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EMPIRICAL ANALYSIS OF IMPACT OF EMPLOYEE SKILL THROUGH EMPLOYEE INNOVATION ON MANUFACTURING INDUSTRY INTELLIGENCE

Rong Lin[1], Chonlavit Sutunyarak[2] *

[1,2]Chakrabongse Bhuvanarth International College of Interdisciplinary Studies (CBIS),
Rajamangala University of Technology Tawan-OK, Thailand.
[1]rong.lin@rmutto.ac.th,
[2]chonlavit_su@rmutto.ac.th
* Corresponding author: chonlavit_su@rmutto.ac.th

Abstract This study investigates the impact of staff skill training investment on enterprise organizational performance in the context of intelligent manufacturing, with a focus on the mediating role of employees' innovation ability. Based on 385 valid questionnaire responses from Chinese manufacturing enterprises, a structural equation model was employed to test the hypothesized relationships. The results demonstrate that training investment significantly enhances both innovation ability and organizational performance. Moreover, innovation ability partially mediates the relationship between training and performance, suggesting a dual-path influence mechanism. The findings contribute to human capital and innovation theories by highlighting the strategic role of enterprise-led training in digital transformation. Practically, the study provides guidance for firms to optimize training strategies aligned with innovation goals, thereby enhancing their competitiveness in intelligent manufacturing environments.

Keywords: Staff Skill Training Investment; Employee Innovation Ability; Enterprise Organizational Performance;Intelligent Manufacturing;Human Capital Development; Structural Equation Modeling;Industrial Transformation; Organizational Innovation; Digital Capability; Workforce Empowerment

1. Introduction

In the era of artificial intelligence and digital transformation, the manufacturing sector is undergoing unprecedented changes characterized by the deep integration of intelligent technologies across all segments of the industrial value chain. China, as the world's largest manufacturing hub, finds itself at the critical juncture of transitioning from labor-intensive production models to intelligence-driven innovation. This transformation has been accelerated by rising labor costs, changing industrial structures, and an urgent need to enhance national competitiveness through industrial upgrading (Lee et al., 2022; Yu & Wang, 2021). In response, the Chinese government has launched a series of policies, including the "Intelligent+" strategy and vocational skills enhancement initiatives, aiming to reposition the country within the global value chain by cultivating a technologically proficient and innovation-capable workforce.

Despite the growing emphasis on intelligent transformation, the challenges of labor displacement and widening skill gaps have emerged as critical constraints (Liang et al., 2025). With the increasing application of robotics and AI systems in production, traditional repetitive manual roles are rapidly declining, prompting urgent demand for high-level technical competencies among industrial workers (Wu, 2025). The inadequacy of conventional academic education systems to meet these evolving demands has shifted policy attention toward enterprise-based skill training programs. Particularly, on-the-job training (OJT) is gaining prominence as a vital mechanism to bridge the “knowledge gap” between technological innovation and practical implementation within firms.

While existing research often emphasizes the role of formal education in the development of human capital, the contribution of enterprise-led skill formation—especially its mediating effect on innovation capability—remains underexplored (Angrist et al., 2021; Clifton et al., 2024; Goldin, 2024). This study addresses this gap by adopting a comprehensive analytical framework that connects technological advancement (industrial intelligence), organizational behavior (employee skill training), and systemic outcomes (innovation performance). It investigates how manufacturing intelligence influences enterprises' decisions to invest in skill development, how such investments shape employee innovation capabilities, and how these capabilities, in turn, contribute to broader industrial transformation.

By drawing on empirical data and policy analysis, this research not only enriches the theoretical discourse on skill formation in the context of industrial intelligence but also offers actionable insights for both government and industry stakeholders. The findings are expected to contribute to the design of more effective vocational training policies, foster organizational learning mechanisms, and ultimately enhance the innovation capacity of China's manufacturing sector.

