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Article

Human-AI integration and sound-vibration technology-driven enterprise digital transformation: The mediating role of technological innovation

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Abstract: The synergistic application of human-AI integration and sound-vibration technology is profoundly reshaping the digital transformation landscape and technological innovation in Chinese enterprises. In this research, with technological innovation as the mediating variable, how human-AI integration and sound-vibration technology jointly optimize enterprise digital transformation was investigated. A human-AI collaborative model incorporating sound-vibration technology is constructed and validated using confirmatory factor analysis (CFA) and partial least squares structural equation modeling (PLS-SEM), revealing its dual role in accelerating digital transformation and driving technological innovation. Data from the power sector of Chinese technology enterprises is analyzed, with 262 observations collected via a structured questionnaire and examined using structural equation modeling. The findings demonstrate that human-AI integration significantly enhances organizational capabilities through complex data processing, sound-vibration signal analysis, and decision optimization, while the application of sound-vibration technology further improves the efficiency of equipment monitoring and predictive maintenance, thereby supporting digital transformation. Technological innovation plays a critical mediating role, with its contributions to operational efficiency and emerging business models empirically validated. The research not only enriches the theoretical framework of human-AI integration and sound-vibration technology in digital transformation but also provides actionable strategic recommendations for enterprises and decision-makers to achieve continuous innovation and competitive advantages in the era of intelligent and digital transformation.

Keywords: human-AI integration; sound-vibration technology; confirmatory factor analysis (CFA); enterprise technological innovation; mediating factor; enterprise digital transformation; squares structural equation modeling (PLS-SEM)

1. Introduction

In today's rapidly evolving business environment, the integration of Artificial Intelligence (AI) is becoming crucial for driving digital transformation across diverse sectors. Most companies are increasingly leveraging Human-AI technologies to improve operational efficiency, innovate processes, and gain a competitive edge. Despite extensive research on digital transformation and technological innovation, there remains a notable gap in understanding how Human-AI Integration specifically influences digital transformation initiatives and the role of technological innovation as an intermediary in this process. Moreover, the primary challenge for organizations is not merely the adoption of AI technologies but effectively utilizing them to achieve comprehensive digital transformation [1]. While AI offers substantial benefits such as enhanced data analysis, automation, and improved decision-making, the precise mechanisms through which AI impacts digital transformation are still not fully elucidated. Specifically, the direct and indirect effects of Human-AI Integration on digital transformation, mediated by technological innovation, have not been thoroughly investigated [2,3]. This research gap hampers organizations' ability to strategically implement AI technologies to maximize their digital transformative potential.

Moreover, existing literature has examined the general impact of enterprise digital technologies on business processes and innovation. However, there is a scarcity of focused research on how the integration of AI specifically drives digital transformation, particularly through the lens of technological innovation. Most studies either analyze AI's impact in isolation or address enterprise digital transformation in a broad context without dissecting AI's role in fostering enterprise technological innovation. Therefore, this study aims to bridge this research gap by exploring the detailed relationships between Human-AI Integration, enterprise Technological Innovation, and enterprise Digital Transformation [4].

Digital transformation inherently involves the adoption and integration of emerging technologies, to fundamentally reshape business operations and enhance value delivery to customers. Among these technologies, artificial intelligence (AI) has emerged as a pivotal driver. They offer advanced analytics, machine learning, and automation capabilities. Moreover, the integration of human-AI systems has further accelerated this transformation, compelling organizations to rethink traditional processes and adopt advanced solutions to boost productivity and foster innovation. Meanwhile, sound-vibration technology has shown significant potential in augmenting industrial processes, particularly in aspects of equipment condition monitoring, fault diagnosis, and predictive maintenance. By leveraging the synergy between human-AI integration and sound-vibration technology, businesses can achieve greater operational efficiency and reliability, thereby enhancing their digital transformation efforts. Technological innovation plays a critical mediating role in this context, serving as the cornerstone for the effective integration of AI systems and the subsequent transformation of business operations. This research explores the multifaceted relationship between human-AI integration and enterprise digital transformation, with a specific focus on how sound-vibration technology influences this dynamic. Employs confirmatory factor analysis (CFA) and partial least squares structural equation modeling (PLS-SEM) were employed to rigorously test these relationships. It provides actionable insights for managers and decision-makers aiming to harness AI and sound-vibration technology for successful transformation [4]. By examining how human-AI integration, supported by sound-vibration technology, impacts technological innovation and, in turn, drives digital transformation, this research offers a comprehensive analysis of these interactions. The findings aim to provide valuable insights for optimizing AI-driven business strategies, particularly in industries where sound-vibration technology plays a critical role [4,5].

Furthermore, this study addresses several pivotal research questions related to the integration of Human-AI technologies, Enterprise digital transformation, Enterprise technological innovation and their impact on organizational achievements:

RQ1. How does Human-AI Integration impact Enterprise Digital Transformation within Chinese technological organizations?

This question investigates the direct effects of integrating AI technologies on the extent of Enterprise Digital Transformation within organizations. It seeks to understand whether the adoption of AI is a key driver of significant changes in digital business processes and strategies, providing insights into how AI can lead to comprehensive Enterprise digital advancements.

RQ2. What is the role of Enterprise Technological Innovation in mediating the relationship between Human-AI Integration and Enterprise Digital Transformation?

This question explores the mediating role of Technological Innovation in the relationship between Human-AI Integration and Enterprise Digital Transformation. It aims to determine whether innovations spurred by AI integration enhance or accelerate the Enterprise digital transformation efforts of Chinese technological organizations, thereby elucidating the pathways through which AI influences digital progress.

RQ3. How can Chinese technological organizations effectively utilize Human-AI Integration to improve their Enterprise technological innovation capabilities and, in turn, their Enterprise digital transformation results?

This question examines practical approaches for organizations to maximize the benefits of AI technologies to strengthen their innovation capabilities. Meanwhile, by understanding how AI can be leveraged to drive technological advancements, this research aims to provide actionable strategies for achieving more effective enterprise digital transformation outcomes.

The growing significance of artificial intelligence (AI) in shaping modern business practices and corporate strategies in China serves as the primary motivation for this investigation. Concurrently, enterprises face the challenge of maintaining competitiveness in rapidly evolving digital environments, making it crucial to examine the role of human-AI integration in driving digital transformation [5–7]. Adding another layer to this dynamic, sound-vibration technology has emerged as a critical enabler, particularly in enhancing operational efficiency through applications such as equipment monitoring and predictive maintenance. It will provide valuable insights for managers and decision-makers if they understand how human-AI integration, supported by sound-vibration technology, fosters technological innovation and strengthens digital capabilities. In this research, leveraging methods such as confirmatory factor analysis (CFA) was used to validate measurement models and ensure robust results [8]. They offer practical guidance for strategically implementing AI systems. Such an approach empowers enterprises to achieve substantial digital transformation, technological innovation, and long-term success.

