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The Interplay of Artificial Intelligence and Digital Transformation in Shaping Corporate Strategy: Insights from Chinese Enterprises

Xuexiu Li[1], Linyu Xie[2*], Dan Hou[3], Ziyan Yuan[4]

[1,2,4]Yunnan Technology and Business University, Kunming City, Yunnan Province, China
[3]College of Economics and Management, Honghe University, Mengzi City, Yunnan Province, China
E-mail. [1]21756880@qq.com; [2]409838749@qq.com; [3]113052250@qq.com; [4] yzyaini07182022@163.com*
** Corresponding author*

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In the quest for a sustainable and innovative future, the integration of Artificial Intelligence (AI) with Digital Transformation has emerged as a pivotal strategy for businesses navigating the rapidly evolving digital economy. This research explores the dynamic relationship between AI adoption and corporate transformation, with a focus on publicly listed companies in China. Drawing on a multi-theoretical framework-comprising dynamic capabilities theory, the resource-based view, and the technological innovation systems perspective-the study employs robust panel econometric techniques, including Westerlund panel cointegration tests, dynamic panel OLS, and panel vector error correction models, to analyze 3,602 firm-year observations from 2010 to 2020. The results reveal significant long-term cointegration and a bidirectional causality between AI and DT, supporting a mutually reinforcing relationship. Moreover, technology-oriented businesses achieve greater levels of transformation. The findings demonstrate that AI integration significantly influences both current and future corporate transformation, underscoring a mutually beneficial relationship where AI and transformation drive each other. These insights are crucial for enterprises and policymakers aiming to harness the transformative potential of technological innovations.

Keywords: *Artificial Intelligence; Digital Transformation; Corporate Strategy; Technological Innovation; Dynamic Capability Theory.*

Introduction

In the contemporary business environment, where digitization and data-driven operations are paramount, organizations are confronted with unprecedented challenges in sustaining their competitive advantage (Kun, 2024). This reality has ignited a burgeoning curiosity in exploring the convergence of AI (artificial intelligence) and digital transformation (transformation- hereafter) as a means to navigate and thrive in this rapidly evolving landscape (Yang *et al.*, 2025). AI refers to the imitation of human aptitude by machines, chiefly computer systems (Paesano, 2021). It involves the establishment of techniques like NN (neural networks), NLP (natural language processing), ML (machine learning) etc. to imbue computer systems with enhanced intelligence, enabling them to autonomously execute tasks that traditionally required human intelligence (Stanley & Aggarwal, 2019). Transformation, on the other hand, is the strategic utilization of emerging digital innovations to fundamentally renovate business happenings, procedures, models, and client purchasing practices. While definitions may vary, transformation generally encompasses the application of CP (cyber-physical) systems and unconventional 4.0 technologies to create smart, connected, and data-driven organizations (Yang *et al.*, 2025). It involves leveraging technologies like social media, mobile, analytics, and embedded devices to reimagine and deliver novel value propositions to customers (Gigauri, 2020; Yang *et al.*, 2025).

In recent decades, AI has ascended to prominence as one of the most promising and potentially transformative technologies for a vast array of industries and applications (Yanqing *et al.*, 2019). As new AI techniques become available, businesses can now analyze insights from enormous data to enter new markets and offer more products and services to existing customers (Xiaofeng *et al.*, 2020). Partly due to the triumph of star digital organizations in an extremely competitive environment and the necessity of making quick decisions with limited resources, numerous businesses have shown willingness to implement AI (Li, 2024; Mohamed, 2019). Businesses in a variety of disciplines and industries are becoming aware of the need to incorporate AI into their transformation strategies.

Despite the widespread use of AI across industries, our knowledge of AI's potential effects on transformation is still in its initial stages (Yang *et al.*, 2025). Researchers have delved into the applications of AI across various domains, shedding light on its potential in specific fields (Pradhan & Chawla, 2020). Complementing these explorations, scholars have also scrutinized the theoretical (Wang & Goertzel, 2012) as well as philosophical (Vernon & Furlong, 2007) foundations. Beyond these, extensive research has investigated the practical implementations of AI technologies across diverse sectors (Sanchez *et al.*, 2020). These studies identified the barriers and challenges organizations face in adopting AI solutions (Haefner et al., 2021), in addition to AI competence to augment and streamline organizational processes (Frank *et al.*, 2019). Additionally, researchers have explored AI's role in aiding decision-making processes, optimizing operational efficiency, driving the development of corporate models, and supporting the achievement of broader corporate objectives (Belhadi *et al.*, 2021; Verganti *et al.*, 2020).

Recent research by Yang et al. (2025) has revealed the positive impact of AI technologies in accelerating corporate transformation efforts. However, it is worth mentioning that transformation and AI within organizations are highly interrelated. As organizations embrace transformation initiatives, they are concurrently laying the foundation for increased implementation of AI. Numerous empirical studies have demonstrated that corporate transformation initiatives tend to significantly enhance innovation growth (e.g., (Zhang & Yang, 2023). As AI is widely regarded as a technological innovation (Johnk *et al.,* 2021), it is conceivable that AI and transformation will co-evolve within businesses over time. Thus, the relationship between transformation and AI is not unidirectional rather a multifaceted and synergistic, underpinned by several key factors.

The integration of Artificial Intelligence (AI) and Digital Transformation (DT) has attracted growing scholarly interest, yet existing literature often treats these constructs in isolation or assumes a unidirectional influence from AI to DT (Di Vaio *et al.,* 2020; Hutchinson, 2020; Yang *et al.,* 2025). What remains underexplored is the possibility of a *symbiotic, long-term, and reciprocal relationship* between the two, particularly in the context of emerging economies such as China-where the pace and scale of both AI deployment and digital transformation efforts are particularly intense.

The central aim of this research is to answer the above key questions by performing an in-depth analysis of Chinese corporate data spanning the period 2010 to 2020. Our methodological approach involves employing panel co-integration tests, more precisely the WPCT (Westerlund panel cointegration test) (Westerlund, 2007), to investigate the two way relationship between AI and transformation within enterprises. We utilize DPOLS (Dynamic Panel Ordinary Least Squares) and the PVECM (panel vector error correction model) to examine the potential reciprocal causal relationship between corporate transformation and AI implementation. Additionally, we conduct subsample analyses to control for issues of endogeneity and serial correlation.

