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DYNAMIC RELATIONSHIP OF DIGITAL TRANSFORMATION, HUMAN CAPITAL, INNOVATION, AND FINANCIAL PERFORMANCE IN CHINESE MANUFACTURING FIRMS

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Abstract

Chinese enterprises are increasingly turning to digitalization to tackle the complexities of modern challenges. In the face of external disruptions, the adoption of digital technology has become indispensable for firms across various sectors. This study delves into the specific impact of digital transformation on the financial performance of automobile manufacturing companies, aiming to provide detailed insights into how digitalization affects individual businesses, particularly in terms of human capital and innovation performance. Through the utilization of novel variables and analytical methods, this research addresses existing ambiguities in the literature surrounding the relationship between digital transformation and financial performance. By analyzing an imbalanced panel dataset spanning from 2016 to 2022 and covering 865 instances from 132 A-share automobile manufacturing firms, the study employs a two-way fixed-effects model to scrutinize the data. Additionally, it explores the mediating role of human capital and the moderating effect of innovation performance using stepwise regression and the Bootstrap Test. The findings of the study indicate a positive influence of digital transformation on financial performance in automobile manufacturing companies. Furthermore, it reveals that human capital serves as an indirect mediator between digital transformation and financial performance, with investment in technician training shown to mitigate the effects of digitalization. However, the study does not find a statistically significant relationship between innovation performance and the nexus between digital transformation and financial performance in the automotive manufacturing sector. The practical implications of the study are significant, urging automotive managers to seize digitization opportunities, harness technology for improved efficiency, manage debt prudently, prioritize digital literacy within manufacturing firms, and accelerate efforts to embrace digitization to adapt to the rapidly evolving business landscape. This research contributes timely insights and actionable recommendations for navigating the evolving terrain of digital transformation within the Chinese automotive industry. By shedding light on the specific impacts of digitalization on financial performance and offering practical guidance for industry practitioners, the study enriches the understanding of digital transformation dynamics and its implications for business success in the contemporary context.

Keywords: Digital Transformation, Firm Performance, Text Analysis, Panel Data, Fixed Effects Regression.

INTRODUCTION

The surge in corporate digital transformation reflects an increasing reliance on digital technology to address external challenges, highlighting the pivotal role of the digital economy in China's economic growth. Projections from the Research Report on the Development of China's Digital Economy (2023) forecast a substantial 41.5% contribution to China's GDP by

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2022, with a 24% penetration rate in the secondary industry (China Academy of Information and Communication Research, 2023). Adoption of digital technologies like artificial intelligence (AI), cloud computing, and big data has revolutionized economic sectors and propelled industrial evolution, empowering enterprises to enhance competitiveness (Guiding Digital Transformation in Small and Medium Enterprises, 2023; Liang & Li, 2022; Zhang et al., 2022). Chinese firms are intensifying their digital strategies, with the Accenture China Enterprise Digital Transformation Index 2022 indicating a significant uptick in digital spending intentions over the next 1-2 years, driven by a nuanced approach to transformative financing (Accenture, 2022). Industrial policies, particularly in sectors like automotive manufacturing, have spurred the integration of digital technology and intelligent manufacturing since 2016, highlighting digital transformation's role in augmenting enterprise performance (Chen & Xie, 2019; Li et al., 2022).

In the automotive sector, digital transformation is critical for optimizing production flow, accelerating product development, and fortifying competitiveness (Zeng et al., 2022; Chakraborty et al., 2023; Men et al., 2023). While research underscores the positive link between digital transformation and product development performance, challenges persist, including a shortage of skilled personnel, IT security concerns, and an inadequate grasp of digital solutions (Rupeika-Apoga & Petrovska, 2022; Wang et al., 2022; Borovkov et al., 2021).

Scholars have extensively researched the impact of digital transformation on enterprises' financial performance, revealing a direct and favorable association between the two such as Liu et al. (2023), Wang and He (2022), and Teng et al. (2022). However, in studies of Wang et al. (2022) and Xie and Wang (2023) highlighted the need for further research into the underlying processes. Moreover, several studies with conflicting views emphasized the crucial role of human capital (Fan & Wang, 2022; Le Viet & Dang Quoc, 2023) as a catalyst for successful transformation and innovation performance (Wang & Cao, 2022; Nasiri et al., 2020; Lee et al., 2022; Adams et al., 2019; Liang & Li, 2022) as metric for assessing the effectiveness of digital technologies in value generation.

This study aims to bridge critical gaps in the current literature by examining how process innovation performance and product innovation performance interact with digital transformation to shape organizations' financial performance. Focused on automotive manufacturers, it delves into the nuanced mechanisms involving human capital and innovation success in this relationship, offering insights into the complexities of digital transformation's impact on financial outcomes. By elucidating the mediating role of human capital and the moderating effect of innovation success, this research endeavors to deepen the understanding of how creative performance integrates into diverse business domains. Acknowledging the challenges of quantitatively analyzing enterprise digital transformation, this study adopts textual analysis as a novel method for measurement. By leveraging textual data, it seeks to overcome traditional quantitative limitations and offer a nuanced understanding of digital transformation's impact. Through multifaceted analyses, it strives to provide valuable contributions to the evolving discourse on digital transformation's implications for financial success.

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LITERATURE REVIEW

Concepts and Challenges of Digital Transformation

Digital transformation refers to the comprehensive integration of digital technologies across all aspects of an organization, leading to a fundamental reconfiguration of its operational framework and business processes (Verhoef et al., 2021). It encompasses not only the adoption of digital technologies but also the cultural, organizational, and strategic shifts necessary to fully harness the potential of these technologies in driving business growth and competitiveness (Fitzgerald et al., 2014).

Verhoef et al. (2021) proposed a framework delineating digital transformation into three stages: digitization, digitalization, and digital transformation. Digitization involves converting analog data into a digital format (Li et al., 2016). Digitalization enhances business operations through digital technologies like online communication channels (Ramaswamy & Ozcan, 2016) and encompassing tools like AI, cloud computing, and IoT (Guandalini, 2022; Nyagadza, 2022).

The adoption of digital technology in the business model can reshape value generation, distribution, and retention (Autio et al., 2018; Frank et al., 2019; Matarazzo et al., 2021). While digital transformation enhances corporate operations, it poses challenges like modifying procedures and integrating digital platforms (McCausland, 2021; Furr & Shipilov, 2019).

Despite its benefits, digital transformation encounters obstacles across various dimensions. Borovkov et al. (2021) highlighted some technological hurdles that often arise due to the complexity of implementing new digital technologies and integrating them into existing systems. Some organizational challenges involve modifying operational procedures, enhancing the employee experience, and adjusting business models to align with digital initiatives (Furr & Shipilov, 2019; McCausland, 2021).

And market-related obstacles such as competition, changing consumer preferences, and the need for sustainability in manufacturing processes (Iansiti & Lakhani, 2020; Moghrabi et al., 2023). These studies collectively emphasize the multifaceted nature of challenges faced during digital transformation efforts. Thus, this study aims to develop a thesaurus of digital transformation using text analysis of annual reports to quantify its occurrence and understand its implications on business models and operations.

Digital Transformation and Financial Performance

Financial performance encapsulates the financial condition and operational efficacy of a company, serving as a key metric to evaluate strategic effectiveness (Zhang et al., 2023). The impact of digital transformation on financial performance has been extensively studied across different sectors.