2.Literature Review

1. Technological Advancement and Industrial Intelligence

The emergence of industrial intelligence represents a new phase in the integration of artificial intelligence with manufacturing systems. Unlike traditional automation, industrial intelligence involves the use of advanced technologies—such as big data, cloud computing, machine learning, and the Internet of Things (IoT)—to create adaptive, self-learning production environments (Kumar et al., 2025). The development of industrial intelligence has led to a paradigm shift in the role of labor, replacing routine manual work with complex, non-repetitive, and technology-mediated tasks (Leoste et al., 2021). As such, industrial intelligence is not only a technological phenomenon but also a transformational force reshaping organizational structures and workforce requirements.

Several scholars have emphasized that the integration of intelligent technologies in manufacturing processes drives both operational efficiency and innovation capacity (Shen & Zhang, 2023; Yang et al., 2021; Zong & Guan, 2025). However, the introduction of intelligent systems also demands a reconfiguration of human capital, particularly in terms of digital competencies, cognitive flexibility, and interdisciplinary knowledge (Zenk et al., 2024). In this context, intelligent transformation becomes inseparable from the need to reskill and upskill the industrial workforce, thus necessitating a more systemic view of skill formation.

2. Employee Skill Training and Organizational Innovation

Employee skill training serves as a critical internal mechanism for firms to respond to technological disruptions (Apascaritei & Elvira, 2022). Building on the human capital theory, skill training can enhance productivity, foster knowledge absorption, and enable organizations to translate technological inputs into innovative outputs. The German "dual education" system provides empirical validation of this theory, demonstrating that sustained investment in employee training leads to higher value-added output and industrial competitiveness, even among non-R\&D-intensive enterprises (Valaskova et al., 2022; Ye, 2025).

Moreover, employee training not only contributes to individual learning but also strengthens organizational learning capabilities. According to the concept of absorptive capacity, firms must develop the ability to internalize external knowledge for innovation (Ge & Liu, 2022). Skill training acts as a conduit for this transformation, particularly when it aligns closely with job functions and production demands. Studies in both developed and developing countries show that enterprises that systematically invest in OJT can stimulate incremental and breakthrough innovations (Attarpour et al., 2023; Ma & Xiang, 2025).

3. Interactions Between Industrial Intelligence, Training, and Innovation

Recent theoretical advancements advocate for a holistic analytical framework that integrates technology, organization, and systems. Within this triadic model, industrial intelligence acts as the technological foundation, employee skill training functions as the organizational process, and innovation represents the systemic outcome. This perspective is grounded in the evolutionary economics tradition, particularly the "technology–institution" dichotomy, which views technological change as both a driver and product of institutional transformation (Kirupainayagam & Sutha, 2022; Santos & Sant' Anna, 2024).

From this viewpoint, employee skill training is not merely a human resources function, but an organizational response mechanism to the pressures and opportunities introduced by industrial intelligence. It facilitates the transformation of intelligent infrastructure into innovative capacity by equipping workers with the skills necessary to operate, adapt, and improve upon emerging technologies. Simultaneously, the training process itself becomes a site of innovation, as enterprises adopt new methods such as digital platforms, virtual simulations, and AI-assisted learning to enhance training outcomes.

4. Research Gaps and Theoretical Contribution

Although previous studies have individually examined the effects of technological advancement, skill training, and innovation (Dilekçi & Karatay, 2023; Ibrahim et al., 2022), few have analyzed the mediating role of employee training within the context of industrial intelligence. Most literature treats skill formation as either a function of educational institutions or an exogenous variable in productivity models (Barra & Ruggiero, 2022; Liu et al., 2021). This study contributes to the literature by explicitly positioning employee training as a dynamic organizational process that both responds to and reinforces technological transformation. It addresses the "black box" problem in existing models by empirically validating the pathways through which employee training mediates the relationship between manufacturing intelligence and innovation performance.

Thus, it leads to the following hypotheses:

H1: Investment in staff skills training has a positive effect on employee innovation capacity.

H2: Employee innovation capacity positively influences enterprise organizational performance.

H3: Investment in staff skills training positively affects enterprise organizational performance.

H4: Employee innovation capacity mediates the relationship between investment in staff skills training and enterprise organizational performance.