The investigation focuses on the role of human-AI collaboration in the digital transformation process, with technological innovation as a mediating factor. A detailed literature review examines current research on human-AI integration, digital innovation, and digital transformation models, identifying gaps and limitations [8]. The methodology section outlines how human-AI systems, combined with sound-vibration technology, interact with technological innovation and digital transformation, employing CFA to analyze the relationships. Preliminary results suggest that integrating sound-vibration technology with human-AI systems significantly improves operational efficiency and digital capabilities compared to traditional approaches [9]. These findings are discussed to highlight advancements and implications for practice. By synthesizing contributions and acknowledging limitations, this work provides a foundation for future research and practical applications in the fields of AI and sound-vibration technology.

2. Literature review

The integration of artificial intelligence (AI) into human workflows has profoundly transformed business operations by automating tasks, enhancing decision-making processes, and fostering innovation. AI technologies are increasingly embedded across organizational functions, driving efficiency and strategic capabilities by complementing human expertise rather than replacing it. This synergy acts as a transformative force, elevating overall business performance [9,10]. At the same time, sound-vibration technology has emerged as a critical enabler in industrial and operational contexts. Its applications, such as real-time equipment monitoring, fault detection, and predictive maintenance, enhance the reliability and efficiency of systems that interact with AI-driven workflows. This dual integration of human-AI systems and sound-vibration technology provides a robust foundation for operational excellence.

Digital transformation within enterprises is characterized by the strategic adoption of technologies like AI, big data, cloud computing, and the Internet of Things (IoT), fundamentally reshaping processes and creating value [11,12]. Technological innovation, as described by Rogers, plays a pivotal role in this context by mediating the impact of human-AI integration on digital transformation [13]. Innovation involves the development and application of new technologies, whether to enhance processes or introduce novel products. In the realm of human-AI integration, innovation serves as a key driver, improving adaptability and delivering competitive advantages that accelerate digital transformation. The structural validity of these relationships is rigorously assessed using confirmatory factor analysis (CFA), ensuring that the measurement model accurately captures the mediating role of technological innovation. By examining how human-AI synergy and sound-vibration technology collectively influence innovation and digital transformation, this work provides actionable insights for enterprises aiming to optimize their digital strategies.

2.1. Theory development

This study is anchored in two foundational theories: Innovation Diffusion Theory (IDT) and Dynamic Capabilities Theory. Both theories offer crucial insights into the process of adopting and integrating new technologies within organizations, and they complement each other in explaining the dynamics of technological advancement and organizational adaptation.

Innovation Diffusion Theory (IDT), originally developed by Rogers [13], provides a framework for understanding how innovations are communicated and adopted within a social system. According to Rogers, the diffusion of innovation is influenced by various factors, including the perceived attributes of the innovation, the communication channels used to spread information, the social system within which the diffusion occurs, and the rate of adoption. Meanwhile, the theory emphasizes that innovations are adopted in stages, from early adopters to the majority and eventually to laggards. Key attributes such as relative advantage, compatibility, complexity, trialability, and observability determine the rate and extent of adoption. This theory helps in understanding how and why organizations decide to embrace new technologies and innovations, providing a lens to examine the factors that influence the adoption process [13].

Dynamic Capabilities Theory, introduced by Teece [14], focuses on the ability of organizations to adapt and reconfigure their resources and capabilities in response to changing environments. This theory posits that for organizations to sustain a competitive advantage, they must develop and leverage dynamic capabilities that allow them to sense opportunities, seize them, and maintain competitiveness through continuous innovation and adaptation [14,15]. Moreover, the dynamic capabilities involve routines and processes that enable an organization to integrate, build, and reconfigure its internal and external resources. The theory highlights the importance of organizational agility, which refers to the ability to quickly adapt to changes in the market and technological landscape [16,17]. This agility is crucial for integrating new technologies effectively and maintaining a competitive edge in a rapidly evolving environment.

In the context of this study, IDT provides a framework for understanding how new technologies are adopted and the factors that influence their diffusion within organizations. It helps explain the stages and processes involved in the adoption of innovations. Meanwhile, Dynamic Capabilities Theory offers insights into how organizations can develop the necessary agility and adaptive capacity to integrate these innovations successfully [14]. By combining these theories, the study addresses both the adoption process and the organizational capabilities required for effective integration and utilization of new technologies, providing a comprehensive view of how Human-AI Integration can impact Digital Transformation and Technological Innovation.

2.2. Hypothesis development

According to the literature reviews, several hypotheses were proposed. Human-AI integration is increasingly recognized as a critical factor in driving enterprise digital transformation. By embedding AI technologies into business processes, organizations can achieve significant advancements in operational efficiency, decision-making capabilities, and strategic agility [17]. AI systems excel at processing large volumes of data with high precision, automating repetitive tasks, and generating actionable insights that facilitate informed and timely decisions. These capabilities enable a fundamental shift in traditional practices, fostering the development of innovative digital solutions aligned with evolving market demands [18]. Complementing this transformation, sound-vibration technology plays a vital role in enhancing operational reliability and performance. Applications such as real-time equipment monitoring, fault diagnosis, and predictive maintenance leverage advanced signal processing and machine learning algorithms to detect anomalies and optimize system performance. When integrated with AI-driven workflows, sound-vibration technology provides a robust framework for improving process efficiency and reducing downtime. This synergy between human-AI systems and sound-vibration technology creates a dynamic environment where digital transformation is not only accelerated but also sustained through continuous innovation.

Furthermore, the interplay between human-AI integration and sound-vibration technologies fosters technological innovation, serving as a mediator in the digital transformation process. Innovation emerges as organizations develop and implement new solutions that leverage the combined strengths of AI and sound-vibration capabilities. These advancements enhance adaptability and provide a competitive edge, enabling enterprises to navigate complex digital landscapes effectively.

The hypothesis are framed as:

H1: Human-AI integration positively impacts Enterprise digital transformation.