Liu et al. (2023) reveal a notable enhancement in financial performance among A-share listed companies in China following digital transformation, with disclosure and operational expenses playing mediating roles. Similarly, Yonghong et al. (2023) present evidence supporting the positive effects of digital transformation on manufacturing firms' operational capacity and profitability.

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Contrarily, Zhang et al. (2023) propose that political connections and internal control quality influence financial performance, with digital transformation moderating this relationship. Studies in e-commerce by an and Yoon (2023) demonstrate that digitally transformed firms outperform non-digitized ones in terms of profitability and stability, although they lag in activity and productivity. Ren and Li (2022) emphasize the positive impact of digital transformation on financial performance in renewable energy firms, especially when coupled with green technological innovations.

However, the influence of digital transformation may vary based on factors like ownership type and regional location. Wang et al. (2022) highlight the differential impacts of digital transformation across enterprise types, with state-owned enterprises (SOEs) benefiting significantly. Consequently, to enhance comprehension of the association between the variables being investigated, this study hypothesized:

H1 Digital transformation positively affects the financial performance of automotive manufacturers.

Human Capital and Digital Transformation

The organization's human capital significantly shapes the digital transformation process (Ghi et al., 2022; Blizkiy et al., 2021). Recognized as a key driver of innovation, strategic deployment of human capital is vital for business success (Dong et al., 2023). Digital technology facilitates knowledge exchange among employees, enhancing human capital caliber and organizational resilience (Wang and Chen, 2022). Leadership attitudes pose challenges, with digital gaps between urban and rural areas exacerbating disparities (Le Viet & Dang Quoc, 2023; Sun et al., 2023).

Similarly, Nguyen et al. (2023) found that improving managers' human capital, social capital, and access to resources can hasten the pace of digital transformation in enterprises in start-up enterprises in Vietnam.

Studies elucidate human capital's role in guiding digital transformation, emphasizing talent acquisition, cultivation, and retention (Montero-Guerra et al., 2023; Kuzior et al., 2022; Le Viet & Dang Quoc, 2023). Digital transformation influences employee educational structures, with profound effects on the manufacturing sector's human capital and innovation (Liu et al., 2022; Guo and Chen, 2023).

Effective human capital management is crucial for mitigating digital transformation's impact on innovation processes (Lai et al., 2023). Although previous studies examine digital transformation's influence on manufacturing firms' performance and resilience, further investigation into the effects of employee functional structure is warranted (Wang et al., 2022; Wang & Chen, 2022). With this, the present investigation posits the subsequent hypothesis:

H2 Human capital mediates the relationship between digital transformation and financial performance.

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Digital Transformation, Innovation Performance, and Firm Performance

Digital innovation encompasses various dimensions and significantly impacts innovation performance. According to Ge et al. (2023), digital technology innovation networks strongly influence enterprise innovation performance. Conversely, Li et al. (2022) explored the impact of multidimensional digital empowerment on technological innovation efficacy, identifying a U-shaped relationship between structural empowerment and innovation effectiveness, moderated by technological embeddedness adaptability.

Nassani et al. (2022) found that integrating digital products and services into markets improves innovation performance, emphasizing the importance of concentrating innovation efforts and leveraging available technology and human resources.

Nassani et al. (2023) highlighted the relationship between technological orientation and innovation performance, showing that technology-focused firms are more inclined to develop digital innovations. Similarly, Hanelt et al. (2020) underscored the mediating role of innovation factors in the relationship between digital transformation and innovation performance.

Growing pieces of evidence show that digital innovation performance plays a crucial for organizational success, driven by factors like digital assets (Nwankpa & Datta, 2017; Liu et al.; Blichfeldt & Faullant, 2021). It encompasses the development of new products, the improvement of existing ones, and the optimization of processes using digital technologies (Nambisan et al., 2019). Moreover, Liang and Li (2022) revealed that digital transformation affects organizational operations and innovation negatively through exploratory R&D skills, yet positively through enhanced capabilities. Wang et al. (2022) demonstrated the positive impact of digital transformation on operational effectiveness, especially in state-owned enterprises and market-oriented regions. Shen et al. (2021) and Yin et al. (2022) highlighted the role of servitization in enhancing innovation performance, while Ardito et al. (2021), Tsai et al. (2011), Xu et al. (2023), and Men et al. (2023) proposed questionnaires as effective tools for assessing innovation success, contingent on research objectives.

Digital transformation, defined as the integration of digital technologies across all facets of an organization, is pivotal for enhancing operational efficiency and driving growth (Verhoef et al., 2021). This multifaceted process involves not only adopting digital tools but also instigating cultural and strategic shifts to leverage technology effectively (Fitzgerald et al., 2014). Verhoef et al. (2021) delineated digital transformation into three stages: digitization, digitalization, and digital transformation, emphasizing the conversion of analog data to digital formats and the establishment of novel digital business models. The adoption of digital technology revolutionizes value generation, distribution, and retention (Autio et al., 2018; Frank et al., 2019; Matarazzo et al., 2021). However, implementing digital transformation poses challenges across technological, organizational, and market dimensions (Borovkov et al., 2021; McCausland, 2021; Iansiti & Lakhani, 2020). Hence, this research presents the subsequent hypothesis:

> *H3 Innovation performance plays a moderating role in the relationship between digital transformation and financial performance.*

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METHODOLOGY

Data Source

This study examines how digital transformation influences the financial performance of Chinese automotive manufacturers, quantitatively assessing it through digital technology integration and innovative business models. Additionally, it explores the mediating role of human capital and the moderating influence of innovation performance on this relationship, which is academically significant. Using an imbalanced panel dataset from 2016 to 2022, covering 865 instances from 132 A-share automobile manufacturing firms listed on the Shanghai and Shenzhen stock exchanges. The China Stock Market and Accounting Research (CSMAR) Database, renowned for its reliability and precision in economic and financial research, was employed alongside textual analysis methods to collect financial information and evaluate digital transformation indicators from annual reports, emphasizing the use of digital technology and innovative business models.

Variable Measurement

Digital transformation (Dx). This research project is centered on the construction of a digital transformation thesaurus leveraging the capabilities of the WinGo data platform to construct a robust thesaurus that encapsulates the multifaceted dimensions of digital transformation, thereby contributing to scholarly discourse and practical applications in the realm of organizational evolution and adaptation to digital disruptions. The study intends to delineate and categorize the spectrum of digital transformation within enterprises through meticulous analysis, focusing specifically on two pivotal indicators: the integration of digital technologies and the innovative evolution of business models. The study intends to delineate and categorize the spectrum of digital transformation within enterprises through meticulous analysis, focusing specifically on two pivotal indicators: the integration of digital technologies and the innovative evolution of business models. Digital technology adoption, including AI, cloud computing, big data analytics, and cybersecurity, drives the transition to Industry 4.0 in manufacturing, enhancing profitability and customer service (Rana & Daultani, 2022). Cloud computing meets the automotive industry's demand for data-intensive computing, facilitating innovation and convergence of IT and OT (Borangiu et al., 2020; Fan et al., 2022). Big data analytics aids operational efficiency and innovation, while cybersecurity is vital for safeguarding networks (Aljumah et al., 2021; Banciu et al., 2023). Business model innovation, encompassing O2O, B2B, B2C, and digital management, reshapes traditional paradigms (Ciulli & Kolk, 2019; Wang et al., 2023).

