# The Effect of Artificial Intelligence Trust on Innovation Performance: Anti-Fragility and Knowledge Sharing Mediation and Identity Moderation

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**Abstract**

As the "new generation" enters the workplace, concerns about work attitudes increase, especially with artificial intelligence (AI) emerging as a disruptive force in the labor market. We explore the influence of AI trust on innovation performance, focusing on the mediating effects of anti-fragility and knowledge sharing, as well as the moderating role of organizational identity. Our findings indicate that AI trust significantly positively affects innovation performance. This effect is partially mediated by anti-fragility and knowledge sharing, and these mediations are moderated by organizational identity. The study enhances understanding of the mechanisms and boundary conditions linking the new generation's AI trust to innovation performance, offering valuable insights for enterprises aiming to foster innovation.

**Keywords:** AI trust, organizational identity, innovation performance, anti-fragility, knowledge sharing

## 1. Introduction

As the digital economy evolves, industries face business disruptions, and organizations must integrate technological advancements to survive and thrive. Artificial intelligence (AI) has become a key driver of economic transformation and upgrading (Wang et al., 2022). Its application demands higher skills from employees, and human–AI collaboration enhances work processes, acceptance, and trust in AI (Gkinko & Elbanna, 2023; Sengul et al., 2019). Consequently, effective people management and the role of human resource management (HRM) are crucial (Budhwar et al., 2023). However, intelligent technology also heightens the risk of unemployment and job insecurity, necessitating greater teamwork and knowledge sharing within organizations (Vera & Sanchez-Cardona, 2021). AI can enhance teamwork by augmenting human team processes, thereby boosting innovation (Bouschery et al., 2023). In facing crises and challenges, increasing employees' anti-fragility may positively influence their organizational identity and innovation performance (Lv et al., 2019).

With the exponential growth of AI and rising global uncertainty, employee insecurity may affect organizational identification and performance (Gardner, 2019). Combining human capital, technology, and risk management, innovation becomes the core competitive advantage for organizations. Thus, exploring the factors that influence innovation is of high importance (Limnios et al., 2014). AI trust, anti-fragility, knowledge sharing, and organizational identity are gaining attention and are widely discussed in managerial innovation, human resource management, positive psychology, and organizational culture. Research on related concepts, structures and measurements, influencing factors, and mechanisms has yielded valuable insights (Koronis & Ponis, 2018; Sengul et al., 2019; Lv et al., 2019; Gardner, 2019; Kantur & Iseri-Say, 2012). For example, AI trust affects organizational identity and enhances innovation performance and capabilities. Anti-fragility and knowledge sharing are dynamic capabilities of organizational identity (Kaplan & Haenlein, 2020). Organizational context and individual cognition were important factors affecting employees' innovation performance. The application of new technologies has proposed higher requirements for employees to innovate, and they may face more technical pressure in their work.

Studies on AI trust have increasingly focused on how trust in AI systems influences employee engagement, decision-making, and overall organizational performance, highlighting its critical importance in the successful integration of AI technologies (Yamamoto et al., 2025). Anti-fragility and knowledge sharing has been extensively studied as key drivers of innovation and competitive advantage, with recent research emphasizing the need for effective knowledge management practices to leverage AI capabilities fully (Yao et al., 2023). Despite the growing body of literature examining various dimensions of AI's influence on work attitudes, significant research gaps remain. There is limited understanding of how trust in AI specifically affects innovation outcomes, and the potential mediating effects of anti-fragility and knowledge sharing has not been fully revealed, leaving a gap in comprehending how these factors might enhance or hinder innovation performance (Do et al., 2025; Pei et al., 2024). Addressing these gaps is crucial for developing a comprehensive understanding on how the new generation's work attitudes and AI integration can be harnessed to foster innovation in the workplace (Kong et al., 2024).

By exploring the pattern of relationships between AI trust and innovation performance, and clarifying the important roles of anti-fragility, knowledge sharing, and organizational identity. We answer recent calls to study the effect of external knowledge, such as that from AI collaboration, on the future of organizations (Ehls et al., 2020; Gama & Magistretti, 2023; Kim et al., 2021). Our contributions to the literature include identifying the mechanisms through which AI influences innovation performance and developing a theoretical framework that enhances the understanding of knowledge management and innovation.