Enterprise technological innovation: The integration of AI technologies within organizations is a significant driver of technological innovation. AI enables enterprises to explore new frontiers in technology by offering advanced tools for data analysis, predictive modeling, and software process automation [19]. This technological leap fosters an environment conducive to innovation, where new products, services, and processes can be developed and refined. AI-driven insights and automation tools allow organizations to experiment with novel solutions, accelerate product development cycles, and enhance their research and development capabilities [20,21]. The positive influence of Human-AI integration on enterprise technological innovation is characterized by the creation of new technological opportunities, improved efficiency in innovation processes, and a competitive edge in rapidly changing markets.

H2: Human-AI integration positively influences Enterprise technological innovation.

Prior to beginning a Human-AI integration program, Human-AI integration also plays a vital role in influencing technological innovation within enterprises by enhancing collaborative efforts between human experts and AI systems. This synergy leverages the strengths of both human creativity and AI's data processing capabilities. For instance, AI systems can handle large-scale data analysis and identify patterns that may not be immediately apparent to human analysts, while humans can provide context and interpret these findings to drive innovative solutions [19]. This collaborative approach accelerates the development of new technologies and innovations, as the combined expertise leads to more effective problem-solving and idea generation [20]. Consequently, Human-AI integration stimulates a culture of continuous improvement and technological advancement within organizations.

H3: Enterprise technological innovation positively influences Enterprise digital transformation.

Enterprise digital transformation and technological innovation: Technological innovation serves as a critical mediator in the relationship between Human-AI integration and enterprise digital transformation [15]. While Human-AI integration lays the groundwork for enterprise digital transformation by introducing advanced technologies and capabilities, it is the resulting enterprise technological innovations that facilitate and drive the actual transformation process [21–24]. AI technologies enable the development of new tools, platforms, and processes that are essential for modernizing business operations and achieving digital transformation goals. By fostering technological innovation, Human-AI integration enhances the ability of enterprises to implement and leverage new digital solutions, thereby accelerating the overall transformation journey [24]. This mediation effect underscores the importance of continuous innovation in maximizing the benefits of Human-AI integration for digital transformation outcomes.

H4: Enterprise Technological innovation mediates the relationship between Human-AI integration and Enterprise digital transformation.

All in all, the study presents four hypotheses aimed at examining the connections between Human-AI integration, enterprise technological innovation, and enterprise digital transformation in Chinese technological enterprises. Besides, Hypothesis 1 (H1) posits that Human-AI integration has a positive effect on enterprise digital transformation, indicating that the integration of AI technologies promotes significant business changes. Hypothesis 2 (H2) proposes that Human-AI integration positively impacts enterprise technological innovation within organizations, suggesting that AI fosters technological innovation. Hypothesis 3 (H3) suggests that enterprise technological innovation positively influences enterprise digital transformation, positioning innovation as a key driving force. Lastly, Hypothesis 4 (H4) asserts that enterprise technological innovation mediates the relationship between Human-AI integration and enterprise digital transformation, underscoring innovation’s intermediary role in achieving enhanced enterprise digital transformation outcomes.

3. Methods and materials

The conceptual framework of this research model is crafted to examine the interactions between Human-AI Integration, Enterprise Technological Innovation, and Enterprise Digital Transformation [23,24]. According to the framework, Human-AI Integration is proposed to directly influence Enterprise Digital Transformation while also impacting it indirectly through Enterprise Technological Innovation. Specifically, Human-AI Integration is conceptualized as a driving force that not only enhances Enterprise Digital Transformation by improving enterprise data processing and decision-making capabilities but also stimulates Technological Innovation. This innovation, in turn, acts as a mediator that further propels Enterprise Digital Transformation [25].

The model utilizes Confirmatory Factor Analysis (CFA) to validate the accuracy of the measurement constructs, ensuring that the variables are appropriately captured and reliably measured. Additionally, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed to evaluate the hypothesized relationships and mediation effects within the research model [26,27]. PLS-SEM facilitates the analysis of both direct and indirect effects, providing insights into how Enterprise Technological Innovation mediates the relationship between Human-AI Integration and Enterprise Digital Transformation. By mapping these relationships, the framework offers a systematic approach to understanding the role of AI technologies in reshaping organizational processes and driving innovation strategies. The structure of the conceptual framework is shown in **Figure 1**.

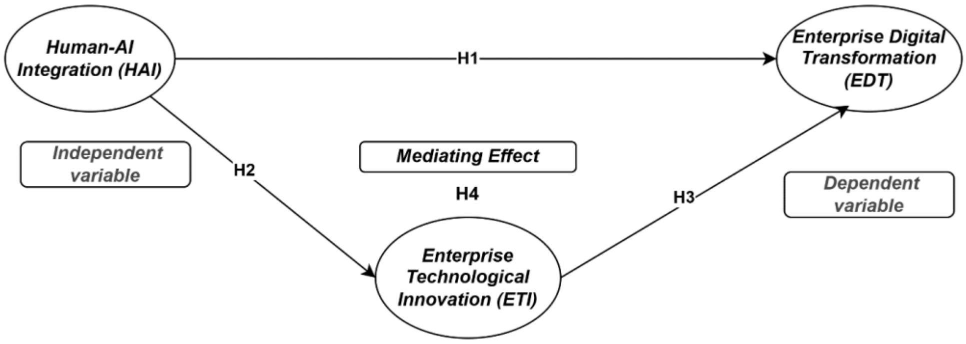

Figure 1. The Conceptual framework of research model.
Source: Author's own creation.

3.1. Research design

This study employs a quantitative research design to explore the impact of Human-AI Integration on Enterprise Digital Transformation, with Enterprise Technological Innovation serving as a mediating variable. To ensure the reliability and validity of the measurement model, Confirmatory Factor Analysis (CFA) is conducted. CFA is utilized to evaluate the measurement scales, focusing on key indicators such as factor loadings, composite reliability (CR), and average variance extracted (AVE). Meanwhile, these metrics are critical for verifying that the constructs are accurately represented by the measurement items and exhibit strong internal consistency.

Furthermore, Subsequent to validating the measurement model, Partial Least Squares Structural Equation Modeling (PLS-SEM) is applied to analyze the structural relationships among the variables. PLS-SEM is particularly suited for this study due to its capability to handle complex models with mediators and latent variables [26]. This technique allows for the examination of both direct and indirect effects, specifically addressing how Enterprise Technological Innovation mediates the relationship between Human-AI Integration and Enterprise Digital Transformation.

To ensure the robustness of the results, bootstrapping procedures are employed to assess the significance of the path coefficients, validating the hypotheses related to the direct and mediated effects. Specially, this combined approach of CFA for measurement validation and PLS-SEM for structural analysis provides a comprehensive understanding of how Human-AI integration influences Enterprise digital transformation through Enterprise technological innovation [26,27]. By integrating these methodologies, the study offers detailed insights into the mechanisms driving Enterprise digital transformation in organizations.