Human capital. The investment expenditure of automotive manufacturing firms in technician training inputs (TTI) is a proxy to measure human capital investment due to challenges in directly quantifying employee quality. This variable is computed following the formula below to account for the functional composition of employees, particularly the proportion of technicians relative to the total workforce which is crucial in quantifying training expenses for technicians within automotive manufacturing firms (Wang & He, 2022; Fan & Wang, 2022).

$$TTI = Percentage\ of\ Technical\ Staff\ x\ Current\ expenditure\ on\ staff\ education$$

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Innovation performance encompasses the utilization of digital technologies to create novel goods or services, integrate digital elements into existing products or services, and offer new products or services with digital attributes (Autio et al., 2018; Khin & Ho, 2018; Hanelt et al., 2020). This study employed two indicators, process innovation (PROC), and product innovation (PROD), to evaluate the innovation performance of automotive manufacturers, as outlined in research by Liang & Li (2022).

Financial performance. This study utilized two financial performance metrics, namely return on equity (ROE) and return on invested capital (ROIC), to evaluate the financial performance of automotive manufacturers (Zhai et al., 2022; Cao et al., 2022). The use of these parameters addresses the concerns about the potential ineffectiveness of Tobin's Q as a measure in the context of China's capital markets market due to inherent deficiencies (Zhang et al., 2023). Moreover, market-based measures are vulnerable to investor expectations and managerial profit manipulation (Wruck & Wu, 2021).

Model Estimation

Following Du and Jiang (2022), Huang et al. (2022), and Zhang and Zhao (2023), a fixed-effects model is employed to examine the influence of digital transformation on the financial performance of automotive manufacturing enterprises. Fixed-effects models offer advantages in controlling unobserved heterogeneity, managing complex data structures, and addressing various types of dependent variables (Chen et al., 2021; Muris et al., 2023). These models obviate the need to estimate between-study variances in random-effects models and effectively handle issues of error term dependence (Lin et al., 2020). By incorporating double fixed effects for both individual and time factors, the proposed models below can identify factors impacting financial performance, with a particular focus on exploring the potential influence of a firm's digital transformation on its performance dynamics. To assess the impact of digital transformation on the financial performance of automotive manufacturers (H1), the following model was constructed:

$$ROE_{i,t} = \alpha_0 + \alpha_1 Dx_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t} \quad (1)$$

$$ROIC_{i,t} = \alpha_0 + \alpha_1 Dx_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t} \quad (2)$$

whereas, ROE and ROIC as explanatory variables respectively represent the degree of digital transformation (*Dx*) of firm i in year t. α_0 stands for the intercept term, α_1 and α_2 are the estimation parameters, and φ_i denotes the regression coefficients of the firm characteristics as control variables, which consist of four items: firm size (SIZE), operating revenue growth rate, (GROWTH), controlling shareholders' shareholding ratio (TOP1), and the firm's leverage or the ratio of total liability to total asset (LEV), u_i and u_{year} denote the fixed effects at the level of the firms and the years, respectively; $\varepsilon_{i,t}$ denotes the residual term.

To address H2 and examine the potential mediating role of human capital in the mechanism under analysis, the study used the stepwise regression analysis based on the framework proposed by Baron and Kenny (1986).

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This analysis offers advantages in determining significant predictors and identifying mediators; thus, the following models were constructed.

$$TTI_{i,t} = \beta_0 + \beta_1 Dx_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t} \quad (3)$$

$$ROE_{i,t} = \lambda_0 + \lambda_1 Dx_{i,t} + \lambda_2 TTI_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t} \quad (4)$$

$$ROIC_{i,t} = \lambda_0 + \lambda_1 Dx_{i,t} + \lambda_2 TTI_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t} \quad (5)$$

In Model 3, the independent variable $TTI_{i,t}$ stands for the input expenditures allocated to technician training by firm *i* in year *t*. β_0 stands for the intercept term, β_1 denotes the regression coefficient of the explanatory variables, and φ_i denotes the regression coefficients of the control variables. u_i and u_{year} denote the fixed effects at the level of the firms and the years, respectively; $\varepsilon_{i,t}$ denotes the residual term. In Models 4 and 5, the explanatory variables $ROE_{i,t}$ and $ROIC_{i,t}$ denote the return on equity and return on invested capital, respectively, for firm *i* in year *t*. The explanatory variable $DT_{i,t}$ represents the degree of digital transformation of firm *i* in year *t*.$TTI_{i,t}$ stands for the input expenditures allocated to technician training by firm i in year t and serves as the mediating variable. $\lambda_1$signifies the regression coefficients associated with the explanatory variables, while λ_2 signifies the regression coefficients related to the mediating variables, φ_i denotes the regression coefficients of the control variables, u_i and u_{year} denotes the fixed effects at the level of the firms and the years, respectively; $\varepsilon_{i,t}$ denotes the residual term.

To comprehensively examine the moderating impact of innovation performance on the relationship between digital transformation and financial performance in the automotive manufacturing sector (H3), moderating analytical models using moderated regression analysis (MRA) were developed. This model was constructed through the incorporation of an interaction term between innovation performance and digital transformation into the existing models 1 and 2.

$$ROE_{i,t} = \eta_0 + \eta_1 Dx_{i,t} + \eta_2 PROC_{i,t} + \eta_3 Dx_{i,t} \times PROC_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t}$$

$$ROIC_{i,t} = \eta_0 + \eta_1 Dx_{i,t} + \eta_2 PROC_{i,t} + \eta_3 Dx_{i,t} \times PROC_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t}$$

(6)

$$ROE_{i,t} = \eta_0 + \eta_1 Dx_{i,t} + \eta_2 PROD_{i,t} + \eta_3 Dx_{i,t} \times PROD_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t}$$

$$ROIC_{i,t} = \eta_0 + \eta_1 Dx_{i,t} + \eta_2 PROD_{i,t} + \eta_3 Dx_{i,t} \times PROD_{i,t} + \sum \varphi_i Controls_{i,t} + u_i + u_{year} + \varepsilon_{i,t}$$

In models 6, 7, 8 and 9, $ROE_{i,t}$ and $ROIC_{i,t}$ denote the explanatory variables for firm *i* in year

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t. The explanatory variable $Dx_{i,t}$ represents the degree of digital transformation of firm i in year t. $PROC_{i,t}$and $PROD_{i,t}$ stand for the firm's process innovation and product innovation in year t, respectively, and they serve as the moderating variables. To enhance the precision of the moderating effects, the study centralizes the moderating variables and their interaction terms with digital transformation to create $Dx_{i,t} \times PROC_{i,t}$. $\eta_0$stands for the intercept term, η_1 denotes the regression coefficient of the explanatory variables, $\eta_2$signifies the regression coefficients for the moderating variables, and η_3 indicates the regression coefficients for the interaction terms involving the moderating variables and digital transformation, and φ_i denotes the regression coefficients of the control variables, u_i and u_{year} denote the fixed effects at the level of the firms and the years, respectively; $\varepsilon_{i,t}$ denotes the residual term.

Furthermore, the study utilized the bootstrapping technique to facilitate parameter estimation within statistical models and support the conduct of statistical hypothesis testing through the generation of multiple resampled datasets, derived from the original sample, without making explicit assumptions regarding the underlying data distribution (Alfons et al., 2021).

All these models and tests were done using Stata 17.0 software. These methodological steps were instrumental in ensuring data quality and enhancing the reliability of the statistical results, thereby bolstering the scientific validity and credibility of this study.

