise KMP (Hamid et al., 2024). KMP links knowledge processes to strategic goals to boost innovation and long-term success in changing companies (Kumar et al., 2020).

Hypothesis 6: KCR positively impacts EIB

Hypothesis 7: KDC positively impacts EIB

Hypothesis 8: KSH positively impacts EIB

Hypothesis 9: KAP positively impacts EIB

3.9 Mediation Role of Knowledge Management Practices (Creation, Documentation, Sharing, Application) Between Ai Trust and Employee Innovative Behavior

AI and KMP are fostering innovation by enhancing knowledge management and enhancing corporate planning, data analysis, and decision-making processes (Olan et al., 2022). Leadership, KSH, and technology infrastructure enhance mediation (Wanner et al., 2022). AI-powered KMP systems improve knowledge access. ATR increases KMP by engaging employees in knowledge systems and driving innovation. Trusting AI improves staff involvement with KMP systems and informs innovation goals (Jarrahi et al., 2023). ATR enables KMP systems evolve with organizations, sustaining EIB despite complexity (Böckle et al., 2021). This cycle of ATR, KMP, and innovation determines organizational adaption and long-term performance (Kim et al., 2021). Sustainable innovation requires AI-KMP integration (Maier et al., 2022).

Hypothesis 10: Employee knowledge practices mediate the relationship between ATR and EIB

3.10 The Moderating Role of Career Resilience Between AI Trust and Employee Innovative Behavior

AI and CR are crucial for fostering CRL and innovation, as they enable employees to adapt to professional changes and recover from mistakes (Coetzee & Potgieter, 2019). AIT and professional resilience mediate creativity, say Lee & See (2004). CRL and ATR promote experimentation, risk-taking, and teamwork (Li et al., 2021).

CRL promotes organizational learning and teamwork, which sustains creativity. When faced with new challenges, resilient people collaborate. J. D. Lee & See (2004) found that ATR and resilient people boost organizational learning and creativity. CRL impacts risk-taking and experimentation, which are essential for creative problem-solving (Yildiz et al., 2023). AI and AIT are fostering innovative and CRL, enhancing learning and fostering a more agile and successful company (Maier et al., 2022).

Hypothesis 11: CRL moderates the relationship between ATR and EIB

3.11 Conceptual Model

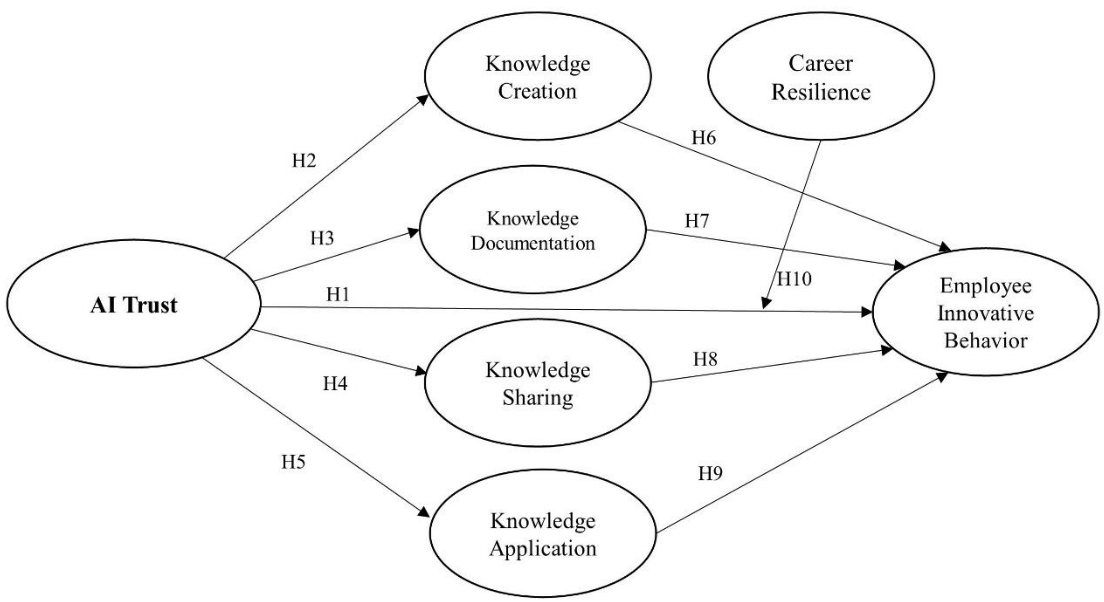

Figure 1. Proposed Model

4. Research Methodology

This study will examine trust in AI, EIB, Knowledge Management Practices (Creation, documenting, Sharing, and Application), and CRL. The study's approach and strategy include the research approach, demographic, sample, data collection method, questionnaire design, and analysis tools. Thus, the research combines a quantitative approach and a closed-ended questionnaire to gather departmental opinions.

