Journal of Business Research 155 (2023) 113387

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The effect of manufacturing agent heterogeneity on enterprise innovation performance and competitive advantage in the era of digital transformation

Jing Gao [a], Wanfei Zhang [a], Tao Guan [b,*], Qiuhong Feng [a], Abbas Mardani [c]

[a] School of Economics and Management, Harbin University of Science and Technology Harbin, Harbin 150000, China
[b] School of Economics and Management, Harbin Institute of Technology Harbin, Harbin 150001, China
[c] University of South Florida, Tampa, FL, United States

A R T I C L E I N F O

Keywords:
Digital transformation
Agent heterogeneity
Manufacturing industry
Cooperation quality
Enterprise innovation performance
Competitive advantage

A B S T R A C T

The digital transformation of the manufacturing industry has reshaped the collaborative innovation model of multi-agent value co-creation in the value chain. The nature and collaborative behavior of heterogeneous agents in the value chain are key factors affecting innovation performance. This study uses the structural equation model (SEM) and conducts a questionnaire survey on 381 manufacturing enterprises. It examines the different impacts of agent heterogeneity and collaborative behavior on the innovation performance of manufacturing enterprises in digital transformation under different digitization levels and enterprise sizes. The results show that highly digitized or large-scale enterprises can reduce the negative impact of agent heterogeneity on innovation performance. However, the cooperation quality of enterprises with low digitalization levels or small-scale enterprises plays an important role in improving enterprise performance. These results help manufacturing enterprises accelerate digital transformation and provide a strategic reference for transforming and upgrading the digital economy.

1. Introduction

Driven by the impact of the digital economy and the transformation and upgrade of traditional industries, digital transformation promotes the networked, intelligent, and coordinated development of the industrial value chain. The product value chain has changed from a single cycle to a multi-agent network, which is a new development in the manufacturing industry. Therefore, enterprises need to deeply integrate into the digital economy for the efficient realization, aggregation, reorganization, and transfer of heterogeneous knowledge within the product value chain through cross-border integration of digital technology. The enterprise can then promote efficient collaboration and value co-creation among agents based on digital innovation ecology (Dan et al., 2021). Therefore, using digitalization to effectively coordinate the activities of all parts of the value chain in heterogeneous multi-agents eliminates barriers to achieving value co-creation and becomes a key issue to further improve the innovation performance of enterprises. This is also required for enterprises to achieve digital transformation. In this process, the influence of agent heterogeneity on cooperation plays an important role in improving cooperation quality and innovation performance. Through continuous interaction and collaboration, each agent obtains digital technology, knowledge, capital, and other relevant resources to improve innovation performance (Teece, 2018). However, the influence path of cooperative behavior on innovation performance requires further study. Therefore, this study explores the impact of enterprise agent heterogeneity and collaborative behavior on innovation performance from the digital transformation perspective. It aims to provide targeted theoretical support and suggestions for enterprises to realize further digital transformation and efficient cooperation, and encourage enterprises to realize value co-creation and innovation breakthroughs in digital transformation.

Digital transformation makes the value chain three-dimensional, networked, and informational through digital technology. It promotes the formation of a new dynamic network structure between enterprises and their customers, distributors, suppliers, service providers, and other stakeholders. In addition, it fundamentally contributes to changes in the manufacturing production mode. In this regard, scholars explore the driving factors and effects of digital transformation. From the perspective of product innovation under digital transformation, a new innovation network (Lyytinen et al., 2016) or formal model with bilateral network externalities (Parker and Van Alstyne, 2016) is constructed. From the innovation ecosystem perspective, Roszkowska et al. (2017)

* Corresponding author.
E-mail address: hitguantao@163.com (T. Guan).

https://doi.org/10.1016/j.jbusres.2022.113387
Received 29 March 2022; Received in revised form 8 October 2022; Accepted 14 October 2022
Available online 2 November 2022

and Wang (2021) reveal the reconstruction, collaborative interaction, and evolution of agents under the digital transformation. In terms of the digital transformation's effect, Sahut et al. (2020) and Guo et al. (2022) analyze the transformation of the value chain operation mode and business model under digital transformation. Heredia et al. (2022) examine digital technology capability's impact on enterprise performance. Although existing studies focus on the evaluation of the incentives and effects of digital transformation on enterprise behavior, research on the multi-agent heterogeneity of value co-creation and collaborative behavior's impact on enterprise performance in the context of digital transformation is insufficient. In view of this, this study explores the impact of value-*co*-creating agent heterogeneity on enterprise innovation performance in the digital transformation of manufacturing enterprises.

In the face of multi-agent reconstruction of the product value chain and the change in operation mode under digital transformation, the heterogeneity of different agents is more obvious. The concept of agent heterogeneity originates from the differentiation characteristics of enterprises in strategic alliances (Parkhe, 1991). Later, the concept of partner heterogeneity in innovation networks is further extended (Beckman and Haunschild, 2002). Research on agent heterogeneity mainly focuses on the effect and mechanism of agent diversity in innovation organizations. Pascal et al. (2011) compare the mechanism and results of the bidirectional flow connection model of innovation network in the presence of partner heterogeneity. Mao et al. (2020) analyze the influence mechanism of agent heterogeneity on knowledge innovation in industry-university-research cooperation. Feng et al. (2022) evaluate the influence mechanism of internal and external factors generated by firm heterogeneity on enterprise innovation capability. Phillips et al. (2000) analyze the relationship and risk role of heterogeneous agents in innovation alliances. Additionally, some scholars study the positive influence of agent heterogeneity on the innovation environment (Lin, 2012) and decision-making ability (Huang et al., 2019). Therefore, previous studies mainly focus on the impact mechanism and effect evaluation of the cooperation and alliance of heterogeneous agents on innovation under the traditional economy, while the value co-creation behavior of heterogeneous agents under the background of digitalization takes on new characteristics and needs to be further studied. In this regard, some scholars analyze the influence mechanism of the digital economy on labor share from the industrial heterogeneity perspective (Chen et al., 2022). This study further explores the impact of agent heterogeneity in the manufacturing value chain on the innovation performance of digital transformation enterprises by taking manufacturing enterprises as the research object from a micro perspective.

Digital transformation accelerates change in the innovation structure of the product value chain and further improves the innovation performance of enterprises. Therefore, the impact of agent nature and behavior of digital transformation on innovation performance becomes the focus of academic attention. Some scholars discuss digital transformation's influence on enterprise innovation performance from the perspective of the object and subject of digital transformation. From the perspective of the object of digital transformation, some scholars study the influence of digital technology (Usai et al., 2021), digital investment (Nwankpa and Merhout, 2020), knowledge heterogeneity of digital enterprise (Lyu et al., 2022), and digital platform construction (Matarazzo et al., 2021) on innovation performance. From the perspective of the subject of digital transformation, scholars mainly study the impact of R&D partner heterogeneity (von Raesfeld et al., 2012), partner effective communication (Nguyen et al., 2022), and partnership quality (Benhayoun et al., 2021) on enterprise innovation performance. However, these studies mainly focus on traditional enterprises, and digital transformation enterprises are given little attention. In summary, existing studies only explore the impact of digital transformation on enterprise innovation performance from either the object or subject perspectives. By integrating subject and object perspectives, the influence of digital transformation on enterprise innovation performance is explained more deeply and comprehensively. This study discusses the difference in the influence of the subject and object factors of enterprise digital transformation on the innovation performance of manufacturing enterprises.

In conclusion, previous studies identify the impacts of digital transformation and agent heterogeneity on the cooperation of agents and enterprise performance, respectively. However, few studies combine the two to explore the impact of enterprise innovation performance under digital transformation. Therefore, this study proposes a research hypothesis and framework from the perspective of value chain multi-agent value co-creation and constructs an impact model of manufacturing enterprises' digital transformation. On this basis, this study designs the model variables that take manufacturing enterprises in digital transformation as the survey object and carries out a questionnaire survey to obtain empirical data. Then, AMOS software is used to construct a structural equation model (SEM) to examine the influence of agent heterogeneity and synergistic relationship on the innovation performance of manufacturing enterprises in digital transformation. Finally, multigroup analysis is applied to further explore the impact of agent heterogeneity and collaborative behavior on the innovation performance of manufacturing enterprises caused by the different levels of digitization and scale and the improvement countermeasures. This study aims to provide a strategic reference for transforming and upgrading manufacturing enterprises and improving innovation performance in the digital economy. Theoretically, this study supplements the research perspective of related studies on the impact of enterprise innovation performance and enriches the research on the differential impact path of heterogeneous agents' collaboration on enterprise performance improvement under digital transformation. From a practical perspective, the results of this study provide targeted theoretical support and suggestions for enterprises to realize efficient collaborative cooperation and encourage manufacturing enterprises to further realize digital transformation and upgrade and collaborative value co-creation.