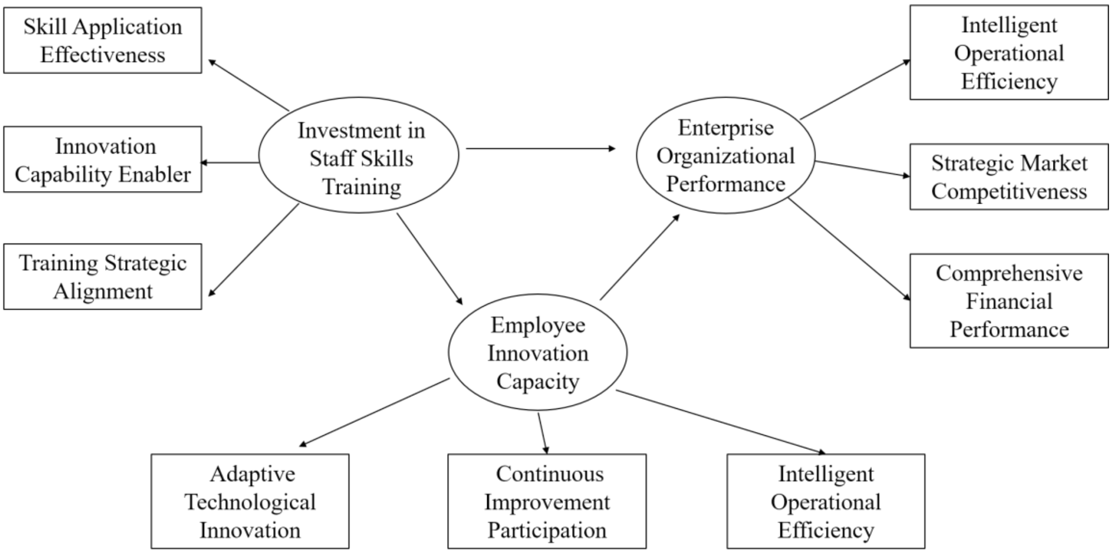

Figure 1. Conceptual Model

3.Research Method

In this study, a structured online questionnaire was distributed through the widely used digital platform Wenjuanxing. The target population comprised employees working in China's manufacturing sector, particularly those engaged in enterprises undergoing intelligent transformation. Respondents included individuals from technical, managerial, and frontline production roles within medium to large-sized manufacturing firms. Over a 30-day data collection period, 385 questionnaires were deemed valid and included in the final analysis. To ensure alignment between participants and the research objectives while minimizing selection bias, a stratified random sampling strategy was employed. Specifically, the sample was stratified based on industry type (e.g., intelligent manufacturing, traditional mechanical manufacturing, and electronic equipment production) and enterprise size. Within each stratum, participants were randomly selected. This sampling approach enhanced the representativeness of the sample and improved the generalizability and accuracy of the findings by capturing a broad spectrum of employee experiences across different industrial and organizational contexts.

The questionnaire consisted of four major sections: demographic information, staff skill training investment, employees' innovation ability, and enterprise organizational performance. This comprehensive structure was designed to systematically capture the multidimensional relationships between individual characteristics, organizational training behaviors, innovation capacity, and performance outcomes. By integrating these elements into a unified framework, the survey instrument enables a robust empirical assessment of how enterprise-level investments in employee skill development influence innovation and, ultimately, organizational performance in the context of industrial intelligence.

Based on the descriptive statistics of the sample (N = 385), the gender distribution is relatively balanced, with 52.99% male and 47.01% female respondents. In terms of age, the majority of participants are between 20 and 40 years old (64.16%), with the largest group aged 30–40 (33.77%), indicating that the sample primarily represents a young to middle-aged workforce. Regarding marital status, 47.01% of respondents are married, while 25.19% are unmarried and 25.45% are divorced, suggesting a diverse range of social backgrounds. Educationally, the sample is relatively well-educated, with 36.10% holding a master's degree and 22.86%

possessing a doctoral degree or higher. In terms of income, most respondents earn between 3,000–10,000 yuan per month (64.93%), reflecting a moderate income level typical of skilled workers in the manufacturing sector. Finally, 60.26% of participants live in urban towns, while 39.74% reside in rural areas, indicating a slight urban predominance in the respondent base. Overall, the demographic profile demonstrates a diverse and representative sample of employees across gender, age, education, income, and living conditions within the Chinese manufacturing industry.