Leveraging the Westerlund methodology (Westerlund, 2007), renowned for its superior size precision and strength compared to earlier residual-based cointegration analyses, we initially explore if a positive long-run association exists between AI adoption and the success of corporate transformation efforts. We confirm the presence of long-run cointegeration and assess the cointegration vector by estimating using a DPOLS approach, which mitigates biases arising from endogeneity and serial correlation. Recognizing the potentially bidirectional nature of the links between corporate transformation and AI, we employ the PVECM method to unravel these causal dynamics. To further reinforce the robustness of our estimates, we divide our sample into polluting and non-polluting enterprises, and re-estimate the cointegration correlation and causality between the two variables.

While recent studies, Hutchinson (2020), Di Vaio et al. (2020) and most notably Yang et al. (2025), have laid important groundwork by demonstrating that artificial intelligence (AI) can serve as a significant driver of digital transformation (DT), the present study advances the literature by offering a more comprehensive, dynamic, and theoretically integrated view of the relationship between AI and DT. Rather than treating AI as a unidirectional enabler of transformation as in Yang et al. (2025), this research reconceptualizes the relationship as bidirectional and co-evolutionary, wherein AI and DT mutually reinforce one another over time. This represents a critical departure from prior research, which has primarily focused on the impact of AI on transformation, neglecting the possibility that transformation itself may serve as a precursor and facilitator of more effective AI adoption.

Second, drawing on dynamic capabilities' theory (Teece *et al.,* 1997) this study posits that digital transformation enhances a firm's ability to sense and seize emerging technological opportunities such as AI, and reconfigure internal resources accordingly. At the same time, AI technologies provide firms with the analytical capabilities, automation potential, and strategic flexibility that are essential to advancing their digital transformation agendas. This mutual shaping process is theoretically consistent with the notion that dynamic capabilities are both path-dependent and future-oriented (Bharadwaj, 2000), implying a recursive relationship between technological capability development and strategic adaptation. The findings challenge the static assumptions present in earlier empirical models such as Yang et al. (2025).

From a methodological standpoint, the current study diverges from Yang et al. (2025), which employs static regression techniques such as two-stage least squares and propensity score matching. Instead, it adopts a more sophisticated panel econometric approach that includes the Westerlund Panel Cointegration Test (WPCT), Dynamic Panel Ordinary Least Squares (DPOLS), and the Panel Vector Error Correction Model (PVECM). These methods are specifically designed to capture long-term equilibrium relationships and short-term dynamic interactions, offering a more rigorous basis for causal inference in the presence of temporal dependence and bidirectional causality. By doing so, the study contributes a novel empirical framework that better reflects the endogenous and time-sensitive nature of the AI–DT relationship.

In contrast to prior work of Yang et al. (2025) that has examined the moderating role of ownership structures-particularly the lagging performance of state-owned enterprises (SOEs) in digital transformation post-AI adoption-this study explores sectoral heterogeneity by conducting subsample analyses across high-tech and non-tech industries. Drawing from the technological innovation systems (TIS) framework (Bergek *et al.,* 2008) and the resource-based view (Barney, 1991), the study reveals that the AI–DT relationship manifests differently across industry contexts. In high-tech sectors, digital transformation appears to provide a stronger foundation for subsequent AI integration, while in non-tech sectors, AI adoption tends to be a stronger catalyst for digital advancement. This layered understanding highlights the importance of context-specific strategies in leveraging AI and DT for organizational development.

Furthermore, the study enhances existing measurement techniques by combining and extending text mining methodologies used in Yang et al. (2025). In addition to applying computer-assisted textual analysis (CATA) to detect AI-related keywords in annual reports, the study introduces a transformation intensity measure based on a curated lexicon of DT-related terms derived from Chinese national policy documents and corporate disclosures. This dual-measurement framework allows for a more accurate and comprehensive assessment of both constructs at the firm level, controlling for document length and other confounding variables.

Theoretical integration is also a distinguishing feature of this research. While Yang et al. (2025) is grounded primarily in agency theory, particularly in its exploration of ownership effects, the current study synthesizes insights from dynamic capabilities theory, the resource-based view, and technological innovation systems theory to build a multilevel conceptual model. This theoretical triangulation enables a more holistic understanding of how firms accumulate, apply, and scale AI and DT capabilities within diverse institutional and technological environments.

Finally, the findings of this study have important implications for policy and practice. They suggest that firms and policymakers must adopt a more nuanced and sequenced approach to technological innovation-one that views digital transformation not only as an end in itself but also as a necessary foundation for successful AI integration. Conversely, investments in AI must be aligned with existing transformation readiness to avoid suboptimal implement-tation. For firms, this calls for aligning AI initiatives with broader strategic transformation plans; for policymakers, especially in emerging economies like China, it highlights the importance of fostering transformation infrastructure alongside promoting AI adoption.

The subsequent sections of this paper are organized as follows. Section 2 provide the Background and Theoretical Framework; section 3 presents the Literature Review and Hypothesis Development. Section 4 delineates the methodological approach employed and provides details on the data utilized in the study. Section 5 presents the empirical findings as well as include the robustness checks performed through subsamples. Finally, Section 6 offers concluding remarks, underscoring the implications and broader significance of the research findings.

Background and Theoretical Framework

The AI–DT Convergence in Contemporary Business Landscapes

The Fourth Industrial Revolution has ushered in a period of unprecedented technological advancement, wherein the interplay between Artificial Intelligence (AI) and Digital Transformation (DT) has become a defining force of corporate strategy and innovation. AI-broadly defined as the ability of machines to mimic human intelligence and perform cognitive tasks such as learning, reasoning, and problem-solving (Russell & Norvig, 2021) is increasingly recognized as a catalytic tool that enables firms to optimize operations, enhance decision-making, and personalize customer experiences (Belhadi *et al.,* 2021).