2. Influence model construction in digital transformation

2.1. Influence of agent heterogeneity on cooperation quality and innovation performance

In the digital transformation of manufacturing enterprises, the network and digitalization of the product value chain make each link participant expand and deepen continuously. Therefore, agent heterogeneity has an impact on innovation (Huang et al., 2018). This study analyzes the differentiation and diversity of enterprise value chain agents in targets, technologies, markets, organizations, and other aspects of digital transformation. It is divided into three dimensions: target, knowledge, and organizational heterogeneity (Dai and Hu, 2016). First, in value chain digital innovation projects, the dynamics and flexibility of digital products require each agent to be consistent with strategic goals and product concepts. Suppose that the target heterogeneity caused by the different business philosophies, development backgrounds, and resource allocations of each value-creation agent cannot be solved and digested in time. In this case, it inevitably affects the innovation process and product development; thus, negatively affecting innovation performance. Second, because of the different positions and roles of each agent in the value chain, the digital technology acquired and market information fed back by big data are different. Under knowledge heterogeneity, each agent realizes intelligent and synergistic integrated production of the value chain. It also accurately grasps customer needs according to the market information of all parties through data sciences (Saura, 2021) to realize the digital production process and effective update and iteration of innovative products. However, excessive heterogeneous knowledge leads to knowledge overload, which reduces the efficiency of knowledge learning and absorption in the innovation process; thus, negatively affecting innovation performance. Therefore, an inverted U-shaped relationship exists between knowledge heterogeneity and innovation performance. Finally, different value chain agents produce organizational heterogeneity at different digitalization levels, organizational structures, and enterprise scales. Appropriate cooperation between heterogeneous entities can guide each other and directionally acquire resources and technologies; thus, improving innovation performance under synergistic interaction. However, high organizational heterogeneity increases management costs and free-rider risks. A U-shaped relationship between organizational heterogeneity and innovation performance also exists. Therefore, this study proposes the following hypotheses:

Hypothesis 1: Target heterogeneity negatively affects innovation performance.

Hypothesis 2: Knowledge heterogeneity has an inverted U-shaped relationship with innovation performance.

Hypothesis 3: Organizational heterogeneity has an inverted U-shaped relationship with innovation performance.

In digital transformation, the innovation performance of the manufacturing enterprises' product value chain depends not only on the heterogeneity of each value creation agent but is also closely related to cooperation quality, which is measured from four aspects—cooperation persistence, cooperation trust, cooperation satisfaction, and cooperation effect (Song et al., 2015). With the increase in target and organizational heterogeneity, the demand for cooperation and trust also increases. When the target heterogeneity is too large or difficult to be compatible with, enterprises need to invest more for target fusion, and it is easy to deviate from the overall goal and damage the collective interest in the process of cooperation. When organizational heterogeneity is large, the risk of free-riding increases. An increase in cooperation risk and cost decreases cooperation quality (Angel et al., 2009), which negatively impacts cooperation satisfaction and durability. Knowledge heterogeneity brings the latest marketable data and digital technology into cooperation, which helps value chain innovation keep pace with market changes, improve the quality of cooperation, constantly innovate technologies and products, and improve cooperation results and satisfaction (Lee and Yang, 2014). Therefore, this study proposes the following hypotheses:

Hypothesis 4: Target heterogeneity negatively affects cooperation quality.

Hypothesis 5: Knowledge heterogeneity positively affects cooperation quality.

Hypothesis 6: Organizational heterogeneity negatively affects cooperation quality.

2.2. *Influence of partnership on innovation performance and competitive advantage*

The increase in interaction frequency helps enterprises reduce the risks brought by agent heterogeneity, increases mutual familiarity among enterprises, clarifies the needs of each other, and enhances the adaptability and integration of the resource capacity and organizational structure of cooperation agents (Bruyaka, 2008). This is conducive for agents to exchange and learn rapidly flowing knowledge and resources in the digital economy, improve cooperation efficiency, and accelerate the improvement of innovation performance. An effective guarantee of cooperation quality enables value chain agents to establish a long-term stable cooperative relationship, improve cooperation stability and agent trust, help each agent to exchange and absorb resources and technology in-depth, and reduce the time to adapt to each other's goals, positively impacting innovation efficiency (Song, 2016). Additionally, good cooperation quality contributes to and improves enterprise development, directly reflecting the impact on innovation performance (Boh et al., 2020). Therefore, this study proposes the following hypotheses:

Hypothesis 7: Interaction frequency positively affects innovation performance.

Hypothesis 8: Cooperation quality positively affects innovation performance.

Quality performance is the result that manufacturing enterprises bring through the quality and activities of production, and represents the quality performance of enterprises. On one hand, good cooperation with other agents in the value chain effectively guarantees the raw material quality of upstream products and improves the production capacity and efficiency of enterprises through technical communication. On the other hand, multi-agent participation in product production effectively ensures product quality and innovation, and the results brought by efficient cooperation meet customer needs and expectations; thus, improving quality performance (Homburg and Jensen, 2007). The increase in interaction frequency between enterprises and cooperative agents promotes the establishment of a trust mechanism based on perceptual identity among knowledge transfer agents. When trust among subjects is high, the subjects' willingness to provide high-quality information and knowledge to each other increases accordingly. This improves the efficiency of the entire process of product design, production, and quality feedback; thus, improving quality performance. Therefore, this study proposes the following hypotheses:

Hypothesis 9: Cooperation quality positively affects quality performance.

Hypothesis 10: Interaction frequency positively affects quality performance.

Improving the quality performance of manufacturing enterprises enhances the technical content and potential market value of products. Good product quality and customer satisfaction increase the added value of innovative products and improve innovation quality. Improving production capacity and technology enhances the sustainability of enterprise product innovation, promotes product replacement, and improves the quantity life cycle of innovation results; thus, improving innovation performance (Zhou and Gu, 2019). In digital transformation, the effective improvement of innovation performance changes the previous resource model, competition rules, and operation mode, and uses digital transformation and upgrade to enhance the competitive advantages of enterprises, which have unique competitiveness from internal, external, and comprehensive performance. On one hand, enterprises acquire more digital technologies and resource capabilities through multi-agent collaborative innovation; thus, enhancing their overall strength and comprehensive quality (Chen et al., 2009). On the other hand, digital innovation quickly establishes market advantages and creates more value for customers (Skare and Ribeiro Soriano, 2021). Therefore, this study also proposes the following hypotheses:

Hypothesis 11: Quality performance positively affects innovation performance.

Hypothesis 12: Innovation performance positively affects competitive advantage.

2.3. *Conceptual model construction*

According to the above analysis on the influence mechanism of agent heterogeneity and interaction frequency in digital transformation of manufacturing enterprises, agent heterogeneity and interaction frequency are studied as independent variables. Agent heterogeneity is divided into target, knowledge, and organizational heterogeneity. Target heterogeneity is the difference between enterprise strategic goals and product concepts. Knowledge heterogeneity involves the difference and diversity of technical and market knowledge. Organizational heterogeneity is the difference in partner organization size and digitization level. Interaction frequency refers to the frequency of communication among agents in the cooperation process; it is divided into formal interaction, informal interaction, and interaction intention.

Cooperation quality is influenced not only by agent heterogeneity but also by innovation and quality performance. Therefore, it is considered a mediating variable of the relationship between agent heterogeneity and innovation performance and measured from four aspects of cooperation persistence, cooperation trust, cooperation satisfaction, and cooperation effect. Innovation performance, quality performance, and competitive advantage are considered as dependent variables.

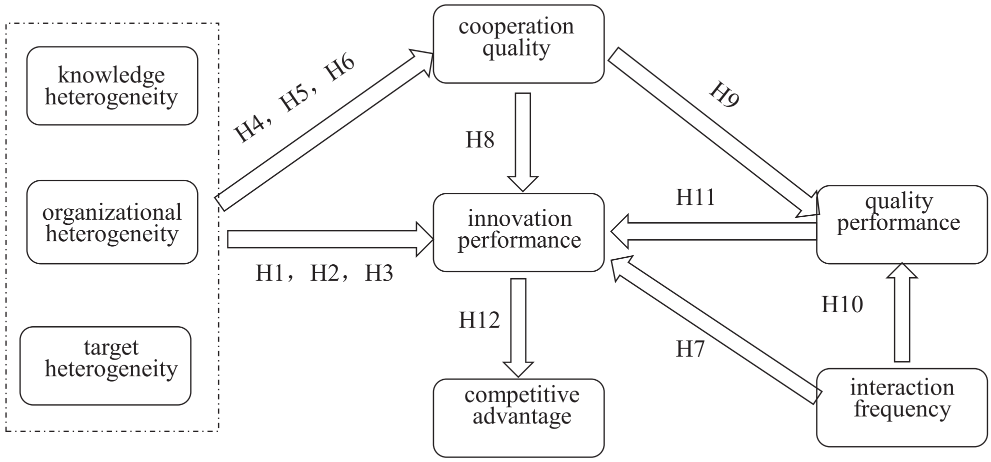

Fig. 1. Conceptual model.