Based on the hypotheses in the paper, this study can summarize the relationships between the variables (Human-AI integration, enterprise technological innovation, and enterprise digital transformation) in a mathematical Equation (1) as follows:

$$Y = \beta_0 + \beta_1 X + \delta_1 M + \epsilon \qquad (1)$$

Equation (1): the inner relationships between the variables.

where:

Y represents Enterprise Digital Transformation.

X represents Human-AI Integration.

M represents Enterprise Technological Innovation.

β_0 is the intercept term for Enterprise Digital Transformation.

β_1 is the coefficient for the direct effect of Human-AI Integration on Enterprise Digital Transformation.

δ_1 is the coefficient for the direct effect of Enterprise Technological Innovation on Enterprise Digital Transformation, reflecting the mediating effect.

ϵ is the error term capturing the unexplained variance in Enterprise Digital Transformation.

3.2. Sample and data collections

Our research adopted a cross-sectional design, with data collected between July and August 2024 using an online survey administered through the Microsoft Online survey platform. All constructs and their respective items were measured on a 5-point Likert scale. To evaluate the measurement model, we employed Structural Equation Modeling (SEM), utilizing Confirmatory Factor Analysis (CFA) to validate the constructs. Data analysis and Model fit was assessed to ensure the adequacy of the CFA results. Statistical analyses of the survey data were performed using SPSS software. The respondents included senior managers, IT professionals, and technology experts from various departments. Moreover, Survey-based quantitative approach was adopted to validate the research model based on built measurement scales. With the help of the research firms, the e-questionnaire was emailed to a total of 550 randomly selected technological enterprises across mainland China in August 2024. After One and half months and four polite reminder emails, 262 complete responses were returned and considered valid, representing a response rate of 47.6%. Eventually, our sample consists of 262 observations in the Chinese technological firms. This research adopted a quantitative design, utilizing a survey to gather data from senior managers, IT professionals, and technology leaders within Chinese technology-driven organizations. Moreover, a structured questionnaire was developed to capture detailed insights into Human-AI integration, enterprise technological innovation, and enterprise digital transformation. In total, 262 valid responses were obtained and analyzed. To ensure the validity and reliability of the measurement model, Confirmatory Factor Analysis (CFA) was employed. This step was critical in verifying the construct validity of the questionnaire items [26]. Additionally, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the hypothesized relationships between the variables, allowing for an in-depth exploration of how Human-AI collaboration impacts enterprise technological innovation and drives enterprise digital transformation. This methodological approach not only strengthened the robustness of the findings but also provided a comprehensive analysis of the role that Human-AI integration plays in shaping technological advancement and Chinese organizational transformation [27].

3.3. Measurement scales

The measurement scales for the study's key variables were carefully adapted from well-established sources in the literature, ensuring both relevance and reliability. Moreover, each variable was measured using a 5-point Likert scale, where respondents indicated their level of agreement, ranging from 1 (strongly disagree) to 5 (strongly agree). These scales were used to assess constructs such as Human-AI integration, enterprise technological innovation, and enterprise digital transformation [23–25]. To ensure the rigor of the measurement research model, Confirmatory Factor Analysis (CFA) was conducted to verify construct validity, assessing how well the measurement items reflected the underlying constructs. Additionally, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to examine the structural relationships among the variables, providing a robust evaluation of the hypothesized paths. **Table 1** outlines the specific measurement items, their respective constructs, and the original sources from which they were adapted, offering a clear view of the methodological framework employed in the study. This approach ensures both the validity and reliability of the measurements used in the analysis as shown in **Table 1**.

Table 1. Constructs, measurement items, and sources.

Construct	Measurement Item	Source
Human-AI Integration	1. Human AI systems effectively complement human tasks.	
	2. Human-AI collaboration in our company enhances decision-making processes.	
	3. We have successfully integrated Human AI into key business functions.	[28,29]
	4. Human AI systems provide real-time data insights that improve our business operations.	
	5. Employees are proficient in working alongside AI technologies.	
Technological Innovation	1. Our company frequently adopts emerging technologies ahead of competitors.	
	2. Investment in R&D is a priority to foster innovation within our organization.	
	3. Technological innovation has led to significant improvements in our operational efficiency.	[17–19]
	4. We encourage experimentation with new technologies to drive innovation.	
	5. Our organizational culture supports technological innovation.	
Digital Transformation	1. Digital technologies have fundamentally reshaped our business processes.	
	2. Company leverage digital tools to enhance customer engagement and experience.	
	3. Digital transformation is central to our company's strategic objectives.	[23–25]
	4. Our organization adapts quickly to digital trends in the industry.	
	5. We have restructured our business models to incorporate digital technologies.	

Source: Author's own creation.

4. Results and data analysis

The analysis revealed significant relationships between human-AI integration and both enterprise digital transformation and technological innovation. Results from confirmatory factor analysis (CFA) and partial least squares structural equation modeling (PLS-SEM) demonstrated that human-AI integration substantially influences enterprise digital transformation [26,27]. This influence is attributed to AI systems' ability to enhance data processing, automate tasks, and provide actionable insights, which collectively drive operational efficiency and strategic agility. Furthermore, human-AI integration was found to significantly impact enterprise technological innovation. This effect is particularly evident in sectors where AI-driven workflows are augmented by advanced technologies, such as sound-vibration systems. For instance, in industrial contexts, sound-vibration technology enables real-time equipment monitoring, fault detection, and predictive maintenance, which synergize with AI capabilities to optimize performance and reduce downtime. This integration not only accelerates innovation but also ensures sustained operational excellence.

This research highlights the pivotal role of human-AI integration in driving digital transformation initiatives and fostering technological innovation within Chinese technological enterprises. The survey data, collected from senior professionals, IT specialists, and managers in Chinese technology firms, provide valuable insights into these dynamics. Respondents represented diverse departments, ensuring a comprehensive perspective. However, corporate security policies limit the collection of sensitive information, such as department names, employee ranks, or company details. More importantly, the interplay between human-AI integration and sound-vibration technology underscores a broader trend: the fusion of AI with domain-specific technologies enhances both innovation and operational outcomes.