RESULTS AND DISCUSSION

Impact of Digital Transformation on the Financial Performance of Automotive Manufacturing Firms

The impact of Dx on the financial performance of automotive manufacturing firms was tested. Table 1 presents the key findings from Model 1 (Dx – ROE) and Model 2 (Dx – ROIC). Model 1 suggests that the adoption of Dx in publicly listed automobile manufacturing firms in China significantly and positively impacts their ROE ($p < .05$).

In Model 2, the results reveal a significant relationship between Dx and ROIC in automobile manufacturing enterprises ($p < .001$). Overall, these findings support H1, asserting the positive impact of Dx on the financial performance of automotive manufacturers.

Further examination of control variables reveals a direct correlation between company size, growth rate, equity ownership concentration, and financial performance. This suggests that large automotive manufacturers benefit from economies of scale and increased resource access, enhancing operational and innovative capacities, and leading to improved performance.

High-growth companies attract investors and gain better access to external financing, positively impacting financial success. Higher ownership concentration among shareholders strengthens influence over digital strategy, aiding efficient positioning and decision-making. However, elevated debt ratios may increase financial risk and negatively affect company performance.

Table 1: Fixed Effects Regression Results on the Effect of Digital Transformation on Firm Performance

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Variable	Mean	(Model 1) ROE	(Model 2) ROIC
Dx	1.17	0.016^{**}	0.010^{***}
		(2.51)	(3.06)
SIZE	22.45	0.090^{***}	0.029^{***}
		(5.88)	(4.51)
GROWTH	0.151	0.087^{***}	0.041^{***}
		(7.14)	(8.02)
TOP1	0.433	0.182^{**}	0.109^{***}
		(2.42)	(3.48)
LEV	0.452	-0.530^{***}	-0.227^{***}
		(-8.68)	(-8.95)
_cons		-1.772^{***}	-0.528^{***}
		(-5.30)	(-3.81)
Firm fixed effect		Yes	Yes
Year fixed effect		Yes	Yes
N		865	865
R^2		0.219	0.267
F		18.432	23.901

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. The t-statistics (in parentheses) are based on standard errors adjusted for clustering at the firm level.

The findings support Wang et al. (2022), Guo and Chen (2023), Lui et al. (2023), and Yonghong et al. (2023) who asserted the positive impact of digital transformation on manufacturing firms' operational capacity and profitability. This conveys Dx as an evolutionary process that provides leverage to enable business models, operational processes, and consumer experiences that generate value (Rodriguez & Rosenstiehl, 2022). However, the results contradict Jardak and Ben Hamad (2022) who claim that the negative relationship between Dx and firm performance is explained by the fact that IT investment and the Dx could take years to materialize and to be captured by performance indicators. This affirms the accompanying substantial obstacles in the implementation of Dx. The negative effect of Dx when controlled by LEV conforms to the findings of recent studies (Jardak & Ben Hamad, 2022; Wang & Zhu, 2023). Elevated debt ratios pose significant financial risks and can hinder company performance, especially concerning digital transformation initiatives. Higher debt levels increase interest expenses and limit financial flexibility, potentially constraining investments in crucial technological upgrades and innovation. This can lead to missed opportunities and hinder the company's ability to stay competitive in rapidly evolving markets. In short, Dx promotes corporate risk-taking and requires operating and financing flexibility (Guangning et al., 2022). Therefore, companies must carefully manage their debt levels to ensure they can effectively execute digital transformation strategies while maintaining financial stability.

The Mediating Effect of Human Capital on Digital Transformation and Firm Performance Relationship

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The study also explored the mediating role of human capital, specifically input expenditures on technician training (TTI), in the relationship between Dx and the financial performance of these firms. Table 2 shows the results of the stepwise regression analysis.

Table 2: Regression Results for the Mediating Effect of Human Capital Between Digital Transformation and Firm Financial Performance

	(Model 3)	**(Model 4)**	**(Model 5)**
	TTI	**ROE**	**ROIC**
Dx	0.034^{**}	0.014^{**}	0.007^{**}
	(2.89)	(2.78)	(2.93)
TTI		-0.012^{***}	-0.006^{***}
		(-2.62)	(-2.69)
SIZE	0.918^{***}	0.032^{***}	0.013^{***}
	(13.83)	(5.30)	(4.84)
GROWTH	-0.197^{***}	0.094^{***}	0.040^{***}
	(-3.73)	(7.58)	(7.23)
TOP1	0.564^{*}	0.104^{***}	0.067^{***}
	(1.74)	(3.87)	(5.52)
LEV	-0.648^{**}	-0.361^{***}	-0.161^{***}
	(-2.46)	(-12.50)	(-12.33)
_cons	-7.593^{***}	-0.562^{***}	-0.203^{***}
	(-5.26)	(-5.69)	(-4.55)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	865	865	865
R^2	0.367	0.228	0.238
F	30.429	42.226	44.604
Bootstrap test Ind_eff（p-value）		0.017	0.021

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. The t-statistics (in parentheses) are based on standard errors adjusted for clustering at the firm level.

Model 3 reveals a statistically significant relationship between Dx and TTI ($p < .05$). In Model 4, both Dx and TTI were integrated into a unified model to analyze financial performance (ROE and ROIC). It revealed a statistically significant negative relationship between ROE and TTI with a p-value of 0.017 for the indirect impact based on the Bootstrap test. Similarly, Model 5 reveals a significant negative relationship between ROIC and TTI. The Bootstrap test indicates a p-value of 0.021 for the indirect impact. The heteroskedasticity robustness tests passed for both individual and time-fixed effects, with the indirect effects being significant in all models, thus supporting the H2 of the study. This denotes that TTI mediates the relationship between Dx and firm financial performance, reducing the latter's influence. It supports human capital's pivotal role as a catalyst in digital technology innovation, and its varying levels across enterprises may limit the effectiveness of digital transformation (Blizkiy et al., 2021; Ghi et al., 2022; Dong et al., 2023). The findings acknowledge people are crucial in guiding and advancing the process of digital transformation similar to the works of Guerra et al. (2023) and Kuzior et al. (2022). Further, it denotes that human capital can hasten the pace of digital

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transformation in enterprises (Nguyen et al., 2023) and the firm performance. Therefore, human resource willingness to embrace new technologies and undergo digital transformation training significantly influences project outcomes (Le Viet & Dang Quoc, 2023).

The Moderating Effect of Innovation Performance on Digital Transformation and Firm Performance Relationship

The research combined PROC and PROD to assess the innovation performance of automobile manufacturing companies based on the number of patent applications. Table 3 shows the result of the examination of the moderating effects of PROC and PROD on the relationship between Dx and firm financial performance, a moderating analysis model was created.

Table 3: Regression Results for the Moderating Effect of Innovation Performance

	(Model 6)	(Model 7)	(Model 8)	(Model 9)
	ROE	**ROIC**	**ROE**	**ROIC**
Dx	0.015**	0.013**	0.014**	0.013**
	(2.63)	(2.46)	(2.85)	(2.73)
PROC	0.005	0.001		
	(1.10)	(0.05)		
Dx×PROC	0.004	0.002		
	(0.45)	(0.20)		
PROD			0.003	-0.002
			(0.39)	(-0.63)
Dx×PROD			0.001	-0.000
			(0.20)	(-0.13)
SIZE	0.090*	0.029**	0.090*	0.029*
	(2.09)	(3.78)	(2.11)	(2.23)
GROWTH	0.087***	0.041***	0.087***	0.041***
	(4.00)	(4.53)	(4.24)	(4.58)
TOP1	0.175	0.107*	0.180	0.109*
	(1.32)	(2.54)	(1.61)	(2.25)
LEV	-0.528***	-0.226***	-0.529***	-0.227***
	(-3.15)	(-3.92)	(-3.61)	(-3.56)
_cons	-1.763*	-0.525**	-1.766*	-0.530**
	(-2.93)	(-3.41)	(-2.64)	(-3.49)
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
N	865	865	865	865
R^2	0.221	0.268	0.219	0.267
F	10.331	16.838	10.498	16.503

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. The t-statistics (in parentheses) are based on standard errors adjusted for clustering at the firm level.