Innovation performance is measured in terms of innovation quantity and quality. Quality performance is measured by product quality, enterprise production capacity, customer expectations, and quality feedback (Lin et al., 2019). Competitive advantage is measured based on internal resources and capabilities, external market sales, and comprehensive strength.

Therefore, this study establishes the conceptual model and constructs an empirical model based on the dimensions and variables in the conceptual model for further research. Fig. 1 shows the conceptual model.

3. Research design

3.1. Variable design and measure

Based on the conceptual model, the knowledge, organization, target heterogeneity, and interaction frequency of manufacturing agents are taken as explanatory variables. Cooperation quality is taken as the mediating variable, and quality performance, innovation performance, and competitive advantage are taken as the explained variables. Observation variables are further designed in combination with relevant studies of previous scholars, and empirical data on digital transformation of manufacturing enterprises are obtained through a questionnaire survey. Table 1 presents the variable types and their main components.

3.2. Sample screening and data source

This study aims to examine the digital transformation of manufacturing enterprises. In the random sampling of enterprises, some enterprises may not have carried out digital transformation; thus, affecting data accuracy. Therefore, before the questionnaire is issued, this study refers to the calculation method of the degree of integration between the manufacturing and digital industries. This study uses the complete consumption coefficient method in the input–output method to estimate the digital input level (Park, 1994). It considers manufacturing enterprises above the designated size in industries with a high level of digital investment as the investigation's main object.

The formula for calculating the complete consumption coefficient of manufacturing input digitalization is as follows:

$$digitaldj = adj + \sum_{m=1}^{N} admamj + \sum_{l=1}^{N}\sum_{m=1}^{N} adlalmamj + \cdots \tag{1}$$

In the formula, "j" represents the manufacturing industry to which the enterprise belongs. "d" represents the digital industry. "$digitaldj$" represents digital input in the manufacturing industry. "adj" represents the direct consumption of the dth manufacturing industry to the jth digital industry. "$\sum_{m=1}^{N} admamj$" is the first round of indirect consumption. The item $n+1$ represents round n indirect consumption. The calculated data are from the input–output table of 56 sectors globally in 2014, which have been released by the WIOD database in 2016. Fig. 2 shows the calculated results.

According to the calculation of the digital investment index of the industries, c17-c20 are selected as the main industries for this study. (c17: Computer, electronic and optical products manufacturing; c18: Electrical equipment manufacturing; c19: Machinery and equipment manufacturing; c20: Motor vehicles, trailers, and semi-trailers manufacturing) The WIOD database is classified according to the International Standard Industrial Classification of All Economic Activities (ISIC), while domestic enterprises are classified according to national economy industry. This study matches both according to the main names. The main industries studied are the general equipment manufacturing, special equipment manufacturing, electrical machinery, equipment manufacturing, communication equipment, computer and other electronic equipment manufacturing, and instrument and cultural office machinery manufacturing industries.

The study data are from the 2014 world input–output table released by the WIOD database in 2016 and the issued questionnaire. The world input–output table is mainly used to measure the digital input index of the industry, while the questionnaire is mainly used for the SEM. The respondents to the questionnaire are enterprises above the designated size in the five industries with high digital investment mentioned above. The questionnaires are sent through email and online on the network platform. A total of 1000 questionnaires are sent out, and 368 questionnaires are collected. Of the total, 226 are valid, representing an effective recovery of 22.6 %. At the same time, 13 questionnaires are issued using offline and telephone interviews; 13 are collected and all are valid, representing an effective recovery of 100 %. The methods and standards to judge whether the questionnaire is valid includes checking for the following: (1) the consistency method of items in the factor, that is, whether the answers to homogeneous questions are coordinated, (2) repetition rate, (3) missing values in answers, and (4) overall consistency of the answers. A total of 1013 questionnaires are sent out using the two methods, and 239 valid questionnaires are collected, representing an effective rate of 23.59 %.

Table 2 lists the descriptive statistics of the basic situation of enterprises in the questionnaire survey.

3.3. Validity and reliability of the questionnaire

Before the empirical study, this study first uses SPSS24.0 software to test the reliability and validity of the questionnaire design and research

Table 1
Variable scale.

Variable type		Variable	Explanation
Explanatory variable	Knowledge heterogeneity (X_1)	x_{11}	Differences in knowledge, technology, ability, and resources
		x_{12}	Learning and absorbing ability of heterogeneous knowledge
		x_{13}	Validity or complementarity of the knowledge of the partner
	Organizational heterogeneity (X_2)	x_{21}	Difference in digitization degree
		x_{22}	Differences in enterprise age, size, and organizational structure
		x_{23}	Differences in Value chain location and division of labor
	Target heterogeneity (X_3)	x_{31}	Differences in digital development strategy target
		x_{32}	Differences in product or service concepts
		x_{33}	Target compatibility
		x_{34}	Willingness to support each other's goals
	Knowledge heterogeneity square(X_4)	x_{41}	Residual centralization is used to square the mean deviation of all observed variables of knowledge heterogeneity
		x_{42}	
		x_{43}	
	Organizational heterogeneity square (X_5)	x_{51}	Residual centralization is used to square the mean deviation of all observed variables of organizational heterogeneity
		x_{52}	
		x_{53}	
	Interaction frequency (X_6)	x_{61}	Formal interaction frequency
		x_{62}	Informal interaction frequency
		x_{63}	Willingness to interact with partners
Intervening variable	Cooperation quality (Y_1)	y_{11}	Achievement of goals
		y_{12}	Willingness to continue cooperation
		y_{13}	Degree of trust and depth of cooperation with cooperation agents
		y_{14}	Promotion effect or other harvest of digital transformation
Explained variable	Quality performance (Y_2)	y_{21}	Product quality
		y_{22}	Product production capacity (including technology, equipment, resources, etc.)
		y_{23}	Customer expectations and satisfaction feedback on the product
	Innovation performance (Y_3)	y_{31}	Speed of new product development
		y_{32}	Degree of digital technology development and application
		y_{33}	Number of patent applications
		y_{34}	The ratio of successful patent applications to the total number of applications
		y_{35}	Product or service benefits resulting from cooperation
	Competitive advantage (Y_4)	y_{41}	Enterprise internal resource capability
		y_{42}	Product external market sales situation
		y_{43}	Position of the enterprise in the industry

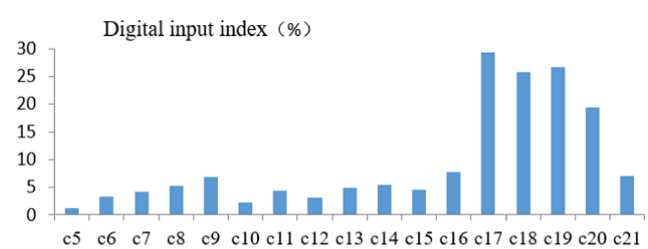

Fig. 2. Industry digital input index.

data. According to the results, the Cronbach's α coefficients of all latent variables are greater than 0.7, and the CITC values of all explicit variables are greater than 0.35. In addition, Cronbach's α coefficients after the deletion of explicit variables are all smaller than those before deletion, indicating that the scale has good internal consistency and reliability. The KMO values of agent heterogeneity and other variables are all above 0.7, and the P-value (significance) of Bartlett's sphere test is 0. These results indicate that the scale structure and data are suitable for further exploratory factor analysis. The analysis results show that all significant variable factor loads are greater than 0.6. The three components extracted from agent heterogeneity are consistent with the index design dimension, whereas only one component extracted from other variables is consistent with the index design dimension. The three components extracted from agent heterogeneity are consistent with the index design dimension, whereas only one component is extracted from other variables. This indicates that the explicit descriptions of each variable are consistent. Therefore, this analysis proves that the scale construction validity of the questionnaire survey is good and the content design is reasonable. Table 3 presents the reliability and validity test results.