## 2. Literature Review and Hypotheses Development

In the age of artificial intelligence, the dynamic capability theory provides a strategic framework for understanding and adapting to changing environments (Wamba et al., 2020; Sullivan & Arthur, 2016). The dynamic capability theory emphasizes that innovation is the key to maintaining organizations' competitiveness (Schelble et al., 2024; Folkman, 2016). The innovation performance depends not only on the development of new technologies but also on how these technologies are integrated and applied to create value (Zhang et al., 2023). Building and maintaining trust relationships with AI may help employees learn from technical failures and anxieties and become stronger. In addition, knowledge sharing is also key for employees to learn and develop their capabilities by constantly obtaining new skills and knowledge to adapt to the changes brought about by AI (Halisah et al., 2021). Employees may identify and catch AI-driven innovation opportunities through dynamic capabilities, and improve innovation performance by continuously improving their own anti-fragility and knowledge-sharing behaviors (Riedl, 2022; Peeters et al., 2022).

### *2.1 Relationship Between AI Trust and Innovation Performance*

Attitude is a leading factor in shaping behavior. Trust acts as a mechanism for reducing uncertainty and perceived risk, leading employees to invest more resources and share more ideas (Kreiner & Ashforth, 2004). AI significantly influences employees' perceptions, which in turn affect their behaviors (Wong et al., 2020; Soffer et al., 2023). A positive attitude toward AI enhances the flexibility of employees' innovative behaviors, encouraging them to work hard and achieve high innovation performance (Kaplan & Haenlein, 2020; Schelble et al., 2024). Integrating human intelligence with AI is a hybrid approach, enabling to benefit from the dual agency and improve organizational outcomes (Wamba et al., 2020).

As a key outcome of technology management in organizations, employees' innovation performance refers to the innovative and feasible ideas or results, which may improve their role performance and work efficiency. The uncertainty and high risks associated with innovative activities require employees to develop strong anti-fragility to overcome challenges and potential risks (Prayag et al., 2018; Sengul et al., 2019).

AI trust may promote employees' psychological identification with technology, significantly positively affecting their innovation performance (Wong et al., 2020). Employees with high AI trust leverage positive psychology and resources to enhance their innovation performance (Lederer et al., 2000). Such employees are more likely to take responsibility, engage in collaborative activities with technology across various fields, improve their organizational identity, and achieve better innovation performance (Kong et al., 2023; Kreiner & Ashforth, 2004). AI trust stimulates employees to maximize technical efficiency, guides their behavior, and fosters innovation (Wang et al., 2022). When employees perceive AI features as beneficial, they develop positive cognition, enabling them to access innovative resources and maintain a high sense of resource acquisition, thus promoting innovation (Kong et al., 2023).

Based on the above discussion, we present the following hypothesis:

Hypothesis 1: AI trust positively influences innovation performance, anti-fragility, and knowledge sharing.

### *2.2 Mediating Effect of Anti-Fragility*

As a competitive advantage, anti-fragility reflects employees' abilities to adapt to changing environments and resolve risks (Linnenluecke, 2017). Anti-fragility helps employees maintain confidence and enthusiasm in organizational activities, leveraging resources to cope with adversity, take risks, face challenges, and promote innovative behaviors (Lv et al., 2019; Gardner, 2019). It also enables to generate a human resource management system that leads to positive outcomes for organizational processes involved with people management (Kleizen et al., 2023). Employees with greater anti-fragility tend to recognize the value of their positions and work, leading to innovative performance in competitive and challenging environments (Lv et al., 2019; Gardner, 2019).

Trust and its dimensions empower people to cope with difficulties and improve their ability to handle harsh conditions (Lukyanenko et al., 2022; Kreiner & Ashforth, 2004). Thus, employees with high levels of AI trust and anti-fragility exhibit a positive and optimistic attitude, promoting active participation in the organization, acceptance of challenging innovation activities, and improved innovation performance (Jaaron & Backhouse, 2015). Anti-fragile employees are more likely to form a strong organizational identity, increase work engagement, and enhance innovation behaviors and performance (Linnenluecke, 2017). The uncertainty and high risks of innovation activities require employees to demonstrate strong anti-fragility to overcome unknown difficulties and potential risks (Kaplan & Haenlein, 2020). Therefore, anti-fragility is an important predictor of individual creativity and innovation performance.

Based on the above discussion, the following hypothesis is proposed:

Hypothesis 2: Anti-fragility partially mediates the relationship between AI trust and innovation performance.

### *2.3 Mediating Effect of Knowledge Sharing*

Knowledge sharing refers to the process of passing, discussing, transferring, and co-creating knowledge with each other, so as to facilitate learning, innovation, and problem solving (Arpaci, 2017). Knowledge sharing contributes to positive self-development and provides the knowledge and abilities necessary for innovation performance (Halisah et al., 2021). Trust is a central element of such an atmosphere. The more trust exists, the more willing individuals are to share and cooperate (Vanhala & Tzafrir, 2021; Arpaci, 2017). Increased sharing raises the likelihood of better outcomes (Tzafrir et al., 2012; Wamba et al., 2020). Knowledge sharing enables employees to achieve mutually beneficial cooperation and breakthrough innovation by sharing personal experiences and skills (Arpaci, 2017). The knowledge-sharing atmosphere within a team can affect employees' connection with the organization.