Parallel to AI's proliferation, DT represents a profound reconfiguration of firms’ operations, business models, and value propositions through the adoption of emerging digital technologies (Vial, 2021). While DT encompasses a range of technologies including cloud computing, Internet of Things (IoT), big data analytics, and blockchain, the integration of AI has been particularly transformative. Scholars and practitioners alike are increasingly viewing AI as both a component of and an enabler for successful digital transformation initiatives (Johnk *et al.,* 2021).

Despite the growing acknowledgment of AI and DT’s mutual significance, most extant literature tends to explore these phenomena in isolation or assumes a linear, unidirectional influence of AI on DT (e.g., (Di Vaio *et al.,* 2020; Yang e*t al.,* 2025). This fragmented perspective leaves a critical research gap regarding the possibility of a recursive, mutually reinforcing relationship between AI adoption and digital transformation over time. This study seeks to address this gap by integrating multiple theoretical lenses to conceptualize and empirically examine the dynamic interplay between these two constructs in the context of Chinese enterprises.

Theoretical Foundations

The Dynamic Capabilities Theory (Teece *et al.,* 1997) provides a foundational lens for understanding how firms sense, seize, and reconfigure resources in response to environmental turbulence. In the context of digital transformation and AI, dynamic capabilities are reflected in a firm’s ability to not only adopt new technologies but to integrate and orchestrate them for strategic advantage (Warner & Wager, 2019). AI, as a strategic resource, becomes valuable only when aligned with the firm’s transformation capabilities that adapt business models and operational processes to evolving digital environments.

The Technological Innovation Systems (TIS) framework (Bergek *et al.,* 2008) offers another perspective by examining how systemic structures-such as networks, institutions, and market dynamics-support or hinder the diffusion of a particular technology. From this viewpoint, both AI and DT adoption are embedded within a broader innovation ecosystem influenced by institutional support, industry maturity, and regulatory frameworks.

China's rapid industrial digitalization, backed by national AI development plans and digital infrastructure investments, provides fertile ground for analyzing these innovation systems (Li, 2024). The TIS framework also justifies our emphasis on sector-specific dynamics, as the maturity and institutional support for AI and DT differ markedly between high-tech and traditional sectors.

The Resource-Based View (Barney, 1991) and its extension in the form of IT Capability Theory (Bharadwaj, 2000) suggest that firms gain competitive advantage by developing unique, inimitable resources-particularly digital and knowledge-based assets. DT can be seen as an organizational process that builds the IT architecture and cultural readiness necessary to deploy AI at scale. Inversely, AI technologies themselves-particularly those embedded in firm-specific applications such as predictive analytics or NLP-driven customer service-can enhance a firm's digital capability set.

Therefore, AI and DT are not just technologies but strategic resources that interact and accumulate over time. This reciprocal accumulation forms the theoretical underpinning of our hypothesis on cointegrated, bidirectional causality between AI and transformation.

Literature Review and Hypothesis Development

Artificial Intelligence (AI) has become a cornerstone of contemporary business strategy, allowing firms to process large datasets, automate complex decision-making, and enhance operational efficiency (Belhadi *et al.,* 2021). AI applications-ranging from predictive analytics to natural language processing-have redefined customer engagement, supply chain management, and innovation processes (Haefner *et al.,* 2021).

Recent studies have highlighted AI's role in fostering corporate agility and innovation. For example, Belhadi et al. (2021) found that AI enables firms to adapt to supply chain disruptions, enhancing resilience and competitive advantage. Similarly, Verganti et al. (2020) noted that AI reconfigures design and innovation strategies, allowing for higher customization and faster time-to-market. Despite these contributions, much of the literature views AI as a downstream outcome of technological readiness rather than a co-driver of organizational transformation.

Digital Transformation (DT) refers to the fundamental shift in business processes, models, and customer engagement driven by digital technologies (Vial, 2021). It is not merely about adopting digital tools, but about embedding digital logic into the fabric of the organization (Warner & Wager, 2019). Transformation involves sociotechnical changes, such as modifying organizational culture, workflows, and value creation mechanisms (Frank *et al.,* 2019).

Yang et al. (2025) demonstrate that DT enables firms to integrate frontier technologies like AI, big data, and IoT, enhancing adaptability and strategic positioning. Other scholars have emphasized that firms undertaking DT are more likely to attract digital-savvy talent (Montero Guerra et al., 2023), reduce information asymmetries (Ashta & Herrmann, 2021), and secure external investment (Dwivedi *et al.,* 2021). However, the reverse influence-AI catalyzing or reinforcing DT-has been understudied.

Emerging research suggests that AI and DT are not orthogonal constructs, but dynamically intertwined. On one hand, AI can function as a trigger and accelerator of digital transformation by automating processes, enabling data-driven strategies, and enhancing customer-centricity (Johnk *et al.,* 2021). On the other hand, successful transformation initiatives create the infrastructural and cultural prerequisites for AI adoption (Uren & Edwards, 2023).

Yang et al. (2025) found preliminary evidence of a positive association between AI indicators and DT performance in Chinese firms. However, most of this evidence is correlational, often lacking methodological rigor in establishing directionality or temporal sequencing. Furthermore, there is little consensus on whether this relationship is symmetric or stronger in specific industry contexts.

As theorized under the dynamic capabilities and resource-based frameworks, we argue that AI and DT co-evolve, each reinforcing the other over time. Firms that invest in transformation become better prepared for AI implementation, which in turn drives deeper digital transformation. This recursive dynamic may vary in strength across different industries, particularly between technology-intensive and non-tech sectors (Li, 2024; Zhang & Yang, 2023).Thus, there exists a cointegrated, bidirectional causal relationship between AI adoption and digital transformation in firms.

Methodology

Description of Data, Variables and Sample

Our data set consists of all companies (that are not financial institutions) that have an A-share listing on the Shanghai and Shenzhen stock exchanges between 2010 and 2020. The data used in this research is obtained from the studies by Yang et al. (2025) and Hussain et al. (2024) after making special data requests from the corresponding author. For the sake of data integrity, we did the following scrutiny: a) publicly traded companies like ST, ST*, and PT were not included, and b) in order to have a well-balanced panel, firms with incomplete data were eliminated. The final sample included 3602 firm-years of observations with no missing.