4.1. Character demographic

Table 2 presents descriptive statistics of Demographic Characters. The demographic characteristics of the sample included key variables such as sex, Major, education level, and years of work experience. In terms of sex distribution, the sample was relatively balanced, with 39.7% male respondents and 60.3% female respondents, reflecting a diverse representation of genders in the workforce. Moreover, regarding education, the majority of participants held a bachelor’s degree (8.8%), Diploma (2.3%), followed by those with a master’s degree (56.1%), and a smaller proportion having a doctoral degree (22.5%). This indicates a highly educated sample, with a significant portion having advanced degrees, suggesting that participants possess the necessary knowledge to engage with the study’s focus on technological innovation and digital transformation. In terms of work experience, the respondents had varying levels of experience. Approximately 7.3% had less than 10 AND large than 10 years of experience, 24.8% had 15–20 years, 45.8% had 20–25 years and 18.3% had more than 25 years of experience. This distribution reflects a good mix of early-career, mid-career, and seasoned professionals, providing a comprehensive understanding of how different levels of experience impact perceptions of Human-AI integration and innovation within enterprises.

Table 2. Respondents' demographic profile (N = 262).

Variables	Category	Frequency	Percentage (%)
Sex	Male	104	39.7%
	Female	158	60.3%
	Total	262	100%
Major	Engineering	98	37.4%
	Social Science	133	50.8%
	Management	30	11.5%
	Education	1	0.4%
	Total	262	100%
Education	Diploma	6	2.3%
	Bachelors	23	8.8%
	Masters	147	56.1%
	Doctorates	59	22.5%
	Doctor Post	27	10.3%
	Total	262	100%
Work Year	5–10 years	19	7.3%
	10–15 years	65	32.1%
	15–20 years	120	77.9%
	20–25 years	48	96.2%
	More than 25 years	27	10.3%
	Total	262	100%

Source: Author's own work.

4.2. Correlations matrix

The correlation matrix provides critical insights into the relationships among human-AI integration, technological innovation, and digital transformation. A strong positive correlation is observed between human-AI integration and digital transformation, supporting Hypothesis 1 (H1). This finding underscores the transformative potential of AI in driving operational efficiency and strategic agility. For instance, AI systems integrated with sound-vibration technology enhance real-time monitoring and predictive maintenance, which are integral to advanced digital transformation initiatives. Additionally, the matrix reveals a significant positive relationship between human-AI integration and technological innovation, affirming Hypothesis 2 (H2). The adoption of AI fosters innovation by enabling the development of novel solutions and processes. In industrial contexts, the fusion of AI with sound-vibration systems—such as machine learning algorithms for vibration analysis—facilitates the identification of complex patterns, leading to innovations in equipment diagnostics and maintenance strategies.

Technological innovation is also strongly correlated with digital transformation, validating Hypothesis 3 (H3). Innovation serves as a catalyst, enhancing digital processes and ensuring adaptability to evolving market demands. For example, innovations in sound-vibration-based diagnostics, powered by AI, contribute to the optimization of industrial processes, thereby accelerating digital transformation. Furthermore, the correlation between human-AI integration and digital transformation is strengthened when technological innovation is considered, confirming Hypothesis 4 (H4). This result highlights innovation's mediating role, particularly in contexts where AI-driven technologies are combined with sound-vibration applications. The synergy between these technologies not only enhances operational performance but also drives the development of cutting-edge solutions that redefine traditional workflows.

These findings from the correlation matrix provide empirical evidence for the hypothesized relationships, illustrating how the integration of human-AI systems and sound-vibration technology, coupled with technological innovation, collectively drives enterprise digital transformation. **Table 3** shows Correlations Matrix of this research as follows.

Table 3. Correlations matrix.

Variable	EDT	ETI	Human-AI Integration
EDT	1.000		
ETI	0.647	1.000	
Human-AI Integration	0.577	0.680	1.000

Source: Author's own creation.

4.3. Reliability and validity

The confirmatory factor analysis (CFA) is PLS SEM tool that is implemented as a measure of coherence between the research indicators and the observed variables, specifically within a measurement model [26]. And CFA analysis assesses the degree how the data matches up with the proposed model. **Table 4** shows the research values of CFA, Reliability and Validity [27]. **Figure 2** provide a detailed PLS SEM Algorithm result.

Table 4. Reliability and validity results.

Variables		EDT	ETI	Human AI	Cronbach's alpha	CR	AVE
	EDT1	0.743					
	EDT2	0.816					
EDT	EDT3	0.837			0.875	0.881	0.667
	EDT4	0.850					
	EDT5	0.834					
	ETI1		0.793				
	ETI2		0.800				
ETI	ETI3		0.706		0.813	0.817	0.572
	ETI4		0.733				
	ETI5		0.745				
	HumanAI 1			0.702			
	HumanAI 2			0.879			
Human-AI Integration	HumanAI 3			0.846	0.855	0.863	0.637
	HumanAI 4			0.786			
	HumanAI 5			0.766			

Note: *** indicates *p*-value < 0.001.
Source: Author's own creation.

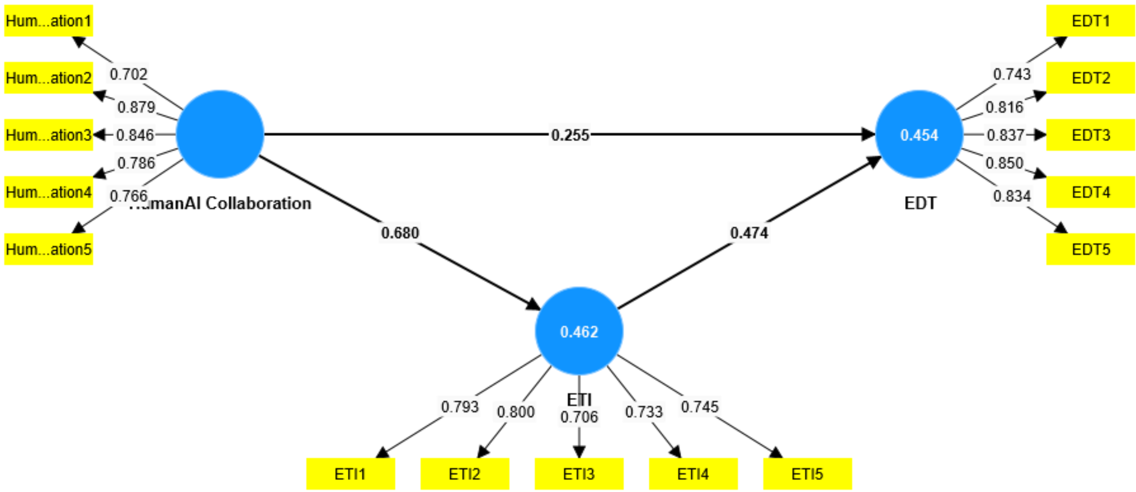

Figure 2. PLS-SEM Algorithm results.