Employees may share and learn professional knowledge and skills within the organization, encouraging innovative behaviors and promoting innovative performance (Arpaci, 2017). Knowledge sharing accelerates the flow of knowledge within the group, and this rapid flow and transformation of knowledge resources stimulate employees' innovation performance (Wamba et al., 2020). Knowledge sharing is crucial for enterprises to develop core competitiveness and achieve innovative development.

Based on the above discussion, the following hypothesis is proposed:

Hypothesis 3: Knowledge sharing mediates the relationship between AI trust and innovation performance.

### *2.4 Moderating Effect of Organizational Identity*

Organizational identity is defined as emotional and intellectual identification with other members of the same social group, emphasizing the extent to which individuals see themselves as part of the organization (Ahmad et al., 2022). It reflects employees' sense of belonging, pride, and loyalty to their organization, influencing their attitudes and behaviors (Zhang et al., 2023). Employees with a high level of organizational identity tend to view themselves as integral members and perform to meet organizational expectations, which is crucial in modern society (Baruch et al., 2016; Smidts et al., 2001). This identity increases the likelihood of employee engagement and helps achieve organizational goals and long-term benefits.

Organizational identity significantly affects employees' mental states, promoting organizational citizenship behavior and innovation performance (Cavanaugh & Boswell, 2000). Employees who recognize themselves as part of a group tend to conform to organizational characteristics, protect group interests, and strive for higher innovation performance (Yuan et al., 2021). Those with a strong sense of organizational identity are likely to take responsibility for innovation and effectively improve organizational innovation performance (Cvetkovic et al., 2024).

Compared with traditional activities, innovation activities are more challenging and risky, requiring higher levels of psychological effort from employees (Cvetkovic et al., 2024). When faced with difficulties and risks, organizational identity can enhance employees' beliefs and motivate their internal drive for innovation (Bach et al., 2022).

Employees with a high level of organizational identity are willing to take risks, tackle problems, and engage in challenging innovative work (Kaplan & Haenlein, 2020). Therefore, employees' innovation behavior is influenced by their organizational identity.

Based on this discussion, we propose the following hypotheses:

Hypothesis 4a: Organizational identity positively moderates the relationship between employees' anti-fragility and innovation performance. The stronger the organizational identity, the stronger the relationship between anti-fragility and innovation performance.

Hypothesis 4b: Organizational identity positively moderates the relationship between knowledge sharing and innovation performance. The stronger the organizational identity, the stronger the relationship between knowledge sharing and innovation performance.

*2.5 Theoretical Model*

In summary, this study explores the influence of AI trust on innovation performance, the mediating roles of anti-fragility and knowledge sharing, and the moderating role of organizational identity. The theoretical model is shown in Figure 1.