Measurement of Variables

Quantifying the adoption of AI and capturing transformation within businesses poses challenges due to the technology's pervasive nature and rapid evolution. Nonetheless, researchers have attempted to gauge AI adoption and transformation in enterprises through text mining approaches. For instance, Yang et al. (2025) quantified a firm's level of digital transformation by text mining their annual reports for the occurrence of DT-related terminology from a custom lexicon, while accounting for document length differences. Similarly, Hussain et al. (2024) used a text mining technique to quantify AI adoption by counting the occurrence of specific AI-related terms in firms' annual reports.

To measure the variables of transformation and AI adoption, the current research obtained datasets from the studies by Yang et al. (2025) and Hussain et al. (2024) after making special data email requests from the authors. For AI adoption, Hussain et al. (2024) employed a three-stage text mining process on firm annual reports using computer-assisted textual analysis (CATA). They developed a lexicon (vocabulary) of AI-related words and phrases in Chinese and used Python code to extract the frequency of these words from firms' annual reports. Specifically, they followed these stages: 1. Developed an initial lexicon of 73 AI-related words/phrases in Chinese, guided by industry reports and using deep learning for synonym recommendations. 2. Screened and refined the lexicon by manually reviewing words/phrases for contextual meaning, removing ambiguous or overly broad terms, and excluding words appearing less than 15 times. 3. Finalized three proxies for AI adoption based on the frequency of the remaining 53 words/phrases in the lexicon: AI_DUM (binary for any AI adoption mentioned), AI_TEXT (log of AI keyword frequencies), and AI_FUND (binary for mentions of AI investment funds). In our study, we adopt AI_DUM represented as *AIbin* and AI_TEXT represented as *AIlog* to test their impact on transformation.

Similarly for transformation, Yang et al. (2025) compiled a list of 68 digital technology terms and text mined corporate reports for these terms. The steps were: a) developed an initial dictionary of key transformation-related terms from major national policy documents on digital innovation in China, b) used a deep learning model trained on their corpus of 37,266 MD&A documents to expand this initial dictionary by suggesting additional semantically related terms with similarity scores above 0.80, c) combined the initial dictionary and suggested new terms to create a final lexicon of 86 Chinese keywords indicative of digital transformation, d) for each firm-year, counted the frequency of these 86 DT keywords appearing in the firm's MD&A text, e) normalized the total keyword frequency by the document length, and f) log-transformed the normalized frequency to create the continuous "DT" variable as a proxy for the firm's degree of transformation. In our research, we represent this proxy by “*Trans*”.

Methodological Approach

Cross-Sectional Dependence (CSD) test

To empirically estimate the proposed connection the study variables i.e., AI and transformation, we utilize econometric methods following the (Liu et al., 2024; Streimikiene & Kasperowicz, 2016). The initial step in panel data analysis involves conducting the CSD (cross-sectional dependence) test, as outlined by (Pesaran, 2021). If the panel dataset shows no evidence of CSD, first-generation URT (unit-root tests) is employed. Otherwise, utilizing second-generation URT might yield more reliable, efficient, and robust estimates.

$$CSD_{LM} = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N-1}.\sum_{j=i+1}^{N} pij^2 - 1} \quad \text{Eq (1)}$$

Ensuring the stationarity of time series data is a crucial aspect of econometric analysis as panel data models have a temporal component and URT are commonly used technique used to assess this. Thus subsequently, the unit root attribute of the panel data is assessed via second-generation stationarity tests such as the " CIPS (Cross-Sectional Augmented LM Pesaran and Shin)" and the " CADF (Cross-Sectional Augmented Dickey Fuller)" tests, considered to be suitable for cross-sectional data.

Upon confirming stationarity, co-integration between variables is estimated employing the WPCT, DPOLS, and PVECM techniques to ascertain short- and long-term relationships. Figure 1 outlines the research procedures followed in detail.

Westerlund Panel Cointegration Test (WPCT)

Aims The examination of the long-term cointegrated association amid AI and transformation is crucial due to the possibility of reciprocal influence between the two. In order to do this, the WPCT with error correction (Westerlund, 2007) is used. WPCT is more advantageous than other panel procedures when working with small but statistically significant samples due to its reduced size misrepresentations and increased statistical power.

$$AI_{jt} = AI_{jt-1} + x_{jt} \quad \text{Eq (2)}$$

$$Trans_{jt} = \gamma_{1j} + \gamma_{2j}t + w_{jt} \quad \text{Eq (3)}$$

Where: AI_{jt} = Artifical Inteligence, $Trans_{jt}$ = Digital Transformation, j = crosssection (firms) and t = time (years).

Equation 2 shows that AI_{jt} is the result of a stochastic process known as a random walk. And Equation 3 represents $Trans_{jt}$ encompasses the terms γ_{1j}, γ_{2j}, and w_{jt}. The construction of a conditional error correction model involves the connection of AI_{jt} and $Trans_{jt}$ via the inclusion of a stochastic component w_{jt}. In the event that the null hypothesis is rejected during the WPCT, it may be inferred that cointegration is present only within the sample of "j" firms.

Dynamic Panel OLS test

Given the assumption of a cointegrated link, we use dynamic panel OLS (DPOLS) estimation for a deeper understanding of the reciprocal impact between AI and transformation. The available evidence indicates that the DPOLS estimate has superior performance compared to the traditional OLS estimator in the context of panel cointegration regression (Yang et al., 2021) as it takes into account all of the metrics, compared to the conventional leads and lags method (Kao & Chiang, 2001). We used the following DPOLS model to investigate the symbiotic nature of AI and DT.

$$AI_{jt} = \lambda_{2j} + \rho_{2j}Trans_{jt} + \sum_{i=n_i}^{n_i} v_{2j}Trans_{j,t+1} + \in_{jt} \quad \text{Eq(4)}$$

$$DT_{jt} = \lambda_{1j} + \rho_{1j}AI_{jt} + \sum_{i=n_i}^{n_i} v_{1j}AI_{j,t+1} + \in_{jt} \quad \text{Eq(5)}$$

Where: AI_{jt} = Artifical Inteligence, $Trans_{jt}$ = Digital Transformation, j = crosssection (firms), t = time (years), λ_{1j} **and** λ_{2j} represent the temporal impacts and $\in_{jt}$ = error term.