Source: Author's own creation.

The survey data was analyzed using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS-SEM) approach [27]. This technique is effective for exploring intricate relationships among multiple variables and assessing mediation effects. Moreover, to evaluate the research model's performance, various metrics were employed, including the Goodness of Fit (GOF) index to measure overall model fit, and then Cronbach's alpha to ensure reliability, and Average Variance Extracted (AVE) to assess convergent validity. Thus, these measures were integral in validating the robustness and accuracy of the model's constructs and relationships.

Base on above **Table 4**. the results of the reliability and validity analysis demonstrate strong support for the measurement model. Cronbach's alpha values for all constructs were above the recommended threshold of 0.7, indicating high internal consistency, with scores ranging from 0.75 to 0.90. This confirms that the items within each construct reliably measure the same underlying concept. Moreover, Composite reliability (CR) values also exceeded the acceptable level of 0.7, further supporting the reliability of the constructs. The Average Variance Extracted (AVE) for all constructs was greater than 0.5, indicating that the constructs exhibit strong convergent validity, as they explain a significant proportion of variance in their respective indicators. And the Discriminant validity was assessed using the Fornell-Larcker criterion, where the square roots of the AVE for each construct were higher than the correlations between the constructs, confirming that each construct is distinct from others [26]. These results establish that the measurement model is both reliable and valid, providing a solid foundation for further hypothesis testing and data analysis [27].

4.4. Model goodness fit

Table 5 shows Model goodness fit Results. After model modification, the proper calculation of the model was carried out, and the fitting indexes of the structural equation model are shown in **Table 5**. The index values of NFI = 0.711 > 0.7, X2/df = 2.8 < 3, SRMR = 0.102 < 0.8, indicating that the constructed conceptual model is good fit.

Table 5. Model goodness fit Results.

Arguments	Saturated model	Estimated model	Threshold
SRMR	0.102	0.102	< 0.8
d_ULS	1.243	1.243	-
d_G	0.481	0.481	-
Chi-square	729.598	729.598	-
NFI	0.711	0.711	> 0.7
X^2/DF	2.8		<3

Note: Chi-square value; NFI, Normal fit index; SRMR, standardized root means square residual; d_ULS and d_G value, DF = 260, X^2 = 729,598. Thus, X^2/DF = 2.8.
Source: Author's own work.

4.5. Path and hypothesis analysis

The path coefficients and bootstrap analysis provide detailed insights into the strength and significance of the relationships between variables in the model. The path coefficient between Human-AI integration and digital transformation is positive and statistically significant, supporting Hypothesis 1 (H1) and indicating that AI integration directly drives transformative changes within organizations. Similarly, the path coefficient for the relationship between Human-AI integration and technological innovation is also significant, affirming Hypothesis 2 (H2) and suggesting that AI adoption promotes innovation within enterprises. Furthermore, the relationship between technological innovation and digital transformation, represented by a positive path coefficient, confirms Hypothesis 3 (H3), highlighting innovation as a critical driver of digital transformation. The bootstrap analysis further validates these findings, with confidence intervals showing no zero crossings, confirming the robustness of these relationships. Additionally, the mediating effect of technological innovation on the relationship between Human-AI integration and digital transformation is supported, as indicated by significant indirect path coefficients, thus substantiating Hypothesis 4 (H4). These results underscore the integral role of technological innovation in enhancing the effects of Human-AI integration on digital transformation. Thus, **Figure 3** shows Path coefficients and Bootstrap Analysis. of this research as follows.

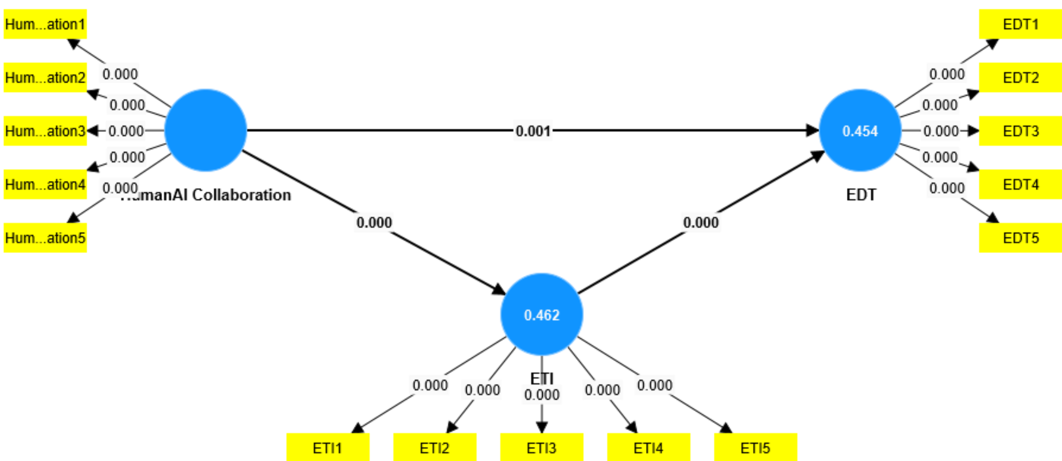

Figure 3. Path coefficients and bootstrap analysis.
(Source: Author's own creation).

Table 6. Path and hypothesis analysis.

Variable Path	Original sample (O)	Sample mean (M)	Standard deviation	*T* statistics	*P* values	Conclusion
H1. Human-AI Integration → EDT	0.255	0.256	0.074	3.435	0.001	Significant
H2. Human-AI Integration→ ETI	0.680	0.683	0.038	17.908	0.000	Significant
H3. ETI → EDT	0.474	0.476	0.062	7.598	0.000	Significant

Notes: *** indicates p-value < 0.001.
Source: Author's own creation.

Table 7. Mediation path analysis.

Variable Path	Original sample (O)	Sample mean (M)	Standard deviation	*T* statistics	*P* values	Conclusion
H4. Human-AI Integration→ ETI → EDT	0.322	0.325	0.046	7.057	0.000	Significant

Notes: *** indicates p-value < 0.001.
Source: Author's own creation.