The regression analysis conducted on two-way fixed effects Models 6 and 7, incorporating fixed effects for specific firms and years, reveals a significant relationship between Dx and firm performance. However, PROC and Dx×PROC exhibited a positive, yet statistically not

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significant influence on ROE and ROIC respectively. Results from Models 8 and 9 of the two-way fixed effects analysis affirm the statistically significant effect of Dx on firm performance, particularly ROE and ROIC. Contrarywise, in terms of the moderating effect of PROD and Dx×PROD, the data revealed a positive but not significant effect on the Dx and firm performance relationship. Overall, this study did not find a significant moderating effect of PROC and PROD, leading to the rejection of H3 of the study.

The findings connote that despite successful Dx initiatives, innovation efforts focused on processes or products may not necessarily directly influence financial outcomes. The missing moderating effect of process and product innovation performance on the relationship between Dx and firm financial performance may be explained by several possible reasons. The first reason may be related to the possible misalignment of innovation efforts of firms. This can occur if process and product innovations do not translate into increased revenues or profitability, or if product innovations fail to resonate with customer preferences or generate sufficient demand. This highlights the importance of strategic fit between product and process innovation strategies and competitiveness and performance (Prajogo, 2016; Chau et al., 2020).

Another reason is the challenges in executing innovation strategies. In Balaz et al. (2023), the firm's innovation strategies are identified as a key mediator of performance among European enterprises which the findings of this study contradict. The result shows that inadequate resources or organizational resistance to change can hinder the translation of innovative ideas into tangible financial benefits despite digital transformation. Furthermore, firms should take note of the relevance of sensing and learning capabilities as triggers of digital transformation (Matarazzo et al., 2021) and its positive effect on performance.

Lastly, even with strong innovation capabilities resulting from digital transformation, its effect on the firm's financial performance is not automatic. Firms may struggle to achieve financial success if they face intense competition, shifting customer preferences, unfavorable market conditions, and other external factors (Prajogo, 2016; Chau et al., 2020). Therefore, while innovation is typically considered crucial for driving financial success, its role as a moderator in the relationship between digital transformation and firm financial performance may vary depending on contextual dynamics and challenges.

Robustness Tests

To ascertain the robustness of prior empirical findings and mitigate the impact of measurement errors and other variables on the conclusions, this study employed the methodology suggested by Zhai et al. (2022), substituting the primary explanatory variables, Dx, with the digital transformation index (Dx_index). This substitution of fundamental explanatory factors serves as a means to validate research outcomes using alternative operational definitions, ensuring the consistency of findings despite variations in measurement or definition. Like before, the text analysis was employed to quantify the occurrence rate of pertinent keywords, while the enterprise Dx_index is computed by assigning weights to six indicators as shown in Table 4.

Table 5 presents the outcomes of substituting the primary explanatory variables. The regression analysis between the DT_index and ROE (Model 10), and ROIC (Model 11), affirms previous

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findings denoting a significant positive effect of digital transformation on firm performance (p < .05) and confirms the H1 of the study. The research explored the influence of digital transformation on enterprises' financial performance by lagging all explanatory factors by one period, based on 733 observations, as presented in Table 6. Incorporating lagged explanatory variables in a two-way fixed effects model with imbalanced panel data serves to address the possible endogeneity issue, thereby reducing the influence of serial correlation on estimates and improving model accuracy. This addition strengthens the model's robustness and reduces susceptibility to outliers, with individual and time-fixed effects accounting for stable individual variations and temporal trends. By including a one-period lag in explanatory variables, the model's fixed effects can be more effectively managed, enhancing precision. Moreover, the inclusion of lagged explanatory

Table 4: Enterprise Digital Transformation Index Detailed Indicators and Weighting

Primary Indicators	Primary Indicator Weights	Secondary Indicators	Secondary Indicator Weights
Strategic lead	34.72%	• Management Digital Job Creation	23.82%
		• Management figures Innovation-oriented forward-looking	27.88%
		• Management Digital Innovation Orientation Sustainability	18.79%
		• Management Digital Innovation Orientation Breadth	12.83%
		• Management Digital Innovation Orientation Intensity	16.68%
Technology-driven	16.20%	• Artificial Intelligence Technology	55.04%
		• Blockchain Technology	12.98%
		• Cloud Computing Technology	18.32%
		• Big Data Technology	13.66%
Organizational empowerment	9.69%	• Digital Capital Input Program	50.22%
		• Digital Human Input Program	25.53%
		• Digital Infrastructure Construction	12.06%
		• Science and Technology Innovation Base Construction	12.19%
Environmental support	3.42%	• Number of patents for inventions in the industry	19.23%
		• R&D activities in the industry	17.79%
		• New product development and sales in the industry	14.98%
		• Intensity of digital technology in the industry	11.57%
		• Intensity of digital capital investment in the host industry	11.4%
		• Intensity of human capital investment in the host industry	7.89%
		• Density of fiber optic cables in the city	4.77%
		• Mobile switch capacity in the city	4.03%
		• Scale of Internet broadband access users in the city	4.00%
		• Mobile Internet users in the city	4.34%
Digitization results	27.13%	• Digital Innovation Standard	36.68%
		• Digital Innovation Thesis	11.74%
		• Digital Invention Patent	23.54%
		• Digital Innovation Qualification	14.73%
		• Digital National Awards	13.31%

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Digital applications	8.84%	• Technology Innovation	63.42%
		• Process Innovation	23.78%
		• Business Innovation	12.80%

Table 5: Robustness Test by Substituting Explanatory Variables

	(Model 10)	(Model 11)
	ROE	**ROIC**
DT_index	0.004**	0.002**
	(2.86)	(2.78)
SIZE	0.089*	0.029***
	(2.57)	(3.55)
GROWTH	0.088***	0.040***
	(5.15)	(5.86)
TOP1	0.179	0.112*
	(1.16)	(2.29)
LEV	-0.530***	-0.227***
	(-4.90)	(-5.76)
_cons	-1.751*	-0.553**
	(-2.37)	(-3.19)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
N	865	865
R^2	0.219	0.268
F	10.762	17.100

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. The t-statistics (in parentheses) are based on standard errors adjusted for clustering at the firm level.

Table 6: Robustness Test by Lagging One Period Explanatory Variables

	(Model 12)	(Model 13)	(Model 14)	(Model 15)
	ROE	**ROIC**	**ROE**	**ROIC**
DT	0.018**	0.009**		
	(2.73)	(2.79)		
DT_index			0.003*	0.001*
			(2.08)	(2.13)
SIZE	0.115***	0.038***	0.115**	0.038***
	(3.14)	(3.43)	(3.13)	(3.46)
GROWTH	0.091***	0.041***	0.091***	0.041***
	(4.04)	(4.90)	(3.99)	(4.88)
TOP1	0.073**	0.109*	0.241*	0.116*
	(2.41)	(2.23)	(1.89)	(2.13)
LEV	-0.638***	-0.284***	-0.642***	-0.284***
	(-5.55)	(-6.69)	(-5.53)	(-6.71)
_cons	-2.254***	-0.696**	-2.204**	-0.700**
	(-2.91)	(-2.87)	(-2.87)	(-2.87)
Firm fixed effect	Yes	Yes	Yes	Yes

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Year fixed effect	Yes	Yes	Yes	Yes
N	733	733	733	733
R^2	0.204	0.244	0.204	0.244
F	9.536	14.574	8.996	14.189

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance, respectively. The t-statistics (in parentheses) are based on standard errors adjusted for clustering at the firm level.