Table 1 Essential Information

Name	Option	Frequency	Percentage (%)
Gender	Male	204	52.99
	Female	181	47.01
Age	Under 20 years old	68	17.66
	20-30 years old	117	30.39
	30-40 years old	130	33.77
	Over 40 years old	70	18.18
Marital Status	Unmarried	97	25.19
	Married	181	47.01
	Divorce	98	25.45
	Bereavement	9	2.34
Educational Background	Junior college or below	57	14.81
	Undergraduate Course	101	26.23
	Master	139	36.10
	Doctorand above	88	22.86
Income	Below3000yuan	62	16.10
	3000-5000 yuan	114	29.61
	5000-10000yuan	136	35.32
	Over10000yuan	73	18.96
Living conditions	Countryside	153	39.74
	Town	232	60.26

The second part of the questionnaire measures staff skill training investment through three dimensions: skill application effectiveness, innovation capability enabler, and training strategic alignment. The third part evaluates employees' innovation ability, focusing on adaptive technological innovation, innovation self-efficacy belief, and continuous improvement participation. The fourth part concerns enterprise organizational performance, including intelligent operational efficiency, strategic market competitiveness, and comprehensive financial performance, aiming to assess the outcomes of training and innovation in the context of intelligent manufacturing. All items in the survey were organized using a five-point Likert scale to ensure comprehensive data collection, thereby enabling a nuanced exploration of the research variables.

4. Results

Table 2 shows indicate that all three constructs demonstrate strong psychometric properties. For Staff Skill Training Investment, factor loadings range from 0.826 to 0.865, with a high Cronbach's alpha of 0.956, composite reliability (ρc) of 0.962, and an average variance extracted (AVE) of 0.718, indicating excellent internal consistency and convergent validity. Employees' Innovation Ability also shows satisfactory reliability, with loadings between 0.759 and 0.804, Cronbach's alpha of 0.929, ρc of 0.940, and AVE of 0.610, all above the acceptable thresholds. Lastly, Enterprise Organizational Performance exhibits the strongest measurement performance, with loadings ranging from 0.842 to 0.865, a Cronbach's alpha of 0.960, ρc of 0.965, and an AVE of 0.735. These results confirm that the measurement model has high reliability and convergent validity across all constructs, supporting the robustness of the scale for subsequent structural equation modeling.

Table 2 Reliability Statistics

Constructs	Items	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average Variance Extracted
Staff skill training investment	SI1	0.842	0.956	0.962	0.718
	SI2	0.844			
	SI3	0.852			
	SI4	0.861			
	SI5	0.845			
	SI6	0.856			
	SI7	0.826			
	SI8	0.865			
	SI9	0.835			
	SI10	0.850			
Employees' innovation ability	IC1	0.780	0.929	0.940	0.610
	IC2	0.759			
	IC3	0.777			
	IC4	0.775			
	IC5	0.789			

	IC6	0.769			
	IC7	0.777			
	IC8	0.794			
	IC9	0.804			
	IC10	0.784			
Enterprise organizational performance	OP1	0.852	0.960	0.965	0.735
	OP2	0.863			
	OP3	0.865			
	OP4	0.842			
	OP5	0.862			
	OP6	0.858			
	OP7	0.858			
	OP8	0.860			
	OP9	0.846			
	OP10	0.865			

Table 3 demonstrates strong discriminant validity among the three constructs—Staff Skill Training Investment, Employees’ Innovation Ability, and Enterprise Organizational Performance. Each item exhibits its highest loading on the intended construct compared to the others. For example, all items under the innovation ability dimension (IC1–IC10) show their highest factor loadings on the “Employees’ Innovation Ability” construct (ranging from 0.759 to 0.804), while their cross-loadings on the other two constructs are significantly lower. Similarly, items OP1–OP10 load most strongly on “Enterprise Organizational Performance” (0.842–0.865), and items SI1–SI10 on “Staff Skill Training Investment” (0.826–0.865). These results confirm that the measurement items are clearly associated with their respective latent variables and are not substantially influenced by unrelated constructs, thereby providing evidence of good discriminant validity in the measurement model.