4. Empirical model analysis

4.1. Construction of structural equation model

The SEM is designed according to the above indicators and is mainly composed of a measurement equation and structural equation. The measurement equation is expressed in the following form:

$$x = \alpha x \mu + ex \tag{2}$$

$$y = \alpha y \lambda + ey \tag{3}$$

In the above, equation (2) is an exogenous variable equation and equation (3) is an endogenous variable equation, where y represents an endogenous explicit variable and x represents an explicit exogenous variable. λ denotes endogenous latent variables (Y_1, Y_2, Y_3, Y_4) and μ denotes exogenous latent variables (X_1, X_2, X_3, X_4, X_5, X_6). The matrices α_Y and α_x are the coefficient matrices of the strength of the relationship between y and x, respectively, *ey* and *ex* represents the measurement errors of y and x, respectively. In the initial constructed model, knowledge heterogeneity (X_1), organizational heterogeneity (X_2), target heterogeneity (X_3), knowledge heterogeneity square (X_4), organizational heterogeneity square (X_5), and interaction frequency (X_6) are exogenous latent variables. Cooperation quality (Y_1), quality performance (Y_2), innovation performance (Y_3), and competitive advantage (Y_4) are endogenous latent variables. Furthermore, e1-e34 and e35-e38 are introduced in the model as the error variables of the explicit variable and the three endogenous latent variables, respectively. Thus, the equation expressions of the exogenous and endogenous latent variables are obtained as follows:

$$\begin{bmatrix} x11\\x12\\x13\\x21\\x22\\x23\\x31\\x32\\x33\\x34\\x41\\x42\\x43\\x51\\x52\\x53\\x61\\x62\\x63 \end{bmatrix} = \begin{bmatrix} \gamma11 & 0 & 0 & 0 & 0 & 0\\ \gamma12 & 0 & 0 & 0 & 0 & 0\\ \gamma13 & 0 & 0 & 0 & 0 & 0\\ 0 & \gamma21 & 0 & 0 & 0 & 0\\ 0 & \gamma22 & 0 & 0 & 0 & 0\\ 0 & \gamma23 & 0 & 0 & 0 & 0\\ 0 & 0 & \gamma31 & 0 & 0 & 0\\ 0 & 0 & \gamma32 & 0 & 0 & 0\\ 0 & 0 & \gamma33 & 0 & 0 & 0\\ 0 & 0 & \gamma34 & 0 & 0 & 0\\ 0 & 0 & 0 & \gamma41 & 0 & 0\\ 0 & 0 & 0 & \gamma42 & 0 & 0\\ 0 & 0 & 0 & \gamma43 & 0 & 0\\ 0 & 0 & 0 & 0 & \gamma51 & 0\\ 0 & 0 & 0 & 0 & \gamma52 & 0\\ 0 & 0 & 0 & 0 & \gamma53 & 0\\ 0 & 0 & 0 & 0 & 0 & \gamma61\\ 0 & 0 & 0 & 0 & 0 & \gamma62\\ 0 & 0 & 0 & 0 & 0 & \gamma63 \end{bmatrix} \begin{bmatrix} X1\\X2\\X3\\X4\\X5\\X6 \end{bmatrix} + \begin{bmatrix} e1\\e2\\e3\\e4\\e5\\e6\\e7\\e8\\e9\\e10\\e11\\e12\\e13\\e14\\e15\\e16\\e17\\e18\\e19 \end{bmatrix} \begin{bmatrix} y11\\y12\\y13\\y14\\y21\\y22\\y23\\y31\\y32\\y33\\y34\\y35\\y41\\y42\\y43 \end{bmatrix} = \begin{bmatrix} \theta11 & 0 & 0 & 0\\ \theta12 & 0 & 0 & 0\\ \theta13 & 0 & 0 & 0\\ \theta14 & 0 & 0 & 0\\ 0 & \theta21 & 0 & 0\\ 0 & \theta22 & 0 & 0\\ 0 & \theta23 & 0 & 0\\ 0 & 0 & \theta31 & 0\\ 0 & 0 & \theta32 & 0\\ 0 & 0 & \theta33 & 0\\ 0 & 0 & \theta34 & 0\\ 0 & 0 & \theta35 & 0\\ 0 & 0 & 0 & \theta41\\ 0 & 0 & 0 & \theta42\\ 0 & 0 & 0 & \theta43 \end{bmatrix} \begin{bmatrix} Y1\\Y2\\Y3\\Y4 \end{bmatrix} + \begin{bmatrix} e20\\e21\\e22\\e23\\e24\\e25\\e26\\e27\\e28\\e29\\e30\\e31\\e32\\e33\\e34 \end{bmatrix} \tag{4}$$

Here, "*xij*" represents the jth explicit variable of the latent variable *Xi*. "*yij*" represents the jth explicit variable of the latent variable *Yi*. "*γij*" represents the relation coefficient of the jth explicit variable of *Xi*, and "*θij*" represents the relation coefficient of the jth explicit variable of *Yi*.

According to the relationships among latent variables in the conceptual model, the structural equation among variables is expressed as follows:

$$\begin{bmatrix} Y1\\Y2\\Y3\\Y4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0\\ \lambda y12 & 0 & 0 & 0\\ \lambda y13 & \lambda y23 & 0 & 0\\ 0 & 0 & \lambda y34 & 0 \end{bmatrix} \begin{bmatrix} Y1\\Y2\\Y3\\Y4 \end{bmatrix} + \begin{bmatrix} \lambda x11 & \lambda x21 & \lambda x31 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & \lambda x33 & \lambda x43 & \lambda x53 & \lambda x63\\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X1\\X2\\X3\\X4\\X5\\X6 \end{bmatrix} + \begin{bmatrix} e35\\e36\\e37\\e38 \end{bmatrix} \tag{5}$$

Here, "*λyij*" represents the path coefficient of the variable *Yi* to variable *Yj*, "*λxij*" represents the path coefficient of variable *Xi* to variable *Yj*, and "*e*" represents the error term.

Fig. 3 shows the SEM, which is constructed using the structural equation.

4.2. Model adjustment and revisions

According to the SEM, the corresponding path and variable data are input into AMOS24.0 software for operation. Fig. 4 shows the initial operation results of the model.

First, the fitting degree of the model is analyzed, and the results show that "$\chi^2/\mathrm{df} < 3$". The fitting coefficients of NFI, IFI, TLI, and CFI are all greater than 0.8, while RMSEA is <0.08. These results indicate that the model fitting results are within the normal range and that the data fitting results are good.

Second, the MI indicators between internal residual items are checked. There are no excessive abnormal relationship coefficients. Finally, the significance of each path in the model is determined. Organizational heterogeneity square > innovation performance and quality performance > innovation performance; hence, the two paths do not pass the significance test. These two paths are deleted and recalculated, and the final structural equation of the model is as follows:

$$\begin{bmatrix} Y1\\Y2\\Y3\\Y4 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0\\ \lambda y12 & 0 & 0 & 0\\ \lambda y13 & 0 & 0 & 0\\ 0 & 0 & \lambda y34 & 0 \end{bmatrix} \begin{bmatrix} Y1\\Y2\\Y3\\Y4 \end{bmatrix} + \begin{bmatrix} \lambda x11 & \lambda x21 & \lambda x31 & 0 & 0 & 0\\ 0 & 0 & 0 & 0 & 0 & 0\\ 0 & 0 & \lambda x33 & \lambda x43 & 0 & \lambda x63\\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X1\\X2\\X3\\X4\\X5\\X6 \end{bmatrix} + \begin{bmatrix} e35\\e36\\e37\\e38 \end{bmatrix} \tag{6}$$

Table 2
Descriptive statistics of enterprises.

Industry		General equipment manufacturing industry	Special equipment manufacturing industry	Electrical machinery and equipment manufacturing industry	Communication equipment, computer, and other electronic equipment manufacturing industry	Instrument and cultural office machinery manufacturing industry
Total number	32	24	111	54	18	
Enterprise scale (people)	<100	8	3	16	24	10
	100–200	10	8	23	16	4
	200–400	12	5	48	8	2
	greater than400	2	8	24	6	2
Enterprise age (year)	<5	10	2	14	22	5
	5–15	12	6	28	24	8
	15–25	8	8	52	5	3
	greater than25	2	8	17	3	2
Positions of interviewee	top management	12	10	42	38	3
	middle management	16	8	54	10	13
	professional	4	6	15	8	2

Table 3
Results of validity and reliability tests.