Panel Vector Error Correction Model (PVECM)

Given the assumption of a cointegrated and bidirectional association between AI and transformation, our final analysis involves the use of a PVECM to assess the presence of short-term and long-term causation. The two-stage technique outlined by Engle and Granger (1987) is used in our analysis as given in Equation (6) and (7). The residual terms, denoted as m_{jt} and n_{jt}, are used in the computation of the error correction terms (ECMs) inside the regression analyses.

$$AI_{jt} = \delta_{2j} + \chi_{2j}t + \theta_{1j}DT_{jt} + m_{jt} \quad \text{Eq (6)}$$

$$DT_{jt} = \delta_{1j} + \chi_{1j}t + \theta_{1j}AI_{jt} + n_{jt} \quad \text{Eq (7)}$$

The use of the panel Granger causality approach enables the estimation of empirical model by obtaining the ECMs and putting them into the model estimated.

$$\Delta AI_{jt} = \Psi_{2j} + \rho_{2j}ECMs_{jt} + \sum_{k}\eta_{2j}\,\Delta AI_{jt-k} + \sum_{k}\tau_{2j}\,\Delta Trans_{jt-k} + z_{jt} \quad \text{Eq (8)}$$

$$\Delta DT_{jt} = \Psi_{1j} + \rho_{1j} ECMs_{jt} + \sum_{k} \eta_{1j}\, \Delta AI_{jt-k} + \sum_{k} \tau_{1j}\, \Delta Trans_{jt-k} + z_{jt} \quad \text{Eq (9)}$$

Equations (8) and (9) provide evidence of a causal association between AI and transformation, highlighting the significance of these exogenous factors. To ascertain the short-run causality relationships, we assess the significance of ρ_{2j}=0 or ρ_{1j}=0 for every value of "k" in Equations (8) and (9). With the intention of investigating the long-term causal relationships, it is essential to assess the significance of the $ECMs_{jt}$ (error correction terms).

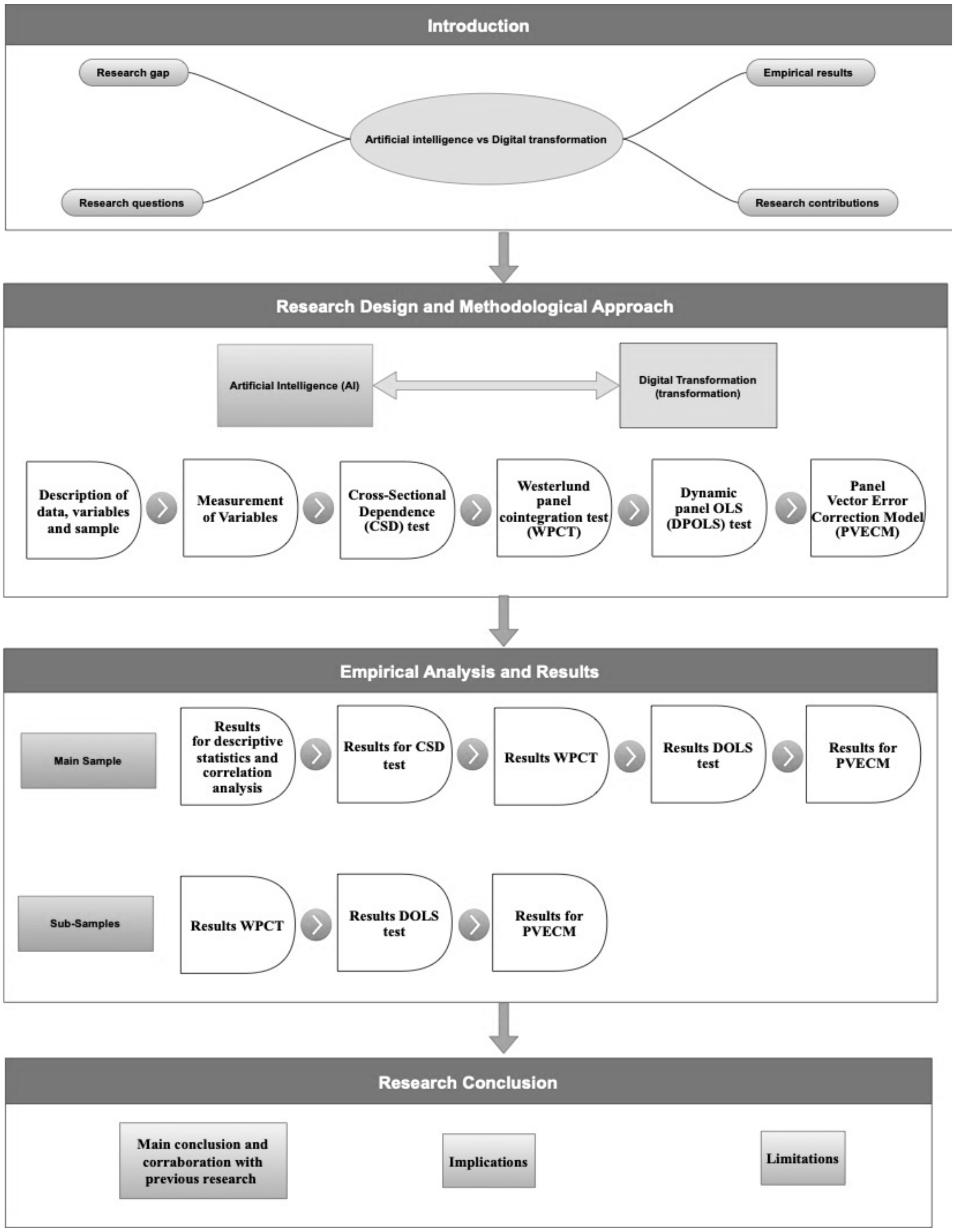

Figure 1. Research Process Flowchart

Empirical Analysis and Results

Results for Descriptive Statistics and Correlation Analysis

Table 1 reports the results for descriptive statistics and correlation analysis. Panel (A) presents the statistical measures of the sample, including mean, median, and standard deviation. Notably, there is substantial variation in firms' transformation of digital processes, evident from the average value of 1.109 and standard deviation of 1.319 for the Transformation metric (*Trans*). Additionally, the average and variability of *AIbin* are 0.24 and 0.42, respectively, while for *AIlog*, they are 0.126 and 0.44, indicating differing levels of interest among corporations in artificial intelligence (AI) use. Panel B illustrates the correlation coefficients, revealing a significant positive correlation between AI indicators (*AIbin* and *AIlog*) and transformation (*Trans*), suggesting that a surge in AI indicators corresponds to an increase in transformation.