Variables facilitates a more accurate depiction of time-dependent effects, contributing to the model's realism (Cheng Hsiao, 2014). Additionally, including a lagged one-period treatment helps clarify the direction of digital transformation's impact on financial performance, ensuring a more reliable causal interpretation of results. Models 12 and 13 reveal a significant positive relationship between the lagged period of Dx and the financial performance of the firms ($p < .05$). Likewise, in models 14 and 15, Dx_index with a one-period lag positively influences firm performance in terms of ROE and ROIC ($p < .1$). These findings support the earlier findings of the study and accepts H1.

Regarding control variables, similar to earlier results, positive relationships are observed between firm size, growth, equity concentration, and the financial performance of the firm, suggesting that larger companies benefit from economies of scale and more resources. However, an inverse relationship exists between the LEV and firm performance, indicating that increased levels of debt may lead to heightened financial risks and negatively impact company performance.

The consistent results of robustness tests in Tables 5 and 6 indicate a reliable relationship between Dx and firm performance. This suggests that the initial findings accurately capture the phenomenon under investigation and are not heavily influenced by methodological variations or confounding factors. The stability of results across different analytical approaches or datasets reinforces the validity and generalizability of the study. Additionally, alignment with existing theories or prior research further supports the robustness of the findings. Overall, consistent results after robustness testing enhance confidence in the study's conclusions and contribute to a better understanding of the relationship between the variables.

CONCLUSION

This study aims to comprehensively examine the impact of Dx on the financial performance of China's automobile manufacturing companies, while also exploring the roles of human capital and innovation performance in this dynamic. To achieve this, the study developed an empirical framework for evaluating these relationships within the context of automobile manufacturing firms, addressing gaps in previous research. Utilizing unbalanced panel data from publicly listed automobile manufacturing firms in China spanning from 2016 to 2022, totaling 865 data points, a fixed-effects model was employed to construct the model.

The research unequivocally concludes that Dx has a significant and favorable effect on the ROE and ROIC of automotive manufacturing enterprises. These findings demonstrate

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resilience across alternative explanatory factors and the inclusion of lagged one-period treatment for all explanatory variables, underscoring the positive impact of digital transformation in the automotive manufacturing landscape. However, a negative effect of Dx on performance was established when controlled by debt ratio, highlighting the financial risks posed by elevated debt ratios, which limit financial flexibility crucial for technology and innovation investments. Thus, companies must manage debt carefully to execute digital strategies and maintain stability.

Furthermore, the study confirms that human capital acts as an intermediary between Dx and financial performance, emphasizing the role of human capital as a catalyst in digital technology innovation and its positive effect on firm performance. Therefore, firms must focus on building a culture that readily embraces new technologies to ensure smoother digital transformation and enhance project outcomes. However, the study suggests that innovation performance, encompassing process and product innovation, may not always moderate the relationship between digital transformation and firm financial performance due to various contextual dynamics and challenges.

Theoretical and Practical Contributions

The insights derived from this study offer valuable guidance for automobile manufacturing organizations undergoing digital transformation. Key areas of focus include professional and technical staff training, integration and utilization of digital technologies, and business model innovation. By concentrating on the automotive manufacturing sector and employing quantitative methodologies, the study develops a model to assess the effects of digital technology-driven transformation on financial outcomes. In essence, this research extends existing knowledge and identifies potential avenues for future exploration, emphasizing the need for further analysis of additional factors and methodologies. The methodology employed in this study lays a solid foundation for comprehensively understanding the impact of digital transformation on firms in the automobile manufacturing sector.

From a practical standpoint, this research enhances understanding of the post-pandemic investment in digital transformation by automotive manufacturers and its immediate financial implications. It also underscores the critical role of human capital in business performance and growth, emphasizing the importance of education, skills enhancement, and factors contributing to high-quality human resources. Furthermore, the study informs policy development aimed at enhancing enterprise innovation capabilities by emphasizing the significance of proficient personnel, digital technology integration, and innovative business model adoption. These insights are crucial for bolstering competitiveness and driving economic growth in the automotive manufacturing sector.

Limitations and Implications for Future Research

Despite providing valuable insights for automobile manufacturing organizations undergoing digital transformation, the study faces limitations in its scope and methodology. These include a narrow focus on Chinese-listed vehicle manufacturing companies, potential measurement inaccuracies in assessing digital transformation's extent through textual analysis, and concerns

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regarding the quantitative methodologies employed. Future research should aim to address these constraints to enhance the comprehensiveness and robustness of findings, offering deeper insights into the relationship between digital transformation and firm financial performance.

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References

1) Adams, P., Bodas Freitas, I. M., & Fontana, R. (2019). Strategic orientation, innovation performance and the moderating influence of marketing management. Journal of Business Research, 97, 129–140. https://doi.org/10.1016/j.jbusres.2018.12.071

2) Alfons, A., Ateş, N. Y., & Groenen, P. J. F. (2021). A robust bootstrap test for mediation analysis. Organizational Research Methods, 109442812199909. https://doi.org/10.1177/1094428121999096

3) Aljumah, A. I., Nuseir, M. T., & Alam, Md. M. (2021). Organizational performance and capabilities to analyze big data: do the ambidexterity and business value of big data analytics matter? Business Process Management Journal, ahead-of-print(ahead-of-print). https://doi.org/10.1108/bpmj-07-2020-0335

4) An, S.-B., & Yoon, K.-C. (2023). The effects of changes in financial performance on value creation in digital transformation: A comparison with undigitalized firms. Sustainability, 15(3), 2083. https://doi.org/10.3390/su15032083

5) Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. Strategic Entrepreneurship Journal, 12(1), 72–95. https://doi.org/10.1002/sej.1266

6) Banciu, D., Vevera, A., & Popa, I. (2023). Digital transformation impact on organization management and several necessary protective actions. Studies in Informatics and Control, 32(1), 49–56. https://doi.org/10.24846/v32i1y202305

7) Baron, R. M., & Kenny, D. A. (1986). The Moderator–Mediator Variable Distinction in Social Psychological research: Conceptual, strategic, and Statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

8) Blichfeldt, H., & Faullant, R. (2021). Performance effects of digital technology adoption and product & service innovation – A process-industry perspective. Technovation, 105, 102275. https://doi.org/10.1016/j.technovation.2021.102275

9) Borangiu, T., Morariu, O., Răileanu, S., et al. (2020). Digital transformation of manufacturing. Industry of the future with cyber-physical production systems. Romanian Journal of Information Science and Technology, 23(1), 3–37. http://hdl.handle.net/10362/148749

10) Borovkov, A., Rozhdestvenskiy, O., Pavlova, E., et al. (2021). Key barriers of digital transformation of high-technology manufacturing: An evaluation method. Sustainability, 13(20), 11153. https://doi.org/10.3390/su132011153