This paper uses quantitative research to analyze ATR, Knowledge Management Practices (Creation, documentation, Sharing, Application), CRL, and EIB. Since data is collected at a certain time, the research uses a cross-sectional survey methodology. This approach is suitable for assessing postulated connections and how Knowledge Management Practices (Creation, documenting, Sharing, Application) modulate the IV, trust in AI, to induce the DV, EIB.

4.1 Population and Sample

The target population for this research includes employees from several organizations and from different IT departments such as Human Resources, Administration, finance, etc., from China, Saudi Arabia, and Pakistan. Departmental sweep sampling guarantees representation from different departments to make the findings more generalizable. The size of target sample is 678 respondents for, which the researchers believe will allow for powerful statistical tests, for example, regression and moderation analysis. Over a while, simple random sampling technique is used to get data from the target population.

4.2 Questionnaire Design

The questionnaire comprises eight sections: Demographic data, trust in artificial intelligence, four sections on KCR, KDC, KSH, KAP and innovation, a section on CRL, and EIB. All the other questions in the survey are given on a 5-point Likert scale, with 1 being ‘Strongly Disagree’ and 5 being ‘Strongly Agree,’ although each section needs more than one item. Below is a detailed description of each section: Below is a detailed description of each section:

Demographic data will be gathered from the respondents' age, level of education, and office or department of the respondents' organization. These findings are important when determining whether the respondents' basic demographic data will allow for a diverse pool of participants.

4.3 Measurement Items

This part used ten AI items to assess respondents' faith in the technology. These factors measure AI confidence, reliability, attitude, and impact on job creation or skill advancement. These are from Wang et al. (2020) investigations. KDC, KSH, and KAP and Innovation each have six items. KCR has four. Eight questions on the CRL scale examine people's ability to adapt, learn, and succeed in changing circumstances. These analyze personal traits that make one robust in work. This section has six criteria that examine the organization's success in developing and improving products, processes, and new market and production strategies.

4.4 Data Collection

The data was collected using an online structured questionnaire. Demographics, faith in AI, knowledge management (creation, documentation, sharing, and application), CRL, and employee innovation were covered in the questionnaire. Respondent confidentiality was maintained. SMART PLS was used to analyze data, including descriptive statistics for demographics, Cronbach's alpha for reliability, and correlation analysis for variable correlations (Hafeez et al., 2023; Hair Jr et al., 2016; Tajdar et al., 2023). The study examined how ATR moderate’s employee innovation using multiple regression analysis. CRL was examined as a mediator between knowledge management techniques and employee innovation.

4.5 Data Analysis Tools

Due to its extensive structural equation modeling capabilities and widespread academic reputation, this study uses SMART PLS 4.0 to analyze complicated interactions, test hypotheses, and assess mediating and moderating effects. Its advanced features streamline data manipulation, statistical analysis, and result visualization (Jahangir et al., 2024).

5. Results

5.1 Demographics

The demographic table 1 shows that 678 respondents from China, Saudi Arabia, and Pakistan make up the study's population, with an equitable distribution. Most participants have a bachelor's or master's degree and five to ten years of professional experience. Participants in the study range in age, with the largest group being 31–40. Only 2.2% of participants are PhD.

Table 1. Demographics of Respondents

Category	Sub-Category	Frequency (n)	Percentage (%)
Total Population		678	100%
Country	China	248	36.6%
	Saudi Arabia	210	31.0%
	Pakistan	220	32.5%
Department	Human Resources	160	23.6%
	Administration	190	28.0%
	Finance	185	27.3%
	Other IT Departments	143	21.1%
Age Group	20–30 years	210	31.0%
	31–40 years	275	40.5%
	41–50 years	155	22.9%
	Above 50 years	38	5.6%
Experience	Less than 5 years	230	33.9%
	5–10 years	280	41.3%
	Above 10 years	168	24.8%
Education Level	Bachelor	320	47.2%
	Master	230	33.9%
	Ph.D.	15	2.2%

5.2 Conformatory Factor Analysis

The table 2 shows a well-structured assessment approach for ATR (ATR), Career Resilience (CRL), Employee Innovative Behavior (EIB), Knowledge Application (KAP), Knowledge Creation (KCR), Knowledge Documentation (KDC), and Knowledge Sharing (KSH). All items have factor loadings more than 0.7, indicating a strong relationship with their constructions. Each construct has composite reliability ratings (rho_a and rho_c) better than 0.7, indicating strong internal consistency. All Average Variance Extracted (AVE) values exceed 0.5, indicating acceptable convergent validity. The model is reliable, consistent, and valid, making it resilient for evaluation. Factor Loading values are also shown in Figure 2.