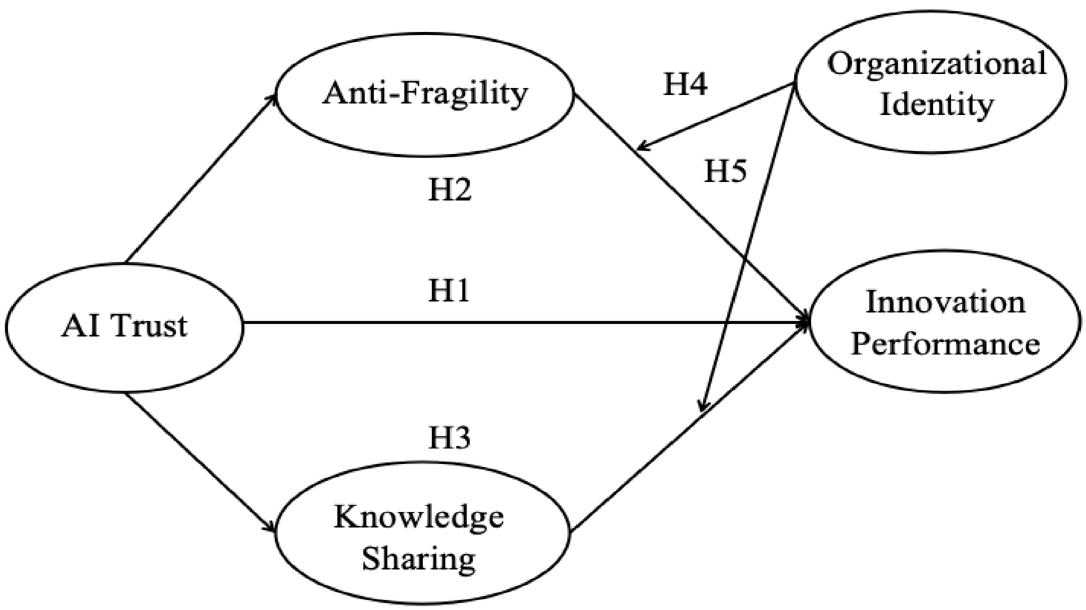


Figure 1. The theoretical model

## 3. Methodology

*3.1 Measurement Scale*

In order to ensure the reliability and validity, the measurement items of the questionnaire were adopted from mature scales in valuable literature of international journals. The measurement scale and items were applied to empirical research on organizational management widely. The questionnaire items were scored using a Likert 5-point scale (as shown in Appendix 1). In addition, gender was selected as a control variable to avoid the influence of irrelevant variables on the causal relationships among the main variables.

*3.2 Sample and Data Collection*

The data was collected with questionnaires to investigate knowledge workers, who had a college education or higher. They are selected as respondents since they were more likely to work with AI and trust the related technologies. It also ensured a higher level of cognitive ability and familiarity with the survey topics.

The online questionnaire survey was distributed through a combination of channels. Firstly, our professional networks and industry contacts were employed to reach out directly to HR departments and senior management within the target companies, requesting their assistance in distributing the survey to eligible employees. Secondly, LinkedIn, a professional networking platform, was used for identifying and connecting with potential respondents who met our criteria. We sent personalized invitations to these individuals, highlighting the importance of their participation and the potential benefits of the research.

To guarantee the quality of the responses, we implemented several quality assurance measures. Firstly, we provided clear and concise instructions at the beginning of the survey, explaining the purpose of the research, the estimated time commitment, and the importance of providing accurate and honest answers. Secondly, we included a progress bar at the bottom of each page to help respondents keep track of their progress and encourage them to complete the survey. Thirdly, cash rewards were offered to encourage respondents to complete the questionnaire. Finally, we conducted a thorough data cleaning process after the survey closed, removing any missing data, outliers, or duplicate responses.

A total of 812 questionnaires were issued with random sampling in the hotel and tourism industries. After deleting the incomplete responses, straight-lining answers, and extreme values, 632 valid questionnaires remained, representing an effective response rate of 77.8%. The sample size and composition are deemed representative of the target population, providing a solid foundation for drawing meaningful conclusions from the study. The demographic breakdown of the respondents also showed a good distribution across job titles, years of experience, and educational backgrounds, further enhancing the generalizability of our findings.

### *3.3 Data Analysis*

We applied Harman's single-factor test to assess potential common method bias. SPSS 22.0 software was used for reliability, validity, and correlation analyses, and Amos was employed for confirmatory factor analysis. Hierarchical regression analysis and the macro program PROCESS were used to test the hypotheses.

## 4. Results

### *4.1 Common Method Bias and Confirmatory Factor Analysis*

Two methods were employed to test for common method bias. First, the data collected were obtained through self-evaluation, so the empirical results may be affected by common method bias, though this does not necessarily influence the findings (Bozionelos & Simmering, 2021). The questionnaire data were collected anonymously to control for potential homologous variance. Harman's single-factor test was performed via exploratory factor analysis to examine potential common method biases. Five factors with eigenvalues greater than 1 were extracted from the unrotated exploratory factor analysis, with the maximum factor explaining 37.79% of the variance, which is below the critical value of 40%. These results indicate that the common method bias was within the allowable range.

To assess discriminant validity, we used Mplus to test the model fit. The results showed that the four-factor model (AI trust, anti-fragility, knowledge sharing, innovation performance) had the best fit. The confirmatory factor analysis results were: x2=407.389, df =157, x2/df=2.595, TLI=0.928, CFI=0.935, RMSEA=0.074, which was better than other models. These results indicate that the common method bias was well controlled and that the questionnaire was reliable. The model showed a good fit, significantly better than other models tested.

### *4.2 Correlation Analysis*

Table 1 presents the correlations and descriptive statistics of the study variables. The results show that AI trust was significantly correlated with innovation performance, anti-fragility, and knowledge sharing. Additionally, anti-fragility and knowledge sharing were significantly correlated with innovation performance. The correlation coefficients were less than 0.6, and the square roots of the AVE were all larger than the corresponding correlation coefficients, indicating high discriminant validity. These results provide preliminary support for the theoretical model and research hypotheses.