Variable	Serial number	CITC	Loadings	Cronbach'α	KMO
Knowledge heterogeneity (X_1)	x_{11}	0.665	0.744	0.821	0.866
	x_{12}	0.668	0.852		
	x_{13}	0.694	0.826		
Organizational heterogeneity (X_2)	x_{21}	0.730	0.882	0.853	
	x_{22}	0.725	0.832		
	x_{23}	0.720	0.814		
Target heterogeneity (X_3)	x_{31}	0.831	0.892	0.915	
	x_{32}	0.784	0.845		
	x_{33}	0.799	0.859		
	x_{34}	0.809	0.887		
Interaction frequency (X_6)	x_{61}	0.692	0.868	0.822	0.720
	x_{62}	0.667	0.857		
	x_{63}	0.673	0.853		
Cooperation quality (Y_1)	y_{11}	0.664	0.816	0.839	0.817
	y_{12}	0.686	0.831		
	y_{13}	0.697	0.840		
	y_{14}	0.642	0.799		
Quality performance (Y_2)	y_{21}	0.737	0.888	0.846	0.726
	y_{22}	0.687	0.858		
	y_{23}	0.718	0.877		
Innovation performance (Y_3)	y_{31}	0.750	0.840	0.913	0.892
	y_{32}	0.773	0.855		
	y_{33}	0.789	0.870		
	y_{34}	0.796	0.874		
	y_{35}	0.802	0.878		
Competitive advantage (Y_4)	y_{41}	0.789	0.909	0.881	0.745
	y_{42}	0.763	0.895		
	y_{43}	0.769	0.899		

The final structural equation is established using AMOS24.0 software for calculation. Model results are analyzed according to the above steps. The fitting results are good, and all the path coefficients are significant; hence, it is taken as the calculation result of the final model in this study. Fig. 5 and Table 4 show the results.

The model results show that the target heterogeneity of partners in digital transformation has a significant negative impact on cooperation quality (-0.663) and innovation performance (-0.238). Knowledge heterogeneity has a significant positive impact on cooperation quality (0.251) in digital transformation and an inverted U-shaped impact on innovation performance (-0.217). Organizational heterogeneity has a significant negative impact on cooperation quality (-0.182) in digital transformation but has no significant impact on innovation performance. Interaction frequency and cooperation quality have significant positive effects on innovation performance (0.220, 0.371) and quality performance (0.615, 0.501). The improvement of enterprise innovation performance also helps enterprises gain more competitive advantages in the digital transformation process and multi-agent collaboration and has a significant positive influence (1.033). Table 5 presents the comparison results of the model and hypothesis testing.

The comparative analysis of the model results in Table 5 shows that most of the hypotheses pass the empirical test, which verifies the reliability of this study's theoretical analysis.

The results of the negative impact of target heterogeneity show that, compared with previous studies, the target consistency of enterprise cooperation agents plays an important role in innovation under digital transformation (Yue et al., 2018). Existing studies show that knowledge heterogeneity has a positive effect on innovation performance (Chen et al., 2020). This study verifies the results and finds that excessive knowledge heterogeneity also has a negative effect. In terms of enterprise cooperation, this study's results are consistent with those of previous studies. In digital transformation, good interaction frequency and cooperation quality also promote the improvement of enterprise innovation performance. Furthermore, similar with the results of previous studies, the results show that the innovation performance of enterprises under digital transformation also positively affects their competitive advantage (Li et al., 2021).

In addition, the results show that the relationship of organizational heterogeneity and quality performance with innovation performance is insignificant. This result differs from previous studies, which find that organizational heterogeneity increases the cooperation risk, and enterprises spend more for it (Laursen and Salter, 2006). Quality performance improves the efficiency of enterprises' innovation activities and promotes innovation performance (Jing et al., 2015). In this regard, the reasons for the different results of this study may be as follows: First, this study considers digital transformation enterprises as the research object. Digital transformation enterprises are more cautious when choosing partners. To avoid the free-riding phenomenon of digital technology and resources, enterprises usually choose organizations with similar structures and a high degree of digital adaptation for cooperation. Therefore, in the model and questionnaire setting, organizational heterogeneity has no significant impact on innovation performance. However, in this model, heterogeneous multiagent synergy has a more prominent impact on innovation performance. Thus, under multiple influencing paths of innovation performance, the impact of quality performance is less than

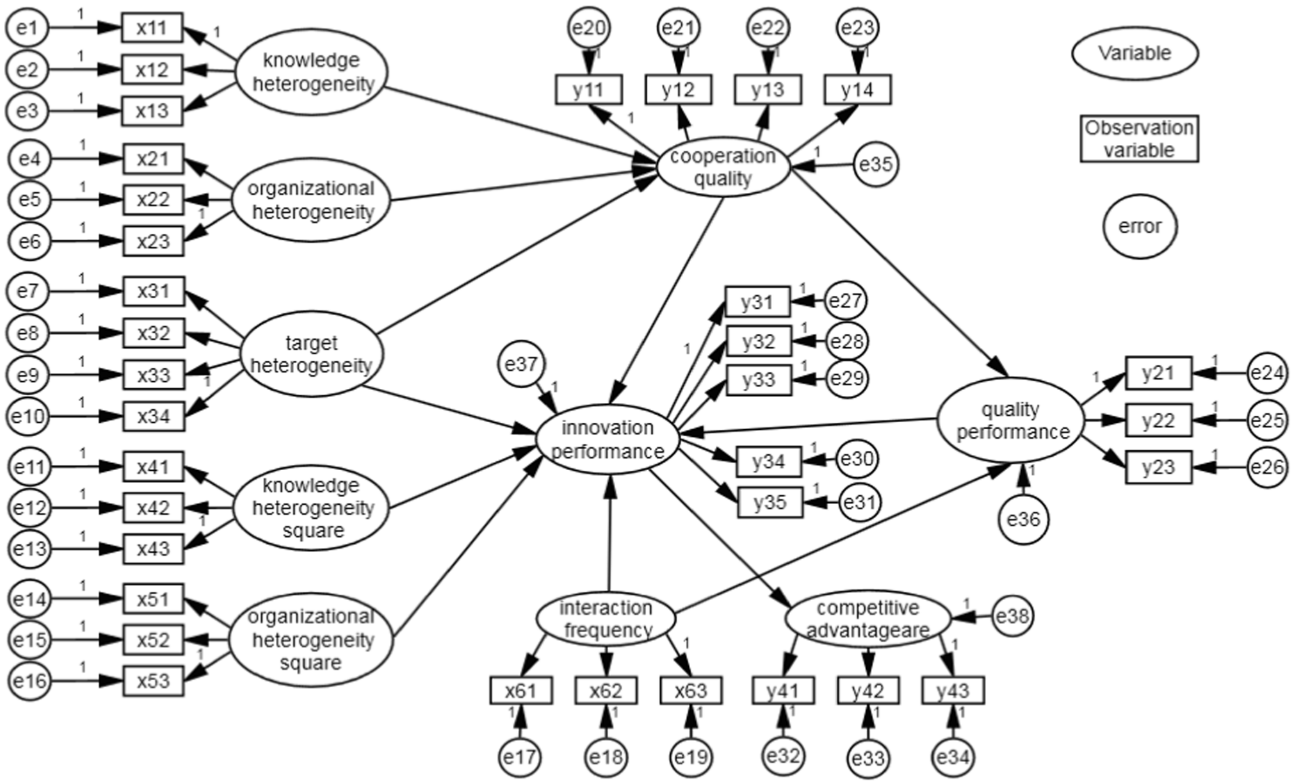

Fig. 3. Initial SEM.