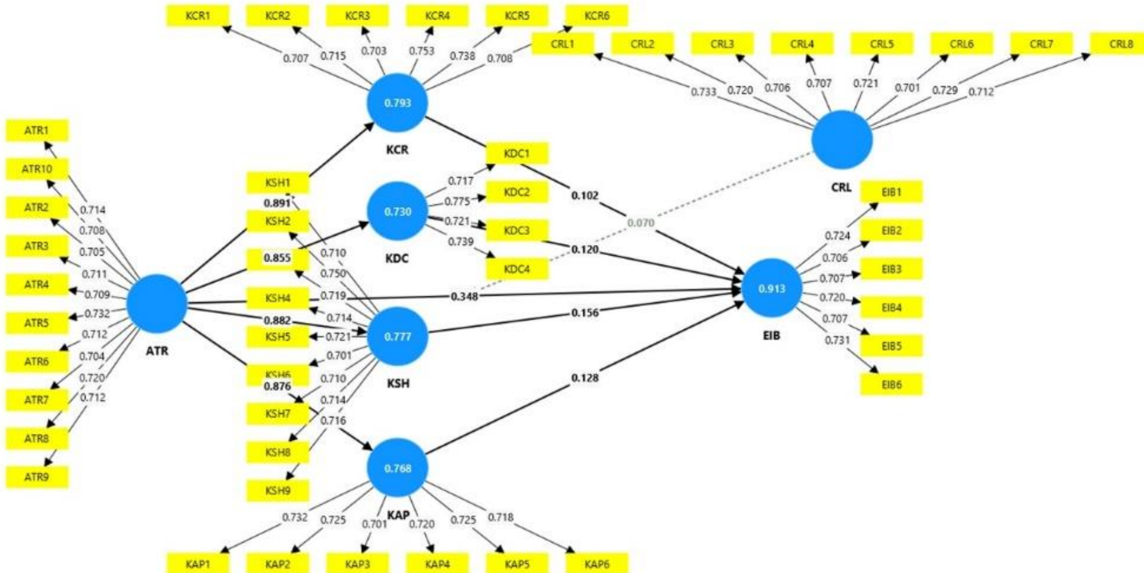

Figure 2. Confirmatory Factor Analysis

Table 2. CFA, Data Reliability and Validity

Items	FL	CA	rho_a	rho_c	AVE
ATR		0.892	0.892	0.912	0.508
ATR1	0.714				
ATR10	0.708				
ATR2	0.705				
ATR3	0.711				
ATR4	0.709				
ATR5	0.732				
ATR6	0.712				
ATR7	0.704				
ATR8	0.720				
ATR9	0.712				
CRL		0.864	0.865	0.894	0.513
CRL1	0.733				
CRL2	0.720				
CRL3	0.706				
CRL4	0.707				
CRL5	0.721				
CRL6	0.701				
CRL7	0.729				
CRL8	0.712				
EIB		0.810	0.810	0.863	0.512

EIB1	0.724				
EIB2	0.706				
EIB3	0.707				
EIB4	0.720				
EIB5	0.707				
EIB6	0.731				
KAP		0.814	0.815	0.866	0.519
KAP1	0.732				
KAP2	0.725				
KAP3	0.701				
KAP4	0.720				
KAP5	0.725				
KAP6	0.718				
KCR		0.815	0.816	0.866	0.520
KCR1	0.707				
KCR2	0.715				
KCR3	0.703				
KCR4	0.753				
KCR5	0.738				
KCR6	0.708				
KDC		0.721	0.722	0.827	0.545
KDC1	0.717				
KDC2	0.775				
KDC3	0.721				
KDC4	0.739				
KSH		0.882	0.882	0.905	0.515
KSH1	0.710				
KSH2	0.750				
KSH3	0.719				
KSH4	0.714				
KSH5	0.721				
KSH6	0.701				
KSH7	0.710				
KSH8	0.714				
KSH9	0.716				

5.3 Model Fit Analysis

The statistics that measure the goodness-of-fit between the saturated model and the data indicate that the model fits the data well. The value of SRMR is 0.037, which indicates that there are almost no residual uncertainties. d_ULS and d_G values of 1.708 and 0.852, respectively, show that the model fits the data well. With additional indices, the Chi-square value of 2788.107 is consistent with the model fit. NFI value is 0.851 which indicates the good model fit. Additionally, the model's high R Square value is 0.913 which indicates that it explains 91.3% of the variance, demonstrating great explanatory power.