Table 1. Construct correlations

| | **AI trust** | **Anti-fragility** | **Knowledge sharing** | **Innovation performance** | **Organization identity** |
|---|---|---|---|---|---|
| AI trust | 1.000 | | | | |
| Anti-fragility | 0.512 | 1.000 | | | |
| Knowledge sharing | 0.583 | 0.523 | 1.000 | | |
| Innovation performance | 0.492 | 0.524 | 0.541 | 1.000 | |
| Organizational identity | 0.526 | 0.535 | 0.466 | 0.527 | 1.000 |
| Mean | 3.891 | 3.762 | 4.071 | 4.013 | 3.914 |
| AVE | 0.417 | 0.506 | 0.447 | 0.558 | 0.573 |
| S.D. | 1.143 | 1.175 | 1.164 | 1.079 | 1.191 |

### *4.3 Hypothesis Testing*

According to Baron and Kenny (1986), hierarchical regression analysis and the macro program PROCESS were applied to explore and test the hypotheses. As shown in Table 1, the independent variable, AI trust, had a significant effect on the dependent variable, innovation performance (β=0.337, p<0.001, M3). Thus, Hypothesis 1 was supported. The independent variable, AI trust, also had a significant effect on the mediating variable, anti-fragility (β=0.223, p<0.001, M1). Additionally, AI trust positively influenced the mediating variable, knowledge sharing (β=0.189, p<0.001, M2). These findings supported further analysis. When AI trust, anti-fragility, and knowledge sharing were added to the regression model of innovation performance, anti-fragility significantly affected innovation performance (β=0.175, p<0.001, M4), and AI trust positively influenced innovation performance (β=0.284, p<0.001, M4). However, the coefficient decreased noticeably (0.284<0.337), indicating that the effect of AI trust on innovation performance was partially mediated by anti-fragility. Therefore, Hypothesis 2 was supported. Moreover, anti-fragility significantly affected innovation performance (β=0.086, p<0.001, M5), and AI trust positively influenced innovation performance (β=0.293, p<0.001, M5). Again, the coefficient decreased noticeably (0.293<0.337), indicating that the effect of AI trust on innovation performance was partially mediated by knowledge sharing. Thus, Hypothesis 3 was supported.

Based on the findings of hierarchical regression analysis, there was a linear relationship between AI trust and innovation performance. The macro program PROCESS further verified the mediating roles of anti-fragility and knowledge sharing in the relationship between AI trust and innovation performance. As shown in **Table 2**, the mediation effect model of anti-fragility was well-fitted. The total effect of AI trust on innovation performance was significant (β=0.394), the direct effect was significant (β=0.299), and the indirect effect of anti-fragility on AI trust and innovation performance was significant (β=0.096, confidence interval [0.043, 0.166]). These results proved that anti-fragility played a partial mediating role in the positive correlation between AI trust and innovation performance. Therefore, Hypothesis 2 was supported.

Table 2. Results of regression analysis

| | Anti-fragility | Knowledge sharing | Innovation performance | | |
|---|---|---|---|---|---|
| **Variables** | ***M1*** | ***M2*** | ***M3*** | ***M4*** | ***M5*** |
| Gender | -0.026 | -0.039 | -0.047 | -0.036 | -0.044 |
| AI trust | 0.223** | 0.189** | 0.337** | 0.284*** | 0.293** |
| Anti-fragility | | | | 0.175** | |
| Knowledge sharing | | | | | 0.086** |
| R2 | 0.090 | 0.066 | 0.217 | 0.259 | 0.286 |
| Adjusted R2 | 0.019 | 0.013 | 0.161 | 0.201 | 0.228 |
| F | 1.294 | 1.149 | 3.947 | 4.677 | 5.128 |

As shown in Table 3, the mediating effect of knowledge sharing was well fitted. The total effect and direct effect of AI trust on innovation performance were significant (β values were 0.280 and 0.013, respectively), and the indirect effect of knowledge sharing on the relationship between AI trust and innovation performance was significant (β=0.072, confidence interval [0.004, 0.122]). These findings indicate that knowledge sharing played a significant role in partially mediating the positive correlation between AI trust and innovation performance. Thus, Hypothesis 3 was supported.