Table 1

Summary Statistics and Correlations

Panel A: Descriptive statistics						
	Mean	**Median**	**St. Dev**	**max**	**min**	**N**
Trans	1.109	.693	1.319	6.252	0	3602
AIbin	.242	0	.428	1	0	3602
AIlog	.126	0	.449	4.543	0	3602

Panel B: Correlations			
	Trans	***AIbin***	***AIlog***
Trans	1		
AIbin	0.584^{***}	1	
AIlog	0.417^{***}	0.478^{***}	1

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Results for Cross-Sectional Dependency and Unit Root Test

The presence of cross-sectional dependency (CSD) in the data is seen in Table 2, namely in column 2. This suggests that there could be an issue with accurately calculating the proposed model in the study. The stationarity of all variables are thereafter assessed via the use of panel-based unit root tests. The CIPS and CADF tests are used in this stationary investigation because of their strong statistical power (Levin *et al.*, 2002; Pesaran, 2007). Table 2, Columns 3 to 6 displays the results of stationarity tests conducted at levels and starting differences. The results reveal that none of the level statistics exhibit significance. This implies that the variables under analysis have remained unchanged during the observed period. At a significance level of 1 %, the statistical analysis reveals that the first difference is statistically significant. This implies that there is no observable pattern or trend in any of the variables under consideration. Therefore, both AI and transformation implemented by firms are friendly advances adhered to a similar method. Hence, it is essential to proceed with the quantification of the co-integration among the variables in the panel data.

Table 2

Cross-Sectional Dependence (CDS) and Unit Root Tests

Variable	**Cross-sectional Dependence**	**Unit root test**			
	CDS-Statistics	**CIPS test**		**CADF test**	
		Level	**1st diff**	**Level**	**1st diff**
Trans	25.517***	-1.454	-5.372***	-1.061	-4.972***
AIbin	11.731*	-3.112	-7.922**	-4.113	-6.344*
AIlog	14.351***	-5.121	-9.116**	-5.441	-6.346**

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Results for Westerlund Panel Cointegration Test (WPCT)

The WPCT is employed to analyze the lasting connections between AI and transformation. Results in Table 3 indicate that the cointegration hypothesis is rejected for both *AIbin-Trans* and *AIlog-Trans*. This suggests a cointegrated relationship between AI and transformation in the long term. This finding is theoretically consistent with the resource-based view (Barney, 1991), which conceptualizes AI and DT as mutually reinforcing strategic assets that, once developed, tend to accumulate and interact over time to sustain competitive advantage.

Table 3

Westerlund (Panel) Cointegration Test

	AIbin vs *Trans*	*AIlog* vs *Trans*
Pt	-25.461***	-28.115***
Pa	-2.321***	-1.712***
Gt	-3.571***	-5.017***
Ga	-7.104***	-5.934***

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Results For Dynamic Panel OLS

After confirming the cointegration between transformation and AI, we employ dynamic panel ordinary least squares (DPOLS) methodology to explore their cointegrated vectors, and reports the results in Table 4. Beginning with Panel 1 and Panel 2 where the dependent variable is AI indicators (*AIbin* and *AIlog*), it can be seen that transformation (*Tran*) of firms has a statistically significant positive effect on AI indicators (panel coefficients for *AIbin-Trans* = 3.014 and *AIlog-Trans*= 2.311). This suggests a long-term effect of DT on AI. These findings suggest that a firm's prior investment in transformation-related capabilities—such as data infrastructure, digital culture, and innovation processes—creates an enabling environment for subsequent AI implementation. This supports the premise of dynamic capabilities theory (Teece *et al.,* 1997), which holds that firms with superior capacity for sensing and reconfiguring resources are better positioned to integrate complex technologies like AI.

In the reverse direction, Panel 3 and Panel 4 where the dependent variable is *Trans*, the results indicate that AI indicators has a statistically significant positive effect on transformation (*Tran*) of firms (panel coefficients for *Trans-AIbin* = 0.419 and *Trans-AIlog* = 0.102). This implies that AI functions as a catalyst for accelerating the scope and depth of digital transformation efforts. These findings align with the view that AI contributes to process optimization, decision-making enhancement, and organizational agility, as suggested in studies by Di Vaio et al. (2020) and Belhadi et al. (2021). AI's ability to analyze vast datasets, automate tasks, and personalize user experiences likely drives firms to redesign core processes and rethink business models, thereby deepening the transformation agenda.

Table 4

Dynamic Panel OLS (DPOLS) Test Results

	Panel 1	Panel 2	Panel 3	Panel 4
AIbin vs Trans	3.014 (301.5)***			
AIlog* vs *Trans		2.311 (223.4)***		
Trans* vs *AIbin			0.419 (152.4)***	
Trans* vs *AIlog				0.10 2 (112.3)***

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results for Panel Vector Error Correction Model (PVECM)

This study employs the panel vector error correction model (PVECM) to investigate the potential bidirectional causal relationship between AI and DT over the short run and long run. The results presented in Table 5 reveals a correlation between AI (measured as *AIbin*) and corporate transformation, indicating a potential short-term causal connection. Empirical evidence supports a positive relationship between the number of *AIlog* and transformation, suggesting that increasing AI could positively impact overall transformation in the long term.

This study's significance lies in its implication that error corrections achieved via Transformation and AI in previous periods could address deviations in AI observed presently.

Statistical analysis shows that jointly examining DT and the error correction term (ECM) yields statistically significant results at a 1 % significance level, indicating a lasting influence of AI(dummy) on DT. Even when substituting AI_text with another dependent variable, the findings remain consistent. These results emphasize the relationship between DT efforts and subsequent AI increases.