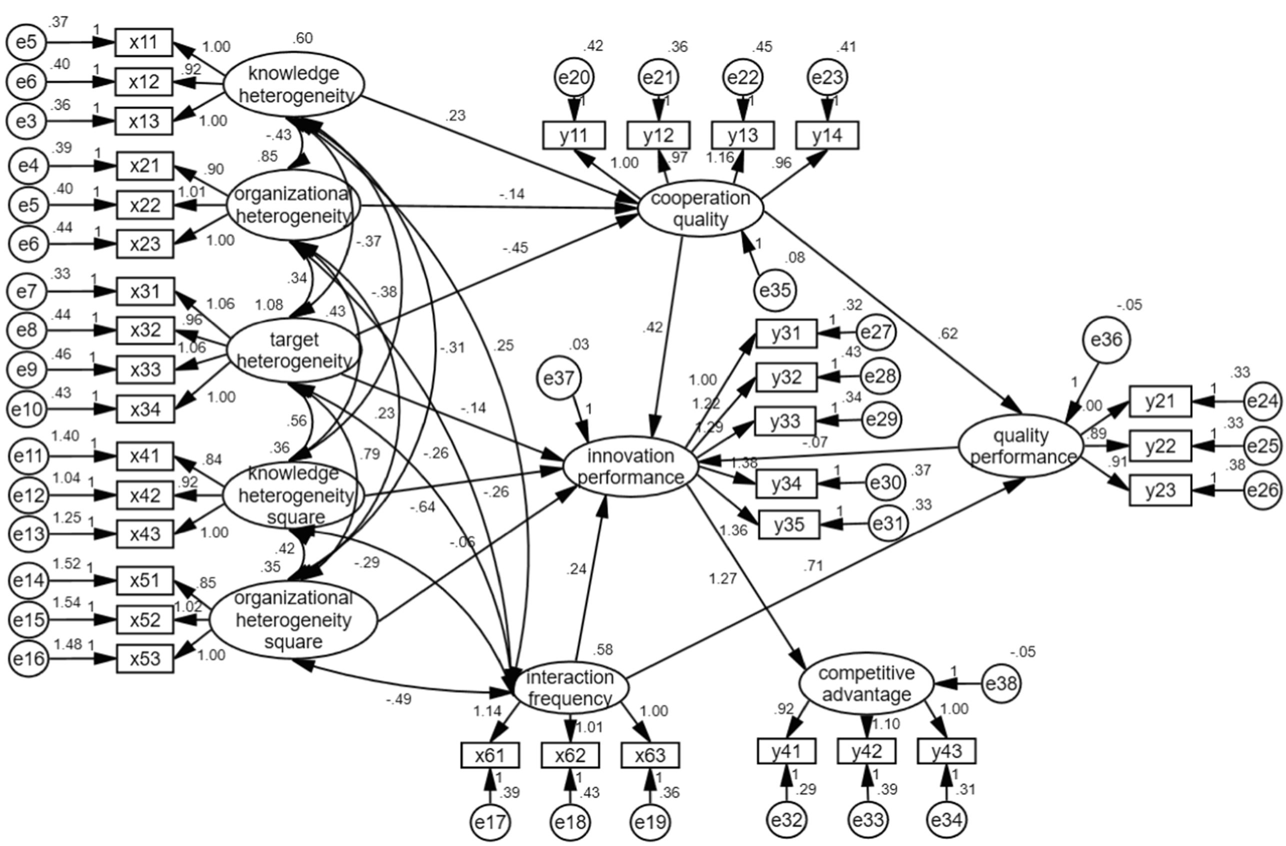

Fig. 4. Initial SEM results.

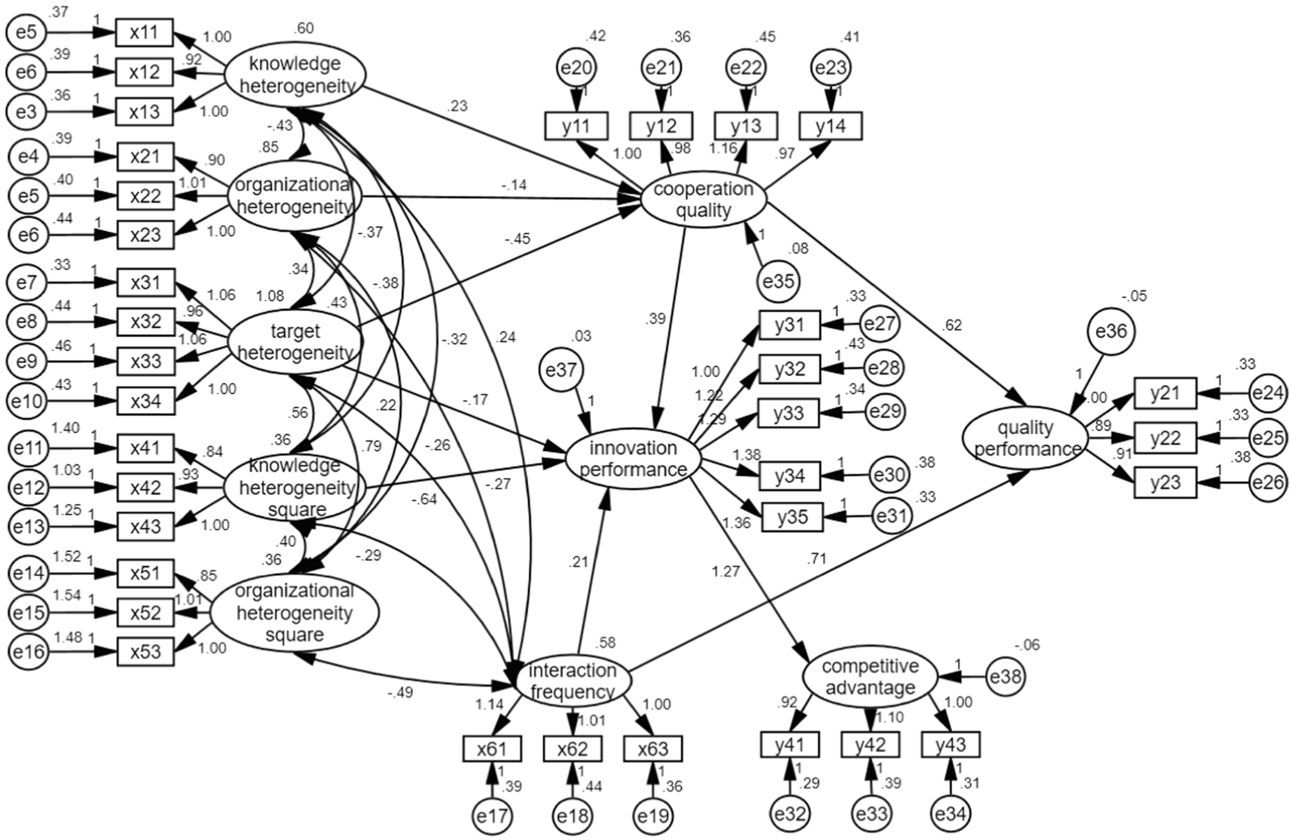

Fig. 5. Final SEM.

Table 4
Final structural equation fitting results.

Path			Standardized path coefficients	Path coefficients	S.E.	C.R.	P
Organizational heterogeneity	→	Cooperation quality	−0.182	−0.139	0.046	−2.983	0.003
Knowledge heterogeneity	→	Cooperation quality	0.251	0.228	0.062	3.687	***
Target heterogeneity	→	Cooperation quality	−0.663	−0.449	0.045	−9.937	***
Target heterogeneity	→	Innovation performance	−0.238	−0.169	0.058	−2.905	0.004
Knowledge heterogeneity square	→	Innovation performance	−0.217	−0.268	0.092	−2.900	0.004
Interaction frequency	→	Innovation performance	0.220	0.213	0.063	3.402	***
Cooperation quality	→	Innovation performance	0.371	0.390	0.092	4.232	***
Cooperation quality	→	Quality performance	0.501	0.623	0.080	7.780	***
Interaction frequency	→	Quality performance	0.615	0.705	0.077	9.131	***
Innovation performance	→	Competitive advantage	1.033	1.274	0.079	16.142	***
χ^2	798.942	NFI	0.878	IFI	0.951		
df	502	TLI	0.945	CFI	0.950		
χ^2/df	1.592	RMSEA	0.056				

$P < 0.05$ is a significant path.

that of agent heterogeneity and synergistic behavior and shows no significant results.

The research results clarify the key influencing factors of innovation performance improvement for digital transformation enterprises and guide enterprises to improve cooperation quality and avoid risks in collaborative cooperation. In addition, in view of the research results of the insignificance of organizational heterogeneity, considering that digital transformation enterprises have great heterogeneity in the degree of digital transformation and enterprise-scale, the analysis shows certain pertinence and differences in the process of choosing the partners. To further analyze the heterogeneous influence of different digital transformations on enterprise cooperation and innovation performance, this study explores agent heterogeneity and its effects on the innovation performance of cooperative behavior through different digital levels and enterprise scales to analyze the influence of external factors on digital transformation.

4.3. *Mediating effect analysis*

The bootstrap method is used to test the mediation effect. The confidence interval is constructed using a repeated sampling method with a put-back, and whether the upper and lower limits contain 0 is used to judge for the significance of the mediation effect between variables. If 0 is excluded, the mediating effect is significant when examining the indirect, direct, and total effects of each path successively. The results show that the mediating effect of the path “target heterogeneity > cooperation quality > innovation performance” is significant. Cooperation quality plays a mediating role in the effect of target heterogeneity

Table 5
Comparison of hypothesis and results.

No.	Hypotheses	Results
H1	Target heterogeneity negatively affects innovation performance.	Supported
H2	Knowledge heterogeneity has an inverted U-shaped relationship with innovation performance.	Supported
H3	Organizational heterogeneity has an inverted U-shaped relationship with innovation performance.	Not Supported
H4	Target heterogeneity negatively affects cooperation quality.	Supported
H5	Knowledge heterogeneity positively affects cooperation quality.	Supported
H6	Organizational heterogeneity negatively affects cooperation quality.	Supported
H7	Interaction frequency positively affects innovation performance.	Supported
H8	Cooperation quality positively affects innovation performance.	Supported
H9	Cooperation quality positively affects quality performance.	Supported
H10	Interaction frequency positively affects quality performance.	Supported
H11	Quality performance positively affects innovation performance.	Not Supported
H12	Innovation performance positively affects competitive advantage.	Supported

on innovation performance. Table 6 shows the results of the mediation effect test.