Table 3 Identification Validity - Cross loading

	Enterprise organizational performance	Employees' innovation ability	Staff skill training investment
IC1	0.350	0.780	0.411
IC2	0.349	0.759	0.394

IC3	0.405	0.777	0.404
IC4	0.365	0.775	0.395
IC5	0.409	0.789	0.423
IC6	0.329	0.769	0.419
IC7	0.369	0.777	0.443
IC8	0.379	0.794	0.431
IC9	0.403	0.804	0.405
IC10	0.381	0.784	0.380
OP1	0.852	0.365	0.438
OP2	0.863	0.432	0.455
OP3	0.865	0.391	0.444
OP4	0.842	0.419	0.474
OP5	0.862	0.410	0.472
OP6	0.858	0.410	0.492
OP7	0.858	0.425	0.478
OP8	0.860	0.416	0.458
OP9	0.846	0.410	0.463
OP10	0.865	0.427	0.460
SI1	0.462	0.460	0.842
SI2	0.451	0.420	0.844
SI3	0.456	0.423	0.852
SI4	0.479	0.430	0.861
SI5	0.478	0.487	0.845
SI6	0.444	0.453	0.856
SI7	0.418	0.443	0.826
SI8	0.440	0.420	0.865
SI9	0.489	0.462	0.835
SI10	0.463	0.452	0.850

Table 4 shows that all three constructs—Staff Skill Training Investment, Employees' Innovation Ability, and Enterprise Organizational Performance—are positively and moderately to strongly correlated, with the diagonal values representing the square roots of the Average Variance Extracted (AVE) for each construct. These diagonal values (0.848, 0.781, and 0.857) are all higher than their corresponding inter-construct correlations, satisfying the Fornell-Larcker criterion and confirming adequate discriminant validity. The strongest correlation is observed between Staff Skill Training Investment and Enterprise Organizational Performance (r

= 0.541), suggesting that higher investment in skill training is closely associated with improved organizational outcomes. A similarly notable correlation exists between Staff Skill Training Investment and Employees' Innovation Ability (r = 0.526), indicating that training also contributes significantly to fostering innovation capabilities. These results support the conceptual framework that positions training as a key driver of both innovation and performance in the context of intelligent manufacturing.

Table 4 Criteria for discriminant validity

	Enterprise organizational performance	Employees' innovation ability	Staff skill training investment
Enterprise organizational performance	0.857		
Employees' innovation ability	0.479	0.781	
Staff skill training investment	0.541	0.526	0.848

Table5 reveals that all items across the three constructs—Employees' Innovation Ability (IC), Enterprise Organizational Performance (OP), and Staff Skill Training Investment (SI)—have VIF values well below the commonly accepted threshold of 5.0, indicating no serious multicollinearity issues. Most VIF values fall within the range of 2.0 to 3.5, suggesting moderate but acceptable levels of collinearity among the items. The highest VIF is observed for SI8 (VIF = 3.529) and OP10 (VIF = 3.353), which remain within acceptable bounds. These results confirm that the items are statistically independent enough to contribute uniquely to their respective constructs, supporting the validity of the structural equation modeling assumptions.