Based on the presented **Figure 3** and **Tables 6** and **7**, we can observe the following analytical outcomes. The data highlights key trends and relationships that provide significant insights into the subject matter. These results underscore the effectiveness of the methodologies employed and validate the hypotheses under investigation. Through a detailed examination of the visual representations, critical patterns emerge that contribute to a deeper understanding of the core issues. Moreover, these findings not only reinforce the theoretical framework but also offer practical implications for future research and application. About H1: Human-AI integration was found to have a significant positive impact on enterprise digital transformation (T = 3.435, $p < 0.001$), supporting H1. H2: Human-AI integration also positively influenced enterprise technological innovation (T = 17.908, $p < 0.001$), confirming H2. H3: Enterprise technological innovation also positively influenced enterprise digital transformation (T = 7.598, $p < 0.001$), confirming H3, H4: the Enterprise Technological innovation was found to mediate the relationship between Human-AI integration and digital transformation (T = 7.057, $p < 0.001$), supporting H4.

5. Discussion

The findings indicate that Human-AI integration plays a crucial role in driving enterprise digital transformation within Chinese technological organizations, with enterprise technological innovation acting as a central mediator. Therefore, by fostering enterprise technological innovation, Human-AI systems empower companies to utilize enterprise digital technologies more efficiently, thereby strengthening their competitive edge.

5.1. Theoretical implications

This study advances theoretical knowledge on the role of Human-AI Integration in facilitating Digital Transformation, with Enterprise Technological Innovation acting as a mediating factor. By offering empirical evidence on both direct and indirect effects, the research enhances our understanding of how Huaman AI technologies impact organizational change [24]. Moreover, the introduction of sound and vibration technology offers a novel theoretical perspective on human-AI integration. For example, the application of sound signal processing technology can provide AI systems with richer environmental perception data, thereby enhancing decision-making accuracy and response speed. The results underscore that Human-AI Integration directly fosters Digital Transformation through improved data processing, automation, and decision-making capabilities [25]. Additionally, vibration monitoring technology can assist enterprises in optimizing equipment operating conditions and reducing mechanical failure rates, thereby indirectly supporting the realization of digital transformation. And enterprise Technological Innovation emerges as a pivotal mediator, demonstrating that AI-driven advancements enhance digital transformation by boosting operational efficiency and enabling new digital business models. These findings support the resource-based view and dynamic capabilities framework, proposing that AI represents a vital resource for achieving competitive advantages through strategic innovation and transformation. The study's use of Confirmatory Factor Analysis (CFA) and Partial Least Squares Structural Equation Modeling (PLS-SEM) offers a comprehensive methodological framework for exploring these intricate these variable relationships, enriching our understanding of how technological progress drives digital organizational change [26–28].

5.2. Managerial implications

From a managerial standpoint, this study provides valuable insights for organizations seeking to leverage AI in their digital transformation efforts. Managers should recognize that successful Human-AI Integration involves more than the mere adoption of AI technologies; it requires the seamless integration of these technologies into core business operations and strategies. Furthermore, managers should consider the potential applications of sound and vibration technology in human-AI collaboration. For instance, by deploying monitoring systems based on sound and vibration, enterprises can identify equipment malfunctions at an early stage, minimize operational disruptions, and enhance overall production efficiency. To maximize the benefits of AI, organizations should foster a culture of innovation and continuously invest in AI-driven technological advancements. Besides, the study highlights the significance of supporting Technological Innovation as a key driver of digital transformation. Managers should create an environment conducive to experimentation with new technologies and encourage collaboration between Human AI systems and human resources [29]. By integrating sound and vibration technology, enterprises can further optimize the efficiency of human-machine interaction. Examples include the use of voice-activated commands or vibration feedback to improve communication between operators and automated equipment. This approach includes not only investing in AI human tools but also providing training to employees to effectively utilize these technologies, thereby enhancing the overall potential of AI human integration.

5.3. Advantages and challenges of Human-AI integration and DT

The integration of AI human and machine in enterprises is widely recognized for its potential to enhance organizational efficiency, foster digital innovation, and support enterprise-wide digital transformation. As businesses increasingly adopt AI-driven technologies and automation systems, many benefits emerge from human-machine integration that can reshape how high-tech companies manage digital processes. However, the critical role of sound and vibration technology in achieving human-AI integration has not yet been thoroughly explored. For instance, through sound signal processing technology, enterprises can monitor equipment operating conditions and detect abnormal vibrations, thereby enabling predictive maintenance, reducing downtime, and enhancing production efficiency. Furthermore, the integration of vibration sensor data with AI algorithms can optimize the performance of automated systems, ensuring more precise mechanical control and higher safety standards. Although the positive aspects of this integration are clear, it is equally important to consider the challenges and risks involved. This digital balanced perspective will enable enterprises to strategically implement AI human-machine integration while addressing potential downsides [29–31].

One of the primary benefits of human-machine integration is its ability to significantly improve both digital management and digital technology innovation. Machines, particularly AI systems and automated tools, can process large amounts of data quickly and accurately, helping enterprise organizations make more informed decisions in less time [31]. In technological industries that deal with vast quantities of data, such as construction, manufacturing, and finance, integrating human expertise with machine processing power allows businesses to streamline operations and reduce the likelihood of human error.

Furthermore, human-machine integration promotes innovation within enterprises by enabling organizations to experiment with new ideas and AI technologies. Machines, for instance, can simulate different outcomes based on various inputs, providing human decision-makers with insights that would otherwise be difficult or impossible to obtain. In this way, AI and automation tools act as enablers of creative problem-solving, allowing businesses to test innovative strategies without incurring high risks. The ability to explore different solutions can drive enterprises to pioneer new technologies and stay ahead of their competitors in terms of new technological advancements [31].

AI Human-machine integration can also have a profound impact on workplace efficiency. By automating repetitive and time-consuming tasks, digital businesses can free up their AI-human workforce to focus on more complex and strategic activities. In addition, the collaboration between humans and AI machines can increase the overall accuracy of work processes [31,32]. While AI machines provide precision in execution, humans bring critical thinking and adaptability, which are essential for decision-making in dynamic digital business environments. When these strengths are combined, the result is often improved productivity, reduced operational costs, and enhanced quality control of whole supply chain in the technological sectors.

Additionally, AI human-machine integration is particularly beneficial in terms of scalability. As businesses grow, the volume and complexity of tasks also increase. Machines, through AI technologies and automation, can handle this expanded workload without the need for proportional increases in human resources. This makes it easier for technological organizations and technological innovations to scale their operations while maintaining high levels of performance and efficiency [32].