The negative impact of target heterogeneity on manufacturing enterprises' innovation performance is primarily due to its negative impact on the cooperation quality of heterogeneous subjects. In the digital transformation of manufacturing enterprises, the target heterogeneity of the value chain is caused by the enterprises' different strategic goals and management concepts. This results in the agent's emphasis on the allocation of limited resources and selective technology learning. In the rapid iteration and update of knowledge and technology in digital transformation, an information barrier or digital divide is easily generated among agents, and the cooperative ideas and goals in value co-creation activities are diversified. To carry out cooperation smoothly, the agents choose corresponding interests to compromise, which decreases cooperation satisfaction and cooperation effect. The decline in cooperation quality indirectly and negatively affects the improvement in the overall innovation performance of the value chain.

Table 6
Mediating effect results.

Effect	Path	Bootstrap(95 % CI) Percentile		Significance
		Lower	Upper	
Indirect effect	knowledge heterogeneity > cooperation quality > innovation performance	0.019	0.190	Yes
	organizational heterogeneity > cooperation quality > innovation performance	−0.150	−0.004	Yes
	target heterogeneity > cooperation quality > innovation performance	−0.310	−0.080	Yes
Direct effect	knowledge heterogeneity > innovation performance	−0.549	−0.034	Yes
	organizational heterogeneity > innovation performance	−0.273	0.060	No
	target heterogeneity > innovation performance	−0.297	0.058	No
Total effect	knowledge heterogeneity > cooperation quality > innovation performance	−0.504	0.125	No
	organizational heterogeneity > cooperation quality > innovation performance	−0.317	0.045	No
	target heterogeneity > cooperation quality > innovation performance	−0.473	-0.075	Yes

5. Extensibility analysis of the model

5.1. Multi-group stability analysis

To verify the robustness of the empirical results, this study uses multi-group analysis to investigate whether firm differences impact the results. Since this study only conducts questionnaires in industries with high degrees of digital investment, the universality of research among different industries is ignored even though the research object is targeted at digital transformation enterprises. Therefore, for further analysis, the research object industries are divided into two groups based on the digital investment index level. The first group comprises industries with high digital transformation levels: general equipment manufacturing, special equipment manufacturing, electrical machinery and equipment manufacturing, and instrument and cultural office machinery manufacturing. The second group includes industries with low digital transformation levels: communication equipment, computers, and other electronic equipment manufacturing. In addition, considering the influence of enterprise size on the number and heterogeneity of value chain agents, the surveyed enterprises are divided into two groups according to the number of employees for further analysis. The first group includes enterprises with < 200 employees, and the second group includes enterprises with more than 200 employees. Through the above two groups, this study investigates whether industry differences with different degrees of digitalization and enterprise size differences impact the above model results.

According to the principle of the structural equation multi-group competition model, five SEMs are obtained by successively adding parameter settings based on the original model. Table 7 presents the five models. On the other hand, Table 8 presents the multi-group invariance test table, which is obtained according to the calculation results of the model compared with the original model.

The results of the invariance test show that the differences in the GFI, AGFI, NFI, RFI, TLI, and CFI coefficients of all models are < 0.05. The results indicate that industry differences in different digital transformation degrees and enterprise size differences have no significant influence on the overall structural fitting of the SEMs. In short, this study's empirical results do not change significantly because of industry or firm size differences. Thus, the empirical results have a certain stability and universality.

5.2. Differentiation analysis of the heterogeneity influence of different digitization degree

Although the group verification of the digitalization degree of the sample enterprises has no significant influence on the stability and fitting degree of the overall model, the coefficients and significance of each path partly change during the test. This indicates that the digital transformation degree has a different impact on the innovation performance of manufacturing enterprises' agent heterogeneity. Therefore, the impact path of agent heterogeneity and collaborative behavior on

Table 7
Multi-group structural models.

	Model	Column parameter
1	Measurement weights	Factor loading equality
2	Structural weights	Path coefficient equality
3	Structural covariances	Covariance equality
4	Structural residuals	Latent error equations equality
5	Measurement residuals	Variances of the error terms of the observed variables equality

Table 8
Multi-group invariant results.

Group	Model	Delta-CMIN	Delta-DF	P	Delta-GFI	Delta-AGFI	Delta-NFI	Delta-RFI	Delta-TLI	Delta-CFI
Degree of digital transformation	1	38.602	24	0.030	−0.004	0.001	−0.006	−0.001	−0.001	−0.003
	2	69.997	34	0.000	−0.008	0.000	−0.011	−0.004	−0.005	−0.007
	3	156.565	55	0.000	−0.020	−0.009	−0.024	−0.013	−0.015	−0.019
	4	160.924	59	0.000	−0.021	−0.009	−0.024	−0.013	−0.015	−0.019
	5	240.186	93	0.000	−0.030	−0.010	−0.036	−0.017	−0.020	−0.027
Enterprise scale	1	15.847	24	0.894	−0.003	0.004	−0.003	0.003	0.003	0.002
	2	60.590	34	0.003	−0.006	0.003	−0.009	−0.002	−0.002	−0.004
	3	155.700	55	0.000	−0.023	−0.001	−0.022	−0.011	−0.014	−0.016
	4	165.168	59	0.000	−0.024	−0.001	−0.023	−0.012	−0.014	−0.017
	5	190.647	93	0.000	−0.028	−0.001	−0.027	−0.009	−0.010	−0.016

innovation performance under different digitalization degrees needs to be further analyzed. Table 9 shows the comparative analysis results of the path coefficient and significance (P-value).

Table 9 shows that in enterprises with a high digitalization degree, the influence of agent heterogeneity and interactive cooperation behavior on innovation performance becomes insignificant. Only cooperative quality, quality performance, and competitive advantage have strong significance, and do not change with the degree of enterprise digital transformation. However, for enterprises with a low digitalization degree, only target heterogeneity and organizational heterogeneity have significant changes in the impact path, whereas other impact paths are significant.

This may be because the multi-agent cooperation has a weak influence on the improvement of enterprise innovation performance in the mature stage of digital transformation. Through the application of digital technology, enterprises realize the required technological innovations and applications. The flexible collection and dredging of big data provide the innovation resources needed by enterprises. The necessity of acquiring technology and resources through interaction between agents decreases with the improvement in the enterprise's own digital capability. However, when enterprises are at a low digitalization level, they are clearer about the strategic planning and goals of accelerating their digital transformation and development and focus on risk avoidance in the digital transformation process. When enterprises with low digitization degrees choose partners, they usually choose organizations who have similar goals and business philosophies; thus, reducing the partners' impact on innovation performance.

The significance of the path indicates whether the influencing factors have obvious effects on the explained variables. The path coefficient reflects the direction and influence level of the variables. In Table 9, the standardized path coefficients are compared and analyzed with the path results of all sample enterprises. Fig. 9 presents the results of the comparison.

Fig. 6 reveals that enterprise agent heterogeneity with a high digital transformation degree has a strong negative effect on cooperation quality and innovation performance. This may be because enterprises at a higher digitalization level have formed a stable innovation ecosystem and have a relatively comprehensive resource and technology system, which further increase the management and absorption costs for heterogeneous agents to cooperate. Therefore, agent heterogeneity has a significant negative impact on cooperation quality, while innovation performance's impact is insignificant and has a negative correlation. In general, for enterprises with a high digitalization level, agent heterogeneity should be avoided to improve cooperation quality and innovation performance. Enterprises should carefully choose partners or take certain measures for the establishment of a stable and high-trust cooperation network to steadily improve cooperation quality.

However, enterprises with low digitization degrees have a greater impact on collaborative behavior and innovation performance. This may be because enterprises with low digitalization degrees have low technical abilities and digital resources; they are more dependent on heterogeneous cooperation for knowledge acquisition. Therefore, collaborative behaviors, such as the interaction between agents and cooperation quality, have significant and strong positive effects on innovation performance. Enterprises should improve the initiative of interactive cooperation, actively carry out high-quality cooperation with heterogeneous enterprises, and improve their innovation ability through interaction and collaborative cooperation.

5.3. Differentiation analysis of the heterogeneity influence of different enterprise sizes

Based on the above multi-group stability analysis, for manufacturing enterprises in digital transformation, the larger the enterprise scale, the stronger the foundation for realizing digital transformation. It can cope with the risks associated with digital transformation using sufficient resources and capabilities. However, this transformation process is complex. Enterprise scale is also an important organizational factor of agent cooperation in digital transformation. Therefore, this study analyzes the differences in the impact of agent heterogeneity and collaborative behavior on innovation performance under different enterprise scales to provide new ideas for improving the innovation performance of

Table 9
Results of grouping models with different degrees of digitization.