In cases where DT is the outcome variable, AI concepts may have an immediate impact, as shown by statistical data. The enduring statistical significance of the error-correction term indicates a substantial causal relationship between AI performance and DT. It suggests that corporations' innovation modifications can be disrupted by prior error corrections. The combined test of AI and the error repair term indicates a sustained impact potential for AI on a company's DT, statistically significant at 28.45. These findings suggest not only contemporaneous influence but also temporal adjustment dynamics, where deviations from long-term equilibria between AI and DT are corrected over subsequent periods. This reinforces the importance of understanding technological change as a path-dependent, recursive process, a key tenet of evolutionary economics and dynamic capabilities theory.

Table 5

PVECM Test Results

Variables	Short run			Long run			
	Δ*Trans*	**Δ*AIbin***	**Δ*AIlog***	**Lembda (λ)**	**Lembda (λ)/Δ*Trans***	**Lembda (λ)/Δ*AIbin***	**Lembda (λ)/ΔText**
AIbin	28.31***			62.41***	931.92***		
AIlog	21.91***			50.73***	754.12***		
Trans		23.41***		-5.03***		19.00***	
Trans			22.42***	-6.22***			21.21***

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results for Subsample Analysis

We conduct a robustness check through subsample analysis to assess the diversity of panel cointegration and enhance its reliability. Technological intensity plays a critical role in shaping the absorptive capacity and infrastructure readiness required for AI adoption and digital transformation. Drawing on the Technological Innovation Systems (TIS) framework and existing empirical studies (e.g. Jöhnk et al., 2021; Warner & Wäger, 2019), we argue that firms in high-tech sectors tend to be more digitally mature and innovation-driven, which may amplify the bidirectional AI–DT relationship. In contrast, low-tech firms may experience AI as a more transformative and disruptive force. Thus, we partition the sample into technology-driven and non-technology-oriented companies, reflecting the distinct AI and transformation requirements of each group. High-tech businesses, in particular, have focused on AI and transformation due to government technology initiatives.

Our analysis shows significant cointegration between AI and transformation among these subgroups, as shown in Table 6. Regardless of the AI proxy used, statistical analysis indicates significant mean values and panel statistics for both groups. This suggests that AI positively influences transformation levels, irrespective of the industry's technological orientation. These findings demonstrate the robustness of the cointegration between AI and tranformation, unaffected by variations in economic composition or individual enterprise technology attributes.

Table 6

Westerlund (Panel) Cointegration Test for Subsamples

	High Tech industry		**Low Tech industry**	
	AIbin* vs *Trans	***AIlog* vs *Trans***	***AIbin* vs *Trans***	***AIlog* vs *Trans***
Pt	-19.151***	-16.413***	-14.231***	-10.335***
Pa	-8.233***	-7.837***	-10.992***	-9.896***
Gt	-4.102***	-4.909***	-3.522***	-3.079***
Ga	-7.996***	-9.338***	-8.113***	-9.900***

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

After that Table 7 presents DPOLS examination outcomes for two distinct subsamples. Panel B features technology-associated businesses, while Panel A showcases non-tech sectors. Panel A reveals a robust positive correlation between AI and transformation within non-tech industries, highlighting the intricate impact of AI and transformation. Panel B illustrates the potential for AI and transformation in tech-oriented sectors, showing a positive association between the two. Thus, firms with advanced digital maturity are more inclined to leverage AI capabilities. Conversely, in low-tech sectors, the effect of AI on DT is relatively stronger, indicating that AI adoption may serve as an entry point into the broader digital transformation journey. These findings resonate with the technological innovation systems (TIS) framework (Bergek et al., 2008), which posits that sectoral and institutional dynamics mediate the development and diffusion of innovation.

The observed variation across sectors also aligns with recent empirical findings. For example, Jöhnk et al. (2021) found that organizational AI readiness is influenced by industry-specific norms and technological requirements, while Warner and Wäger (2019) showed that the sequence and intensity of digital transformation efforts vary considerably by industry maturity and innovation trajectory.

Table 7

Dynamic Panel OLS Test Results (DPOLS) for Subsamples

	Panel A: High Tech industry				**Panel B: Low Tech industry**			
	Panel 1	**Panel 2**	**Panel 3**	**Panel 4**	**Panel 1**	**Panel 2**	**Panel 3**	**Panel 4**
***AIbin* vs**	2.227***				1.612***			
Trans	(219.6)				(186.1)			
***AIlog* vs**		1.004***				1.902 ***		
Trans		(221.5)				(298.5)		
***Trans* vs**			1.001***				1.617***	
AIbin			(201.3)				(106.4)	
***Trans* vs**				0.973***				1.178***
AIlog				(254.7)				(130.6)

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 displays findings from a comparative analysis of two sample sizes, investigating the correlation between AI and transformation in tech and non-tech industries (Panels A and B, respectively). Results align with the whole panel's findings, indicating that technology-focused organizations tend to lead in AI and transformation. This supports the normative conclusions of the panel. The impact of AI on transformation in tech industries, and vice versa, is not immediate; rather, it depends on a company's temporal focus on corporate practices. However, the long-term impact of AI has the potential to shape transformation. Statistically significant correlations between transformation and AI suggest a reciprocal relationship between these variables.

Table 8

PVECM Test Results for Subsamples

Variables	Short-run			Long-run			
	Δ*Trans*	**Δ*AIbin***	**Δ*AIlog***	**Lembda (λ)**	**Lembda (λ)/Δ*Trans***	**Lembda (λ)/Δ*AIbin***	**Lembda (λ)/ΔText**
				Panel A: High Tech industry			
AIbin	14.32***			37.62***	534.11***		
AIlog	13.71***			15.05***	492.37***		
Trans		12.13***		-3.92***		8.97***	
Trans			10.96***	-4.87***			7.67***
				Panel B: Low Tech industry			
AIbin	0.92***			14.51***	49.95***		
AIlog	8.97***			15.32***	112.76***		
Trans		0.88***		-1.94***		0.76***	
Trans			7.08***	-2.62***			2.99***

Where *Trans* = Digital transformation; *AIbin* = Artificial Intelligence (Dummy) and *AIlog* = Artificial Intelligence (*log of frequency*)
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Conclusion and Discussions

The findings of this study substantiate the existence of a dynamic, bidirectional, and sector-sensitive relationship between artificial intelligence (AI) adoption and digital transformation (DT) in Chinese publicly listed firms. By employing robust longitudinal econometric techniques across a large panel dataset, the study provides compelling evidence that AI and DT are not merely related but evolve in tandem—each influencing and reinforcing the other over time. The reciprocal causality suggests that firms should view AI and DT not as discrete strategic initiatives but as interdependent components of a broader digital capability system.