Table 3. Model Fit and R^2 Value

	Saturated model
SRMR	0.037
d_ULS	1.708
d_G	0.852
Chi-square	2788.107
NFI	0.851
R Square	0.913

5.4 Path Analysis

Table 4 shows path coefficients, SD, T statistics, and P-values for variable relationships. All paths from AI Trust (ATR) to Knowledge Application (KAP), Knowledge Creation (KCR), Knowledge Documentation (KDC), Knowledge Sharing (KSH), and Employee Innovative Behavior (EIB) have P-values of 0.000, indicating strong and reliable relationships. ATR has the highest path coefficients to KCR (0.891) and KSH (0.882), showing considerable effect. The correlations between KAP, KCR, KDC, KSH, and EIB are positive, and their path coefficients range from 0.102 to 0.156. Additionally, all T statistics exceed the crucial value of 1.96, supporting the hypothesis.

Table 4. Direct Path Analysis

Hypotheses	**β**	**SD**	**T statistics**	**P values**
ATR -> EIB	0.348	0.044	7.925	0.000
ATR -> KAP	0.876	0.011	83.068	0.000
ATR -> KCR	0.891	0.010	91.974	0.000
ATR -> KDC	0.855	0.011	79.054	0.000
ATR -> KSH	0.882	0.011	83.511	0.000
KAP -> EIB	0.128	0.036	3.530	0.000
KCR -> EIB	0.102	0.050	2.030	0.042
KDC -> EIB	0.120	0.029	4.208	0.000
KSH -> EIB	0.156	0.032	4.909	0.000

The results of the mediation and moderation hypotheses are presented in the table 5, and it can be seen that all of the proposed paths exhibit significant correlations. The indirect impacts of AI Trust (ATR) on Employee Innovative Behavior (EIB) through Knowledge Sharing (KSH), Knowledge Documentation (KDC), Knowledge Creation (KCR), and Knowledge Application (KAP) are substantial, with P-values of 0.000 or 0.043. It is important to note that these effects are not directly related to ATR. To be more specific, the path ATR -> KSH -> EIB has a path coefficient of 0.138 and a T statistic of 4.874, which indicates that it has a considerable and powerful indirect effect. In a similar vein, the effects of mediation through KDC, KCR, and KAP are likewise statistically significant. There is a coefficient of 0.070, a T statistic of 3.653, and a P-value of 0.000, which indicates that the moderation effect of Career Resilience (CRL) on the relationship between ATR and EIB (CRL x ATR -> EIB) is significant. This indicates that CRL strengthens the impact of ATR on EIB. Path Analysis Values are also shown in Figure 3.

Table 5. Mediating and Moderating Path Analysis

Hypotheses	β	SD	T statistics	P values
ATR -> KSH -> EIB	0.138	0.028	4.874	0.000
ATR -> KDC -> EIB	0.103	0.025	4.188	0.000
ATR -> KCR -> EIB	0.091	0.045	2.022	0.043
ATR -> KAP -> EIB	0.112	0.032	3.488	0.000
CRL x ATR -> EIB	0.070	0.019	3.653	0.000