Table 3. Analysis on the mediating effect of anti-fragility and knowledge sharing

| Variables | Effect | Estimate | S.D. | T value | P value | LLCI | ULCI |
|---|---|---|---|---|---|---|---|
| AI trust | Total | 0.394 | 0.041 | 9.622 | 0.000 | 0.313 | 0.475 |
| | Direct | 0.299 | 0.042 | 7.088 | 0.000 | 0.216 | 0.382 |
| | | Estimate | Boot S. E. | | | BootLLCI | BootULCI |
| | Indirect | 0.096 | 0.031 | | | 0.043 | 0.166 |
| Knowledge sharing | Total | 0.280 | 0.050 | 7.065 | 0.000 | 0.202 | 0.305 |
| | Direct | 0.072 | 0.033 | 1.654 | 0.000 | 0.004 | 0.122 |
| | | Estimate | Boot S. E. | | | BootLLCI | BootULCI |
| | Indirect | 0.013 | 0.021 | | | 0.152 | 0.210 |

Next, the moderating effect of organizational identity on the relationship between anti-fragility and innovation performance was examined. The results, shown in Table 4, indicated that the relationship between anti-fragility and organizational identity was significant with a positive regression coefficient of 0.254 (β=0.254, p<0.01, M8). The positive effect of anti-fragility on innovation performance was strengthened by higher organizational identity. Thus, Hypothesis 4 was supported. To further test Hypothesis 4, the relationship between anti-fragility and innovation performance with high and low levels of organizational identification was shown in Figure 2. As illustrated, the slope of anti-fragility on innovation performance in the case of high organizational identity was higher than in the case of low organizational identity. This demonstrates that improving organizational identity enhances the positive effect of anti-fragility on innovation performance. Therefore, Hypothesis 4a was supported.

Finally, the moderating effect of organizational identity on the relationship between knowledge sharing and innovation performance was tested. According to Table 4, the relationship between knowledge sharing and organizational identity was not significant, with a regression coefficient of 0.049 (β=0.049, p>0.05, M9). The moderating effect of organizational identity on the relationship between knowledge sharing and innovation performance was not significant. Therefore, Hypothesis 4b was not supported.

Table 4. Results of regression analysis on innovation performance

| | Innovation performance | | | |
|---|---|---|---|---|
| **Variables** | ***M6*** | ***M7*** | ***M8*** | ***M9*** |
| Gender | -0.036 | -0.043 | 0.092 | 0.15 |
| Anti-fragility | 0.172*** | | 0.126*** | |
| Knowledge sharing | | 0.084* | | 0.055* |
| Anti-fragility*Organizational identity | | | 0.254** | |
| Knowledge sharing*Organizational identity | | | | 0.049 |
| R2 | 0.153 | 0.352 | 0.421 | 0.373 |
| Adjusted R2 | 0.095 | 0.309 | 0.375 | 0.326 |
| F | 2.688 | 7.753 | 9.784 | 7.577 |

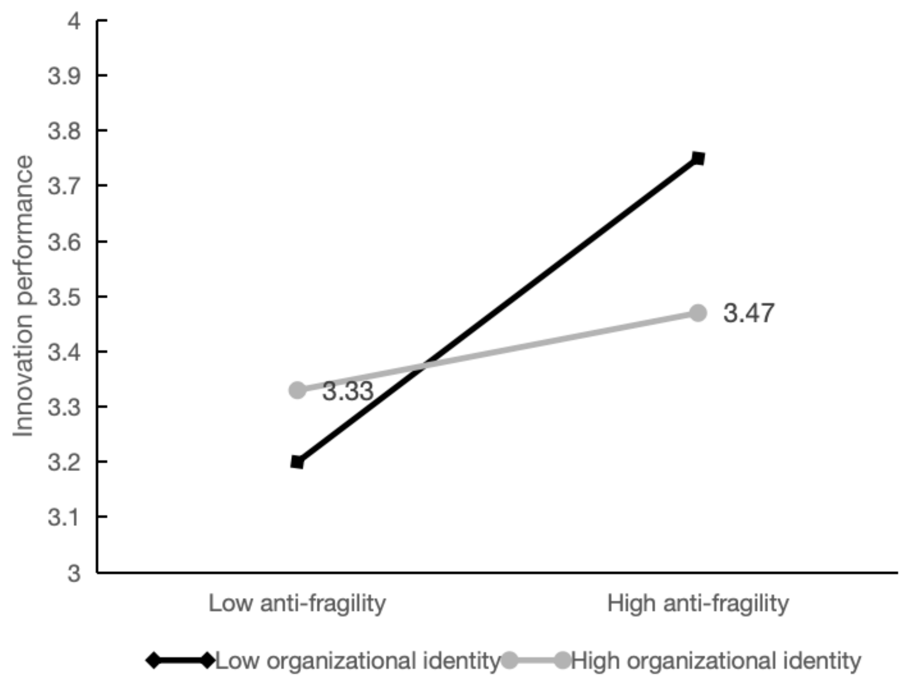


Figure 2. The moderating effect of organizational identity

## 5. Discussion and Conclusion

We studied knowledge workers to identify the prospective effect of AI trust on innovation performance and explored the roles of anti-fragility, knowledge sharing, and organizational identity in this mechanism. The main conclusions are as follows:

First, AI trust showed a significant positive effect on innovation performance (H1 was supported). Employees with a high level of trust in AI technology tend to engage in more creative behaviors, leading to greater innovation performance. This finding is consistent with existing research on the effect of AI trust on innovation performance (Wamba et al., 2020), demonstrating its capacity to improve performance (Chowdhury et al., 2022).