This conclusion offers a substantial departure from existing studies, particularly Yang et al. (2025), who examined the role of AI as a unidirectional driver of DT using static econometric models. Their research revealed that AI significantly enhances corporate digitalization, with the impact moderated by ownership structures such as state-owned vs. non-state enterprises. While important, Yang et al.'s framing limits DT to a dependent outcome of AI investment, missing the reciprocal and co-evolutionary dynamics that this study brings to the fore. In contrast, our use of cointegration and error correction models enables the identification of long-term equilibrium relationships and short-term adjustment processes, affirming that digital transformation itself fosters organizational readiness, infrastructure maturity, and capability alignment that enables more effective AI adoption.

The empirical findings align with earlier work by Di Vaio et al. (2020), who recognized AI's potential to enhance business models and corporate adaptability, and by Belhadi et al. (2021), who emphasized AI's role in supply chain resilience and process optimization. However, unlike these studies which primarily present AI as an input into transformation processes, our results affirm that digital maturity-including robust data infrastructures, agile organizational processes, and digitally literate human capital—are in themselves prerequisites for effective AI deployment. This mutual causality advances the understanding of digital transformation from being an outcome of technological deployment to being a strategic enabler of further technological integration.

From a comparative perspective, this research also engages with insights from Warner and Wäger (2019), who conceptualized digital transformation as an ongoing process of strategic renewal. Our findings extend their work by empirically confirming that such renewal does not occur in isolation but in close interaction with specific technological tools-most notably AI. Similarly, Johnk et al. (2021) argue that organizational AI readiness is essential for successful implementation; our study complements this by showing that successful AI deployment also reinforces and reshapes digital readiness, completing a virtuous cycle.

Theoretical Implications

This research makes several theoretical advancements. First, it redefines the AI–DT relationship as bidirectional, temporally dynamic, and contextually contingent, challenging the linear input-output models that dominate much of the literature. By employing longitudinal data and cointegration analysis, the study demonstrates that AI and DT co-evolve within organizations, reinforcing the notion of technological capability path-dependence from dynamic capabilities theory (Teece *et al.,* 1997). Second, by integrating RBV, we reframe AI and DT not just as tools or technologies, but as **strategic assets** whose mutual development determines firms' long-term competitiveness. Third, our application of the TIS perspective highlights the role of sectoral and institutional environments in shaping the rate and direction of this co-evolution, a contribution largely missing from current models of enterprise digitalization.

Managerial and Policy Implications

The findings have direct implications for corporate decision-makers. Firms should not treat AI implementation and digital transformation as isolated investments or initiatives. Instead, organizations are advised to develop integrated digital capability roadmaps, aligning AI projects with broader transformation goals. For example, investment in digital infrastructure, cultural change, and data readiness will enhance the success of AI projects; conversely, AI applications can catalyze new forms of digital innovation when deployed strategically.

Furthermore, the results also point to the importance of strategic sequencing: in high-tech industries, where digital transformation is more advanced, AI can be more seamlessly integrated. In contrast, in non-tech sectors, AI may act as a disruptive lever to catalyze transformation, though likely with higher risks and resource demands.

From a policy perspective, the findings reinforce the need for holistic national digitalization strategies. Governments-especially in emerging economies-should not only incentivize AI research and application but also invest in the foundational enablers of digital transformation, such as infrastructure, digital education, and industry-specific transformation roadmaps. Moreover, sector-sensitive policies that acknowledge varying levels of digital maturity will be more effective than one-size-fits-all approaches.

Limitations and Future Research

This study has several limitations that must be acknowledged. First, the reliance on text-mining methods to proxy AI and DT intensity from annual reports, while innovative, is dependent on the quality and consistency of corporate disclosures. Second, the sample is confined to Chinese A-share listed firms, which may limit the generalizability of findings to other economic or regulatory environments. Third, although the econometric methods used infer directionality and long-term relationships, they do not directly identify the causal mechanisms-such as leadership decision-making, innovation culture, or organizational structure-that mediate the AI–DT dynamic.

Building on these limitations, future research could pursue several specific directions. First, scholars could employ qualitative or mixed methods approaches-such as case studies or interviews-to uncover the micro-level mechanisms through which AI and DT reinforce each other. Second, future research might examine how organizational variables (e.g., leadership style, culture, governance) moderate the AI–DT dynamic. Third, longitudinal cross-country comparative studies could assess how institutional differences affect the co-evolution of AI and DT, extending the applicability of this model beyond China.

Additionally, expanding the focus to include other digital technologies-such as blockchain, IoT, or augmented reality-and their interactions with AI and DT would offer a more comprehensive understanding of the digital transformation landscape. Finally, future work could assess performance outcomes, investigating how different trajectories of AI–DT interaction impact innovation, productivity, and competitive advantage over time.

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Authors Biographies

Xuexiu Li is affiliated with Yunnan Technology and Business University in Kunming City, Yunnan Province. Li's research interests focus on integrating technology and business strategies to enhance organisational performance and innovation.

Linyu Xie is a researcher at Yunnan Technology and Business University, Kunming City, Yunnan Province. Xie's work primarily explores the intersection of technology and business, striving to develop strategies that drive economic growth and sustainability.

Dan Hou is based at Honghe University in Mengzi, China. Hou's research contributes to the understanding of business dynamics and technological advancements within the regional and global contexts.

Ziyan Yuan is associated with Yunnan Technology and Business University, Kunming City, Yunnan Province. Yuan's academic pursuits focus on the application of technology in business environments to foster innovation and competitive advantage.

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