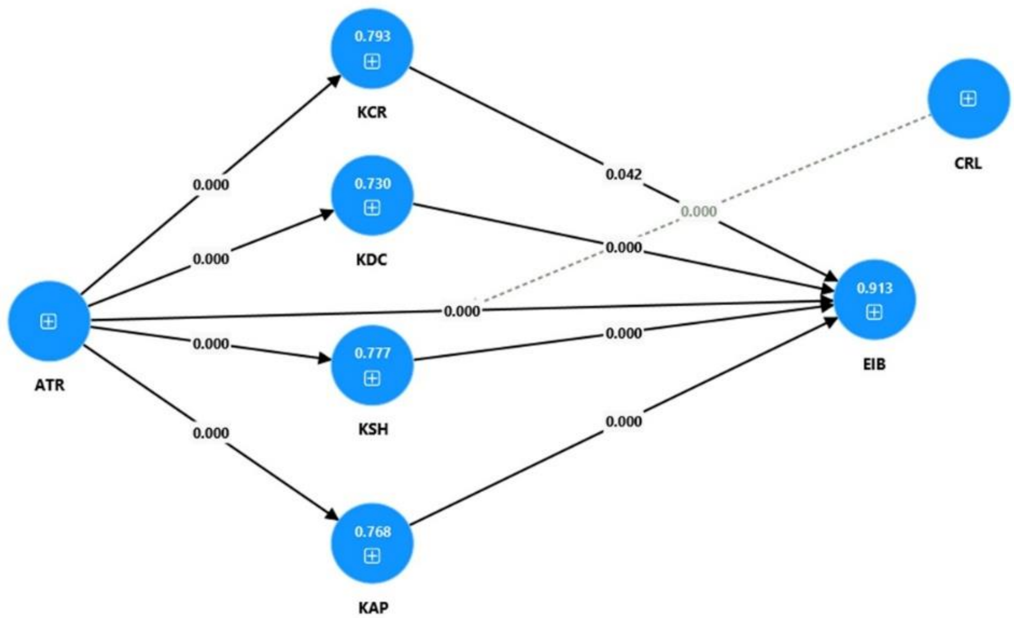

Figure 3. Path Analysis

6. Discussion and Conclusion

The study found that AI Trust (AIT) directly affects Employee Innovative Behavior (EIB) by making employees more open to new technologies, which boosts corporate productivity. Knowledge Management Practices (KMPs) such knowledge production, documentation, sharing, and application improve knowledge capture and use and increase AI confidence. The research shows that enterprises with AI-trusting staff are better able to embrace and deploy AI technology, boosting knowledge management. CRL helps individuals manage workplace changes and stay productive, promoting EIB. The findings underscore the relevance of ATR, resilient personnel, and well-established knowledge management systems in promoting organizational innovation.

The study supports research on technological trust and corporate effectiveness, notably in improving Knowledge Management Practices, which fuel innovation. It supports (Darroch, 2005; Nonaka & Takeuchi, 1995) that knowledge management drives innovation. Similar to (Choung et al., 2023; Omrani et al., 2022), the research emphasizes the significance of ATR in enhancing KMPs and raising EIB. Trust promotes organizational efficiency and creativity. This work fills a gap in the literature by identifying KMPs as mediators of ATR and creativity, providing practical insights for firms using AI to innovate.

Through the use of a number of different knowledge management procedures, such as Knowledge Sharing (KSH), Knowledge Documentation (KDC), Knowledge Creation (KCR), and Knowledge Application (KAP), this study explores the impact that AI Trust (ATR) has on Employee Innovative Behavior (EIB). The results of the study give compelling evidence that ATR exerts a considerable influence on EIB in both a direct and indirect manner, with major mediation effects being found through knowledge management practices. As a result of the moderating influence of Career Resilience (CRL), the association between ATR and EIB is further strengthened. This suggests that employees who have a higher level of CRL are more likely to demonstrate innovative behavior in response to ATR. These findings emphasize the significance of promoting ATR and providing support for knowledge management strategies in order to spur innovation within enterprises.

6.1 Contributions

ATR and Knowledge Management Practices effect firm outcomes in this study. Technology trust facilitates information sharing and utilization, enhancing performance. The paper emphasizes CRL and staff innovation. Knowledge Management Practices might link ATR to innovation. Studies suggest CRL and knowledge management practices may help organizations innovate. The findings suggest CRL and originality.

The Theory of Knowledge Management includes ATR and CRL. It suggests that faith in AI and CRL boost employee creativity, knowledge management, and organizational performance, giving a competitive edge. This study examines trust in AI and its implications on knowledge management and creativity, adding to human-AI interaction literature and providing interdisciplinary digital age innovation techniques.

6.2 Limitations and Future Recommendations

Despite its flaws, this study's findings are striking. First, the cross-sectional approach makes causal links between variables harder to identify. Future research may use longitudinal studies to better understand ATR's temporal dynamics, knowledge management strategies, and innovative human behavior. The study's second restriction is that it only includes personnel from China, Saudi Arabia, and Pakistan, which may limit its applicability to other cultures. Further research could broaden the sample to include more sectors and areas. Although CRL is moderated heavily, other moderators, such as business culture or leadership styles, may be examined. The research would benefit from qualitative methodologies to better understand how ATR affects EIB in corporate contexts.

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Authors' contributions

Muhammad Saddam Hussain: Responsible for writing the original draft, conceptualization, methodology, and revising. **Prof. Haiyan Kong:** Responsible for Conceptualization, Data Curation, and Supervision. **Muhammad Junaid Bashir:** Responsible for review and editing. **Dr. Junaid Jahangir:** Writing, Data curation, and revised it. **Ziwei Yu:** Editing and formatting. All authors read and approved the final manuscript.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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