Second, anti-fragility and knowledge sharing played partially mediating roles between AI trust and innovation performance (both H2 and H3 were supported). This suggests that employees' trust in AI can enhance their innovation performance by improving their anti-fragility and propensity for knowledge sharing. Employees with greater trust in AI are more likely to develop strong anti-fragility and knowledge-sharing capabilities, taking more responsibility for innovation and striving to achieve the organization's innovation goals. This aligns with previous research on the causes and effects of anti-fragility and knowledge sharing (Jaaron & Backhouse, 2015; Wamba et al., 2020).

Third, organizational identity significantly affected the relationship between anti-fragility and innovation performance (H4a was supported). However, organizational identity did not positively affect the relationship between knowledge sharing and innovation performance (H4b was rejected). These results indicate that organizational identity can positively predict employees' innovation performance. Employees with a stronger sense of organizational identity tend to achieve better innovation performance, consistent with previous research on the influencing factors of innovation performance and the aftereffects of organizational identity (Wang & Rafiq, 2014; Arpaci, 2017).

The above empirical results supported the core relationships in the proposed theoretical model. In the context of high anti-fragility and knowledge sharing perception, the positive and predictive effect of AI trust on innovation performance is enhanced. Conversely, the positive influence of AI trust on innovation performance may be weakened without these perceptions. Organizational identity moderates the relationship between employees' anti-fragility and innovation performance positively. The stronger the sense of organizational identity, the stronger the relationship between anti-fragility and innovation performance.

### *5.1 Theoretical Implications*

Our study enriches research knowledge in four pillars, answering calls to better understand the current and future effects of AI on innovation (Gama & Magistretti, 2023). The study examines individual antecedents affecting innovation performance at the employee level, clarifying that AI trust is a significant driver of improved innovation performance. Our results demonstrate that positive employee trust in AI leads to positive and desirable employee outcomes, such as innovation. This aligns with dynamic capability theory, which explains the relationships between beliefs, attitudes, and behaviors. It also enhances the Technology Acceptance Model by incorporating the level of trust in technology as an important aspect alongside perceived usefulness and perceived ease of use. This study develops the understanding of the theory of enterprise innovation. Previous studies have focused on factors affecting innovation performance, including leadership, organizational relations, and organizational communication. However, the effect of several important human interactions, such as AI trust, anti-fragility, and knowledge sharing, has not been clearly explained. We explored the moderating effect of organizational identity on the relationship between AI trust and innovation performance at the micro level, providing methods and a theoretical basis for enterprises to improve innovation performance. The results offer valuable insights for the intelligent transformation of enterprises, promoting innovation through anti-fragility and knowledge sharing. This is a valuable exploration of creating innovative talent advantages and achieving higher innovation performance.

Second, the mediating effect of anti-fragility and knowledge sharing is theoretically and empirically proven. The study illustrates how anti-fragility and knowledge sharing mediate the relationship between AI trust and employees' innovation performance, revealing the profound influence of AI trust on employee innovation performance.

Third, the research perspective on knowledge workers in enterprises is expanded. Existing research mainly focuses on development, construction mode, and management and operation mechanisms, but studies on innovation performance are limited. This study addresses the micro level of enterprise innovation performance, considering the effects of AI trust, anti-fragility, knowledge sharing, and organizational identity. It provides practical insights for accelerating innovation performance development in enterprises.

Fourth, the theoretical research framework of AI trust is enriched. Existing studies on AI trust focus on organizational and social levels, with limited attention to psychological and emotional states and performance. This study further explores the effect of AI trust on innovation performance and expands the theoretical framework of AI trust in positive psychology. It represents a new attempt and exploration of relevant theories, promoting the development of AI trust theory.

### *5.2 Managerial Implications*

First, employees' psychological state should be considered during the transformation to digital intelligence, especially their trust attitude towards AI technology. For employees who may face unemployment because of the transformation or who are anxious about learning AI, HR professionals should explore employees' difficulties and offer support, such as psychological interventions and employee assistance programs. This can help control technical anxiety, improve trust in AI technology, and facilitate a successful digital transformation.