11) Cao, X., Xu, L., & Duan, Q. (2022). EM algorithm-based enterprise digital transformation: Green innovation efficiency of enterprise investment. Mathematical Problems in Engineering, 2022, 1–12. https://doi.org/10.1155/2022/8782652

12) Chakraborty, A., Jinil Persis, & Kamran Mahroof. (2023). Exploring the academic–industry collaboration in knowledge sharing for supplier selection: Digitalizing the OEM. IEEE Transactions on Engineering

DOI: 10.5281/zenodo.11384408

Management, 1–11. https://doi.org/10.1109/tem.2023.3260042

13) Chau, D., Ngai, E., Gerow, J., & Thatcher, J. (2020). The effects of business–it strategic alignment and it governance on firm performance: A moderated polynomial regression analysis. MIS Quarterly, 44 (4), 1679. 10.25300/MISQ/2020/12165

14) Chen, D., Chen, J., & Li, S. (2021). Instrumental variable quantile regression of spatial dynamic durbin panel data model with fixed Effects. 9(24), 3261–3261. https://doi.org/10.3390/math9243261

15) Hsiao, C. (2014). Analysis of panel data. Cambridge University Press.

16) Chen, J., & Xie, L. (2019). Industrial policy, structural transformation and economic growth: evidence from China. Frontiers of Business Research in China, 13(1). https://doi.org/10.1186/s11782-019-0065-y

17) Ciulli, F., & Kolk, A. (2019). Incumbents and business model innovation for the sharing economy: Implications for sustainability. Journal of Cleaner Production, 214, 995–1010. https://doi.org/10.1016/j.jclepro.2018.12.295

18) Dong, P., Zhu, Y., Duan Sheng-sen, Wu M, & Jiang, B. (2023). How does the digital economy promote a culture of business innovation? A study based on human capital allocation perspective. Sustainability, 15(8), 6511–6511. https://doi.org/10.3390/su15086511

19) Du, X., & Jiang, K. (2022). Promoting enterprise productivity: The role of digital transformation. Borsa Istanbul Review. https://doi.org/10.1016/j.bir.2022.08.005

20) Fan, D. & Wang, Y. (2022). Research on the impact of traditional enterprise digital transformation on its innovation - Taking automotive manufacturing companies as an example.Soft Science, 36(06), 63–70.

21) Fan, X., Wang, Y., & Lu, X. (2022). digital transformation drives sustainable innovation capability improvement in manufacturing enterprises: Based on FsQCA and NCA aproaches. Sustainability, 15(1), 542. https://doi.org/10.3390/su15010542

22) Fitzgerald M, Kruschwitz N, Bonnet D, Welch M. Embracing digital technology: a new strategic imperative[J]. MIT Sloan Management Review, 2014, 55(2):1–15.

23) Frank, A. G., Mendes, G. H. S., Ayala, N. F., & Ghezzi, A. (2019). Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. Technological Forecasting and Social Change, 141, 341–351. https://doi.org/10.1016/j.techfore.2019.01.014

24) Ge, C., Lv, W., & Wang, J. (2023). The impact of digital technology innovation network embedding on firms' innovation performance: The role of knowledge acquisition and digital transformation. Sustainability, 15(8), 6938. https://doi.org/10.3390/su15086938

25) Ghi, T. N., Thu, N. Q., Huan, N. Q., & Trung, N. T. (2022). Human capital, digital transformation, and firm performance of startups in Vietnam. Management, 26(1), 1–18. https://doi.org/10.2478/manment-2019-0081

26) Guangning, T., Bo, L., & Yue, C. (2022). Does digital transformation matter for corporate risk-taking? Finance Research Letters, 49, 103107, https://doi.org/10.1016/j.frl.2022.103107.

27) Guerra, J. M., Danvila-del-Valle, I., & Méndez-Suárez, M. (2023). The impact of digital transformation on talent management. Technological Forecasting and Social Change, 188, 122291. https://www.sciencedirect.com/science/article/pii/S0040162522008125

28) Guiding Digital Transformation in SMEs. (2023). Management and Production Engineering Review. https://doi.org/10.24425/mper.2023.145369

29) Guo, X., & Chen, X. (2023). The impact of digital transformation on manufacturing-enterprise innovation: Empirical evidence from China. Sustainability, 15(4), 3124. https://doi.org/10.3390/su15043124

30) Hanelt, A., Firk, S., Hilebrandt, B., & Kolbe, L. M. (2020). Digital M&A, digital innovation, and firm

ISSN 1533-9211
DOI: 10.5281/zenodo.11384408

performance: an empirical investigation. European Journal of Information Systems, 30(1), 1–24. https://doi.org/10.1080/0960085x.2020.1747365

31) Huang, J., Ling, Z., & Lu, R. (2022). Directors' and officers' liability insurance and digital transformation – the mediating role of explorative innovation. Business Process Management Journal. ttps://doi.org/10.1108/bpmj-08-2022-0419

32) Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI : strategy and leadership when algorithms and networks run the world. Harvard Business Review Press.

33) Jardak, M. K., & Ben Hamad, S. (2022). The effect of digital transformation on firm performance: evidence from Swedish listed companies. The Journal of Risk Finance. https://doi.org/10.1108/jrf-12-2021-0199

34) Khin, S., & Ho, T. C. (2018). Digital technology, digital capability and organizational performance. International Journal of Innovation Science, 11(2). https://doi.org/10.1108/ijis-08-2018-0083

35) Kuzior, A., Arefieva, O., Kovalchuk, A., et al. (2022). Strategic Guidelines for the Intellectualization of Human Capital in the Context of Innovative Transformation. Sustainability, 14(19), 11937–11937. https://doi.org/10.3390/su141911937

36) Lai, Z., Wang, B., & He, X. (2023). Research on the digital transformation of producer services to drive manufacturing technology innovation. Sustainability, 15(4), 3784–3784. https://doi.org/10.3390/su15043784

37) Le Viet, H. & Dang Quoc, H. (2023). The Factors Affecting Digital Transformation in Vietnam Logistics Enterprises. Electronics, 12(8), 1825. https://doi.org/10.3390/electronics12081825

38) Lee, H. S., Shin, N., & Choi, J. (2022). Exploring the impact of innovation activities on financial performance in developed and emerging markets. Systems, 11(1), 16. https://doi.org/10.3390/systems11010016

39) Li, Z., Li, H., & Wang, S. (2022). How multidimensional digital empowerment affects technology innovation performance: The moderating effect of adaptability to technology embedding. Sustainability, 14(23), 15916. https://doi.org/10.3390/su142315916

40) Liang, S., & Li, T. (2022). Can digital transformation promote innovation performance in manufacturing enterprises? The mediating role of R&D capability. Sustainability, 14(17), 10939. https://doi.org/10.3390/su141710939

41) Lin, E., Tong, T., Chen, Y., & Wang, Y. (2020). Fixed-effects model: the most convincing model for meta-analysis with few studies. ArXiv (Cornell University). https://doi.org/10.48550/arxiv.2002.04211

42) Liu, J., Zhou, K., Zhang, Y., & Tang, F. (2023). The effect of financial digital transformation on financial performance: The intermediary effect of information symmetry and operating costs. Sustainability, 15(6), 5059–5059. https://doi.org/10.3390/su15065059

43) Liu, Y., Deng, W., Luo, K., & Tang, M. (2023). Impact of environmental taxation on financial performance of energy-intensive firms: The role of digital transformation. Emerging Markets Finance and Trade, 1–19. https://doi.org/10.1080/1540496x.2023.2228462