Table5 Collinearity Statistics (VIF)

Items	VIF	Items	VIF
IC1	2.162	OP5	3.201
IC10	2.170	OP6	3.134
IC2	2.018	OP7	3.247
IC3	2.115	OP8	3.221
IC4	2.109	OP9	2.973
IC5	2.173	SI1	2.916
IC6	2.112	SI10	3.131
IC7	2.075	SI2	3.078
IC8	2.215	SI3	3.094
IC9	2.338	SI4	3.373
OP1	3.053	SI5	2.907
OP10	3.353	SI6	3.185
OP2	3.223	SI7	2.656
OP3	3.340	SI8	3.529
OP4	2.846	SI9	2.736

Table 6 presents the Q^2 values, which assess the predictive relevance of the structural model using the blindfolding procedure. The results indicate that Enterprise Organizational Performance (Q^2 = 0.251) and Employees' Innovation Ability (Q^2 =

0.166) exhibit meaningful predictive relevance, as both values exceed the threshold of zero. This suggests that the model has adequate explanatory power for these two endogenous constructs. In contrast, Staff Skill Training Investment has a Q^2 value of 0.000, indicating that it functions as an exogenous variable and is not predicted by other constructs in the model. Overall, the table supports the conclusion that the structural model is capable of predicting key outcome variables, particularly innovation ability and organizational performance, within the context of intelligent manufacturing.

Table 6 Regarding Q^2

	Q^2
Enterprise organizational performance	0.251
Employees' innovation ability	0.166
Staff skill training investment	0.000

Table 7 presents the F^2 values, which indicate the proportion of variance in each endogenous construct explained by the exogenous variables in the model. The F^2 value for Enterprise Organizational Performance is 0.176, suggesting that 17.6% of its variance is explained by Staff Skill Training Investment and Employees' Innovation Ability. The F^2 value for Employees' Innovation Ability is 0.383, indicating a moderate level of explanatory power, with Staff Skill Training Investment accounting for 38.3% of the variance. As Staff Skill Training Investment is an exogenous construct in the model, no F^2 value is reported for it. Overall, these results demonstrate that the model explains a meaningful proportion of variance in the key outcome variables, supporting its empirical robustness in the context of intelligent manufacturing.

Table 7 Results of F^2

	Enterprise organizational performance	Employees' innovation ability	Staff skill training investment
Enterprise organizational performance			
Employees' innovation ability	0.080		
Staff skill training investment	0.176	0.383	

Table 8 shows the R^2 and adjusted R^2 values, which reflect the explanatory power of the structural model. For Enterprise Organizational Performance, the R^2 value is 0.345, with an adjusted R^2 of 0.342, indicating that approximately 34.2% of the variance in organizational performance is explained by the model after accounting for the number of predictors. For Employees' Innovation Ability, the R-square is 0.277 and the adjusted R^2 is 0.275, suggesting that 27.5% of the variance is explained by its antecedent variable(s), primarily Staff Skill Training Investment. These values demonstrate a moderate level of explanatory strength and suggest that the model provides a reasonable fit for understanding the relationships among training investment, innovation ability, and performance in the context of intelligent manufacturing.

Table 8 Results of R^2

	R-square	R-square adjusted
Enterprise organizational performance	0.345	0.342
Employees' innovation ability	0.277	0.275

Table 9 presents the results of the hypothesis testing for the structural model, including path coefficients, standard deviations, t-values, p-values, and confidence intervals. All three hypotheses are statistically supported at the 95% confidence level. Specifically, H1 (Staff Skill Training Investment → Employee Innovation Ability) shows a strong and significant effect, with a t-value of 9.83 and a p-value < 0.001, indicating that investment in employee training significantly enhances innovation ability. H2 (Employee Innovation Ability → Enterprise Organizational Performance) also demonstrates a significant relationship (t = 4.611, p < 0.001), suggesting that employee innovation capability positively contributes to organizational performance. Finally, H3 (Staff Skill Training Investment → Enterprise Organizational Performance) reveals a robust direct effect (t = 7.051, p < 0.001), confirming that training investment directly enhances enterprise-level performance. The confidence intervals for all paths do not include zero, further reinforcing the reliability of these relationships within the intelligent manufacturing context.