Second, improving the screening of employees with anti-fragility is essential. Employees with stronger anti-fragility may persist in the face of difficulties, adapt to their environment and work, and reduce anxiety about being replaced. Interviewees' anti-fragility can be assessed through standardized tests and resume analysis during recruitment. Experts can provide anti-frustration training and stress education to improve employees' anti-fragility. This helps promote organizational identity, enhance team connection, and improve innovation performance effectively.

Third, targeted and systematic AI knowledge and skills training should be conducted to foster a knowledge-sharing team atmosphere. Experts and trainers can provide various levels of training, including network training, to show more care to employees. Encouraging team members to help and support each other in learning AI, solving difficulties together, and building a learning team can enhance confidence in AI learning and prepare for future crises.

In conclusion, through scientific and effective knowledge and innovation management, the value of knowledge resources and innovation performance can be maximized.

### *5.3 Limitations and Future Research*

This study has some limitations. It focused on individual-level variables such as AI trust, anti-fragility, knowledge sharing, organizational identity, and innovation performance. A solid theoretical foundation is needed to support any field, and the theoretical construction of AI trust needs further improvement and exploration. Future research can introduce more variables to enrich the study of AI trust and analyze the relationship between AI trust and innovation performance at the leadership, team, and organizational levels, such as exploring the role of humorous leadership. In-depth cross-level exploration is necessary to extend and enrich the value chain of relevant research.

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**Authors' contributions**

**Haiyan Kong:** Writing – original draft, Methodology, Data curation, Conceptualization, Supervision. **Muhammad Junaid Bashir:** Writing – original draft, Conceptualization. **Saddam Hussain:** Writing – review & editing, Methodology. **Yujie Han:** Writing – review & editing. **Sabahat Bashir:** Writing – original draft.

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**Data sharing statement**

No additional data are available.

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## Appendix. Survey Instrument

| Construct | Measuring items | References |
|---|---|---|
| AI trust (AT) | I have confidence in the use of AI technology.<br>I believe AI technology can facilitate with routine and trivial tasks through automation.<br>I believe my organization will be able operate AI technology reliably or consistently without failing.<br>I believe that AI technology will consistently operate providing adequate and efficient results within a broad spectrum of processes.<br>I believe AI adoption will result in creation of new jobs.<br>I have a positive attitude towards adoption of AI.<br>I believe AI technology can help in developing new skills which will benefit my career development activities.<br>I have a positive attitude towards its impact of intra-organizational business operations.<br>I believe AI will positively change employee dynamics within the organization.<br>AI adoption won't result in reduced focus on human skills such as creative intellect in my job.<br>I believe AI adoption will enhance the quality of my work. | Chowdhury et al., 2022 |
| Organizational identity (OI) | I am connected with my organization.<br>I have a strong sense of belonging to my organization.<br>I am very proud to work in my organization.<br>I fully recognize my organization.<br>5. I am honored to be a member of my organization. | Smidts et al., 2001 |
| Innovation performance (IP) | My organization has successfully developed and/or introduced new products.<br>My organization has successfully improved existing products.<br>My organization has successfully developed and/or introduced new processes.<br>My organization has successfully improved existing processes.<br>My organization has successfully explored a new market.<br>My organization has successfully employed new methods of production. | Wang & Rafiq, 2014 |
| Anti-fragility (AF) | I tend to bounce back quickly after hard times.<br>I have a hard time making it through stressful events.<br>It does not take me long to recover from a stressful event.<br>It is hard for me to snap back when something bad happens.<br>I usually come through difficult times with little trouble.<br>I tend to take a long time to get over setbacks in my life.<br>When I work, I feel energetic.<br>When I get up in the morning, I am happy to go to work. | Jaaron & Backhouse, 2015 |
| Knowledge sharing (KS) | My organization provides means and mechanisms to employees to share knowledge for AI Adoption.<br>My organization has means and mechanisms to store knowledge shared and disseminated among employees, for AI adoption.<br>My organization has means and mechanisms to make knowledge accessible among employees, for AI adoption.<br>My organization has means and mechanisms to explore and experiment with the knowledge for AI adoption.<br>My organization has means and mechanisms to apply knowledge in sandbox/pilot projects, for AI adoption.<br>My organization recognizes the importance of knowledge sharing within the teams for AI adoption, integration and managing this change.<br>My organization has training programs for employees' AI education.<br>My organization has knowledge sharing workshops for employees' AI education.<br>My organization has means and mechanisms for knowledge co-creation within teams in the context of technology adoption.<br>I have attended training programs through my organization to gain AI knowledge. | Chowdhury et al., 2022 |