44) Liu, Y., Dong, J., Mei, L., & Shen, R. (2022). Digital innovation and performance of manufacturing firms: An affordance perspective. Technovation, 102458. https://doi.org/10.1016/j.technovation.2022.102458

45) Masoud, R., & Basahel, S. (2023). The effects of digital transformation on firm performance: The role of customer experience and it innovation. Digital, 3(2), 109–126. https://doi.org/10.3390/digital3020008

46) Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in made in Italy SMEs: A dynamic capabilities perspective. Journal of Business Research, 123, 642–656. https://doi.org/10.1016/j.jbusres.2020.10.033

47) McCausland, T. (2021). Digital Transformation. Research-Technology Management, 64(6), 64–67. https://doi.org/10.1080/08956308.2021.1974783

48) Men, F., Dong, F., Liu, Y., & Yang, H. (2023). Research on the impact of digital transformation on the product R&D Performance of automotive enterprises from the perspective of the innovation ecosystem. Sustainability, 15(7), 6265. https://doi.org/10.3390/su15076265

49) Muris, C., Raposo, P., & Sotiris Vandoros. (2023). A dynamic ordered logit model with fixed effects. The review of economics and statistics, 1–36. https://doi.org/10.1162/rest_a_01336

50) Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. Research Policy, 48(8), 103773. https://www.sciencedirect.com/science/article/abs/pii/S0048733319300812

51) Nasiri, M., Ukko, J., Saunila, M., Rantala, T., & Rantanen, H. (2020). Digital-related capabilities and financial performance: the mediating effect of performance measurement systems. Technology Analysis & Strategic Management, 1–14. https://doi.org/10.1080/09537325.2020.1772966

52) Nguyen, T. T. Q., Tran, N. G., & Nguyen, T. T. (2023). social capital and digital transformation of startups in Vietnam during the COVID-19 Pandemic: The mediating role of human capital and access to resources. Management Systems in Production Engineering, 31(1), 33–42. https://doi.org/10.2478/mspe-2023-0005

53) Nwankpa, J. K., & Datta, P. (2017). Balancing exploration and exploitation of IT resources: the influence of Digital Business Intensity on perceived organizational performance. European Journal of Information Systems, 26(5), 469–488. https://doi.org/10.1057/s41303-017-0049-y

54) Prajogo, D. (2016). The strategic fit between innovation strategies and business environment in delivering business performance. International Journal of Production Economics, 171(2), 241-249. https://doi.org/10.1016/j.ijpe.2015.07.037.

55) Rana, J., & Daultani, Y. (2022). Mapping the role and impact of artificial intelligence and machine learning applications in supply chain digital transformation: A bibliometric analysis. Operations Management Research. https://doi.org/10.1007/s12063-022-00335-y

56) Ren, Y., & Li, B. (2022). Digital transformation, green technology innovation and enterprise financial performance: Empirical evidence from the textual analysis of the annual reports of listed renewable energy enterprises in China. Sustainability, 15(1), 712. https://doi.org/10.3390/su15010712

57) Rodriguez, R. E., & Rosenstiehl, J. L. (2022). Endogenización como mecanismo evolutivo para la transformación digital de las pymes de turismo de naturaleza. Tendencias, 23(1), 117–138. https://doi.org/10.22267/rtend.222301.185

58) Rupeika-Apoga, R., & Petrovska, K. (2022). Barriers to sustainable digital transformation in micro-, small-, and medium-sized enterprises. Sustainability, 14(20), 13558. https://doi.org/10.3390/su142013558

59) Shen, L., Sun, C., & Ali, M. (2021). Role of servitization, digitalization, and innovation performance in manufacturing enterprises. Sustainability, 13(17), 9878. https://doi.org/10.3390/su13179878

60) Sun, D., Yu, B., & Ma, J. (2023). Research on the impact of digital empowerment on china's human capital accumulation and human capital gap between urban and rural Areas. Sustainability, 15(6), 5458. https://doi.org/10.3390/su15065458

61) Teng, X., Wu, Z., & Yang, F. (2022). Research on the relationship between digital transformation and performance of SMEs. Sustainability, 14(10), 6012. https://doi.org/10.3390/su14106012

62) Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. Sciencedirect.

ISSN 1533-9211

DOI: 10.5281/zenodo.11384408

63) Wang, D., & Chen, S. (2022). Digital transformation and enterprise resilience: Evidence from China. Sustainability, 14(21), 14218. https://doi.org/10.3390/su142114218

64) Wang, D., Shao, X., Song, Y., Shao, H., & Wang, L. (2023). The Effect of Digital Transformation on Manufacturing Enterprise Performance. 25(63), 593–593. https://doi.org/10.24818/ea/2023/63/593

65) Wang, H., Cao, W., & Wang, F. (2022). Digital transformation and manufacturing firm performance: Evidence from China. Sustainability, 14(16), 10212. https://doi.org/10.3390/su141610212

66) Wang, H., & He, H. (2022).Research on evaluation and influence mechanism of digital transformation of manufacturing enterprises- Take automotive manufacturing enterprises as an example.Journal of Industrial Technological Economics, 41(08), 3–11.

67) Wang, X., Gu, Y., Ahmad, M., & Xue, C. (2022). The impact of digital capability on manufacturing company performance. Sustainability, 14(10), 6214. https://doi.org/10.3390/su14106214

68) Xie, X., & Wang, S. (2023). Digital transformation of commercial banks in China: Measurement, progress and impact. China Economic Quarterly International, 3(1), 35–45. https://doi.org/10.1016/j.ceqi.2023.03.002

69) Yin, S., Zhang, N., Ullah, K., & Gao, S. (2022). Enhancing digital innovation for the sustainable transformation of manufacturing industry: A pressure-state-response system framework to perceptions of digital green innovation and its performance for green and intelligent manufacturing. Systems, 10(3), 72. https://doi.org/10.3390/systems10030072

70) Yonghong, L., Jie, S., Ge, Z., & Ru, Z. (2023). The impact of enterprise digital transformation on financial performance—Evidence from Mainland China manufacturing firms. Managerial and Decision Economics. https://doi.org/10.1002/mde.3805

71) Zeng, X., Sun, X., & Zhao, F. (2022). Energy-saving intelligent manufacturing optimization scheme for new energy vehicles. International Journal of Emerging Electric Power Systems, 23(6), 913–926. https://doi.org/10.1515/ijeeps-2022-0127

72) Zhai, H., Yang, M., & Chan, K. C. (2022). Does digital transformation enhance a firm's performance? Evidence from China. Technology in Society, 68, 101841. https://doi.org/10.1016/j.techsoc.2021.101841

73) Zhang, C., Chen, P., & Hao, Y. (2022). The impact of digital transformation on corporate sustainability- new evidence from Chinese listed companies. Frontiers in Environmental Science, 10. https://doi.org/10.3389/fenvs.2022.1047418

74) Zhang, W. J., & Zhao, J. (2023). Digital transformation, environmental disclosure, and environmental performance: An examination based on listed companies in heavy-pollution industries in China. International Review of Economics & Finance, 87, 505–518. https://doi.org/10.1016/j.iref.2023.06.001

75) Zhang, Y., Pan, C., Shu, M., & Wang, K. (2023). The role of internal control and digital transformation between political connections and financial performance: evidence from China. Asia Pacific Business Review, 1–23. https://doi.org/10.1080/13602381.2023.2220606