Table 9 Path Analysis

Hypothesis	Path Relationship	Standard Deviation	T Value	P Value	2.5%	97.5%
H1	Staff Skill Training Investment → Employee Innovation Ability	0.054	9.83	0	0.412	0.625
H2	Employee Innovation Ability → Enterprise Organizational Performance	0.058	4.611	0	0.103	0.303
H3	Staff Skill Training Investment → Enterprise Organizational Performance	0.057	7.051	0	0.205	0.509

Table 10 shows the direct, indirect, and total effects of staff skill training investment on enterprise organizational performance, with corresponding standard deviations, t-values, p-values, and 95% confidence intervals. The indirect effect—mediated through employee innovation ability—is statistically significant (t = 4.266, p < 0.001), with a confidence interval [0.081, 0.215], indicating that part of the influence of training investment on performance operates through enhanced innovation capability. The direct effect from staff skill training investment to enterprise performance remains significant and substantial (t = 7.051, p < 0.001), with a confidence interval [0.289, 0.509], confirming that training exerts an immediate impact on organizational outcomes. The total effect, which combines both direct and indirect effects, is also highly significant (t = 11.543, p < 0.001), with a confidence interval [0.443, 0.628], highlighting the overall strong influence of training investment on organizational performance. These results support a partial mediation model, where employee innovation ability serves as a significant but not exclusive mediator in the relationship between training investment and enterprise performance.

Table 10 Mediation effect of employee innovation ability

Effect Type	Path	Standard Deviation	T Value	P Value	2.5%	97.5%
Indirect effect	Employee skill training investment → Employee innovation ability → Enterprise organizational performance	0.033	4.266	0	0.081	0.215
Total effect	Employee skill training investment → Enterprise organizational performance	0.047	11.543	0	0.443	0.628
Direct effect	Employee skill training investment → Enterprise organizational performance	0.057	7.051	0	0.289	0.509

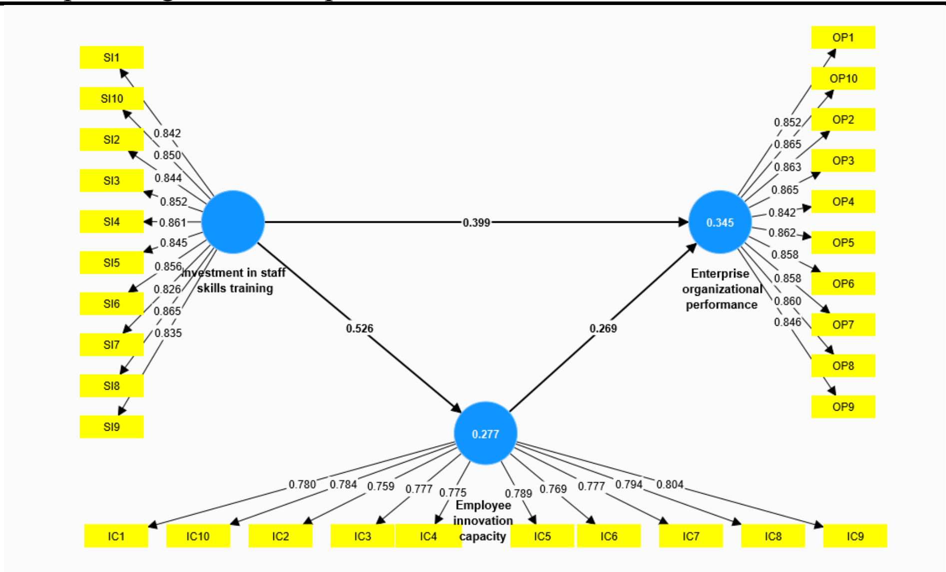

Figure 2 Structural equation

5. Discussion

This study offers important theoretical contributions to the fields of organizational behavior, innovation management, and intelligent manufacturing. By integrating concepts of staff skill training investment, employee innovation ability, and enterprise organizational performance into a structural model, the study advances understanding of how internal human capital mechanisms drive organizational outcomes in the era of digital transformation. Specifically, the confirmation of a partial mediation effect enriches the innovation literature by illustrating how employee innovation functions as a cognitive and behavioral pathway through which training investment influences performance. Moreover, the model transcends traditional views of training as a static, operational activity and reconceptualizes it as a dynamic strategic lever for enabling innovation and competitiveness, thereby expanding the boundaries of existing human capital and organizational learning theories within the context of smart manufacturing.