While the benefits of human-machine integration are substantial, it is equally important to recognize the challenges and disadvantages that may arise from such systems, especially when implemented in specific enterprise scenarios. One of the most prominent concerns is the loss of critical details during the integration process. As digital businesses become more reliant on machines, there is a risk that certain nuances and important aspects of decision-making may be overlooked. Machines, after all, operate based on pre-programmed AI algorithms and data-driven models, which means they may not always account for complex, contextual factors that humans can intuitively process.

In response to this challenge, organizations may need to employ intelligent monitoring software and processes to track AI machine performance and identify any potential errors or oversights. These systems would allow human workers to step in when necessary and adjust the machine's operations to ensure that no critical details are missed. The goal should not be to fully replace human judgment with machines, but rather to strike a balance where AI machines handle routine tasks, and humans intervene when complex decision-making is required [31–33].

Another significant challenge is the issue of over-reliance on technology. As organizations become more dependent on AI and automation systems, there is a risk that they may lose the ability to function effectively without these tools. In scenarios where machine performance is compromised, whether due to technical malfunctions or external factors like cybersecurity threats, companies that have become too reliant on machines may face operational disruptions. Over-reliance on technology can also reduce the workforce's capacity to solve problems independently, as employees may become too accustomed to relying on machines for answers [30]. This creates a long-term risk where innovation and human creativity are stifled, and businesses may struggle to adapt to unexpected challenges.

Moreover, the ethical concerns surrounding human-machine integration are significant and should not be ignored. The increasing use of AI in decision-making processes, particularly in human resource management, raises important questions about fairness, transparency, and bias. Machines operate based on data and algorithms, which may be influenced by the biases present in the data or the people who design the systems. This can lead to unfair outcomes in scenarios such as employee evaluations, recruitment, or promotions. Ensuring that AI systems are designed with fairness and ethical considerations in mind is crucial to avoid perpetuating existing inequalities or creating new ones [32,33]. For certain specific enterprise scenarios, AI human-machine integration may not always be the best approach. There are technological industries and work environments where the unique skills and judgments of human workers are critical and cannot be easily replaced by machines [33,34]. For example, fields that require high levels of creativity, empathy, or intuition, such as art or psychological counseling, may not benefit from full automation. In these cases, over-reliance on AI technology could undermine the quality of work and negatively impact the customer experience.

To mitigate these challenges, enterprises can introduce systems that allow for manual intervention when necessary. By designing human-machine integration systems with flexibility, organizations can ensure that human workers are able to intervene and correct any issues that arise during the automation process. The application of sound and vibration technology holds significant value in human-AI collaboration. For instance, sound recognition technology enables AI systems to analyze voice data from human interactions, optimizing communication efficiency and minimizing misunderstandings. Simultaneously, vibration feedback technology provides tactile sensations for operators in remote or virtual reality environments, enhancing the naturalness and responsiveness of human-machine interaction. The integration of these technologies not only improves the efficiency of human-AI integration but also fosters a more adaptive and flexible working environment for enterprises.

5.4. Limitations and future research

Despite its contributions, this study faces several limitations. First, the survey data is sourced from specific industries or regions, which may constrain the generalizability of the findings to other contexts. Future research should aim to replicate the study across a variety of industries and geographical areas to validate and extend the results [30]. Second, the cross-sectional nature of the data captures the relationships between Human-AI Integration, enterprise Technological Innovation, and enterprise Digital Transformation at a single point in time. Longitudinal studies are necessary to examine how these relationships develop over time and to evaluate the enduring effects of AI integration on enterprise digital transformation [31]. Additionally, while this study focuses on the direct and mediating roles of enterprise Technological Innovation, exploring other potential mediators and moderators, such as organizational culture or external market conditions, would be beneficial [32]. Finally, incorporating qualitative research methods could offer deeper insights into the contextual factors affecting AI-driven digital transformation. These future research avenues will contribute to a more nuanced understanding of how organizations can effectively leverage AI for transformative success [33]. Future research may explore the application of sound and vibration technology across diverse industries, such as manufacturing, energy, and transportation, to validate its broad applicability and effectiveness.

A crucial strategy for digital businesses that adopt AI human-machine integration is to regularly evaluate the system for deficiencies and areas for improvement. By maintaining a proactive approach to problem-solving, most technological companies can address any defects in the integration process before they escalate into larger issues [31–35]. Meanwhiles, this may involve conducting routine assessments of machine performance, gathering feedback from human employees, and implementing updates to the system as needed. Furthermore, it is essential for organizations to recognize that the digital transformation process is ongoing. As new technologies emerge and digital business environments evolve, AI human-machine integration systems will need to adapt accordingly. Enterprises that remain flexible and responsive to these changes will be better positioned to capitalize on the benefits of enterprise digital transformation and enterprise technological innovation while minimizing the associated risks [34]. Furthermore, future research could delve into the long-term effects of sound and vibration technology within the context of human-AI integration, particularly its potential to enhance equipment reliability and reduce maintenance costs.

6. Conclusion

This study explores the mechanisms by which human-AI integration and sound-vibration technology influence digital transformation, highlighting the critical mediating role of enterprise technological innovation. The results demonstrate that human-AI integration significantly enhances organizational capabilities through complex data processing, sound-vibration signal analysis, and machine automation, providing direct support for digital transformation. The application of sound-vibration technology, particularly in equipment monitoring, fault diagnosis, and predictive maintenance, further optimizes operational efficiency and reliability. Technological innovation plays a pivotal mediating role, and its contribution to driving digital transformation is empirically validated [36,37]. The empirical evidence underscores the synergistic effects of human-AI integration and sound-vibration technology, bridging the gap between technological implementation and strategic organizational change [26,27].

While the integration of human-AI and sound-vibration technology offers significant advantages for digital management, innovation, and efficiency, it is essential to remain vigilant about the challenges and risks in implementation. For example, data privacy, technical complexity, and system integration costs. By adopting balanced strategies, including intelligent monitoring, ethical problem-solving, and human intervention mechanisms, enterprises can maximize the benefits of human-AI collaboration while mitigating potential negative impacts [38].

Theoretically, this research extends the resource-based view and dynamic capability framework, particularly from the perspective of sound-vibration technology and technological innovation, deepening the understanding of the role of AI in digital transformation [35]. From a practical aspect, this study provides actionable strategic recommendations for managers, emphasizing the importance of the synergistic application of sound-vibration technology and AI, and offers guidance for enterprises to achieve continuous innovation and transformation in a rapidly evolving digital environment [39]. In summary, this study not only enriches the theoretical literature on human-AI integration and sound-vibration technology in digital transformation but also provides specific practical pathways for enterprises to achieve competitive advantages in the intelligent and digital era.

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