The findings provide strong evidence that enterprise-led skill development initiatives are essential to intelligent transformation. Companies seeking to remain competitive in high-tech environments should regard staff training not merely as a cost center but as a strategic investment with both immediate and long-term returns. The significant effects of training on both innovation ability and organizational performance suggest that human resource strategies must be aligned with broader technological and operational objectives. Training programs should therefore be designed to cultivate not only technical proficiency but also innovation capacity, creative problem-solving, and adaptability. Additionally, the findings support the development of integrated talent development systems that bridge functional departments, helping to embed innovation deeply within organizational culture.

Empirical results from the structural equation modeling provide robust support for the proposed hypotheses. Staff skill training investment was found to exert both a significant direct effect on enterprise organizational performance and an indirect effect through employees' innovation ability, thereby confirming the presence of a partial mediation mechanism. Employees' innovation ability itself was shown to positively influence enterprise performance, underscoring its strategic role in enhancing the adaptability, responsiveness, and competitiveness of manufacturing firms. The model's R^2 and Q^2 values indicate acceptable levels of explanatory and predictive power, affirming its robustness. These findings highlight that enhancing workforce competencies and fostering innovation behaviors are complementary strategies that together contribute to superior organizational outcomes in intelligent manufacturing contexts.

This study has several limitations that should be addressed in future research. First, the cross-sectional design restricts causal interpretation, and future studies should employ longitudinal or experimental methods to better understand dynamic relationships over time. Second, the use of self-reported survey data introduces potential biases, such as social desirability and common method variance, which may affect the reliability of responses. Incorporating multi-source data, such as managerial evaluations or objective performance metrics, would enhance the validity of future investigations. Third, the sample was limited to manufacturing firms in China, which may constrain the generalizability of the findings. Cross-sectoral and cross-cultural comparative studies are needed to test the model's applicability in other industries and national contexts. Finally, the study did not examine potential moderating variables such as leadership style, digital infrastructure, or organizational learning culture, which may further shape the relationship between training, innovation, and performance. Future research should explore these dimensions to provide a more comprehensive understanding of intelligent transformation.

6. Conclusion

This study aimed to empirically explore the impact of staff skill training investment on enterprise organizational performance in the context of intelligent manufacturing, with a specific focus on the mediating role of employees' innovation ability. Drawing on data collected from 385 valid responses within Chinese manufacturing firms undergoing intelligent transformation, the research employed structural equation modeling to test a hypothesized model. The results confirmed that staff training investment significantly enhances both employee innovation capability and overall organizational performance. Furthermore, the analysis revealed that innovation ability partially mediates the relationship between training and performance, suggesting a dual pathway through which human capital development contributes to enterprise success in smart manufacturing environments.

From a theoretical standpoint, the research enriches the literature on innovation and human capital by demonstrating that training serves not only as a technical enabler but also as a cognitive catalyst for innovation in intelligent industrial settings. It also extends existing models by empirically validating the mediating role of employee innovation, thereby strengthening the conceptual link between training input and performance outcomes. Practically, the study provides valuable guidance for manufacturing enterprises and policymakers, emphasizing the strategic importance of aligning training initiatives with innovation goals. Training programs that foster adaptive, creative, and improvement-oriented behavior can significantly accelerate the success of intelligent transformation initiatives.

This study underscores the central role of enterprise-driven training in shaping innovation and performance during the shift toward intelligent manufacturing. By demonstrating both direct and indirect effects of training on organizational outcomes, it highlights the importance of integrating human resource development into broader technological and strategic frameworks. While certain limitations exist, the findings offer a strong foundation for future research and for enterprises seeking to enhance competitiveness through workforce empowerment. Continued attention to the human dimension of intelligence-driven change will be essential as manufacturing evolves in the digital era.

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