Path			Path number	High digitization degree		Low digitization degree	
				Standardized path coefficients	P	Standardized path coefficients	P
Organizational heterogeneity	→	Cooperation quality	A1	-0.642	***	-0.080	0.314
Knowledge heterogeneity	→	Cooperation quality	A2	-0.336	0.024	0.440	***
Target heterogeneity	→	Cooperation quality	A3	-0.850	***	-0.650	***
Target heterogeneity	→	Innovation performance	B1	-0.343	0.139	-0.076	0.442
Knowledge heterogeneity square	→	Innovation performance	B2	-0.564	0.111	-0.157	0.029
Interaction frequency	→	Innovation performance	B3	0.274	0.200	0.314	***
Cooperation quality	→	Innovation performance	B4	-0.107	0.764	0.512	***
Cooperation quality	→	Quality performance	C1	0.633	***	0.473	***
Interaction frequency	→	Quality performance	C2	0.521	***	0.687	***
Innovation performance	→	Competitive advantage	D1	1.050	***	1.035	***

$P < 0.05$ is a significant path.

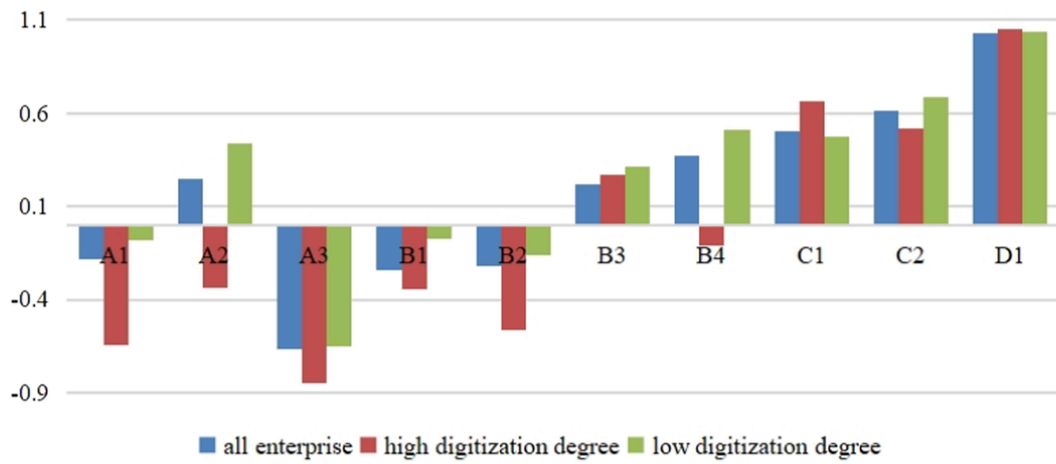

Fig. 6. Comparison of path coefficients of models with different digitalization degrees.

Table 10
Results of grouping models with different enterprise scales.

Path			Path number	Large enterprise		Small enterprise	
				Standardized path coefficients	P	Standardized path coefficients	P
Organizational heterogeneity	→	Cooperation quality	A1	0.438	0.008	-0.334	***
Knowledge heterogeneity	→	Cooperation quality	A2	0.633	***	0.259	***
Target heterogeneity	→	Cooperation quality	A3	-0.749	***	-0.615	***
Target heterogeneity	→	Innovation performance	B1	-0.420	***	0.077	0.744
Knowledge heterogeneity square	→	Innovation performance	B2	-0.082	0.153	-0.333	0.021
Interaction frequency	→	Innovation performance	B3	0.224	***	0.487	0.015
Cooperation quality	→	Innovation performance	B4	0.302	0.008	0.378	0.005
Cooperation quality	→	Quality performance	C1	0.374	***	0.572	***
Interaction frequency	→	Quality performance	C2	0.778	***	0.549	***
Innovation performance	→	Competitive advantage	D1	1.044	***	1.016	***

P < 0.05 is a significant path.

digital transformation enterprises of different scales. Table 10 presents the comparative analysis results of the path coefficient and significance (P-value).

Table 10 shows little difference in the significance of each path calculated according to the group size of enterprises. The U-shaped relationship between knowledge heterogeneity and innovation performance is insignificant for large enterprises. This is because large enterprises usually have a high status in the industry, can grasp the use of market resources and core technologies, and can contain and absorb the knowledge heterogeneity of their partners. Therefore, knowledge heterogeneity's influence on innovation performance is insignificant. Furthermore, target heterogeneity's effect on small enterprises' innovation performance is insignificant. This may be because small enterprises have a single product and business, which is targeted in the process of choosing partners. In addition, their digital transformation usually conforms to changes in the market environment and has the characteristics for digital strategic planning. Therefore, the impact of target heterogeneity on innovation performance is unclear.

Fig. 7 presents a comparison of the influence path coefficients of all enterprises and groups of enterprises of different sizes.

The analysis reveals that, except for a few variables, the influence relationships among most variables are still significant and exhibit

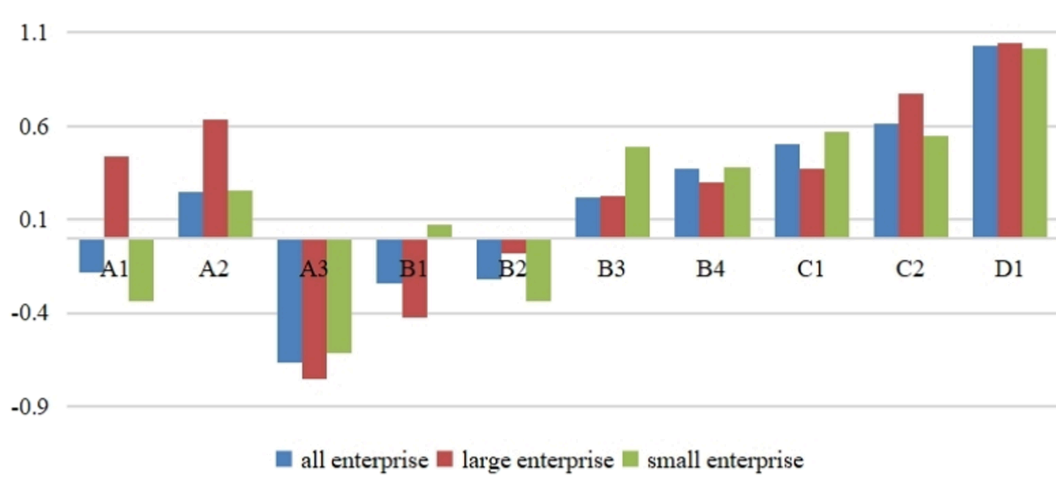

Fig. 7. Comparison of path coefficients of models with different enterprise scales.

different changes. The results also show that agent heterogeneity in larger enterprises has a greater impact on cooperation quality and innovation performance. Organizational heterogeneity's effect on cooperation quality is positively correlated with the other two components, which indicates that large enterprises adapt well to the organizational differences between cooperative agents. This is due to their large scale, strong resources and capacity, dominance, and supervision ability in cooperation with other enterprises in digital transformation, which brings the advantages of different organizations into full play in cooperation; thus, improving cooperation quality. Therefore, large-scale enterprises should play a positive role in absorbing organizational heterogeneity, leading and driving more agents to carry out high-quality cooperation. Assisting small and medium-sized enterprises advance quickly helps drive the overall high-quality transformation and upgrade of the industry and improves industry efficiency.

However, the collaborative behavior of small enterprises has a significant impact on innovation performance. Similar to enterprises with low digitization levels, small enterprises have limited access to resources and technology. The improvement in high-frequency interaction and cooperation quality with heterogeneous agents help enterprises acquire more technologies and resources, excavate transformation advantages at a lower cost in digital transformation, and promote enterprise digital transformation and innovation performance through cooperation and interaction. Therefore, small enterprises should strive for more opportunities to cooperate with heterogeneous agents, especially large-scale leading enterprises in the industry, to quickly improve their strength and market competitive position.

6. Conclusion

The nature and collaborative behavior of heterogeneous agents in the value chain are key factors that affect the innovation performance of multi-agent collaboration in the era of digital transformation. This study uses the SEM to examine the impact of the heterogeneity of manufacturing enterprises' goals, knowledge, and organization on innovation performance in digital transformation. Furthermore, we analyze the impacts of different business scales and digitalization degrees on innovation performance. The results show that agent heterogeneity has a negative or inverted U-shaped impact on cooperation quality and innovation performance of manufacturing enterprises in digital transformation. The synergistic interaction between enterprises and multiagents has a positive impact on innovation performance. Furthermore, improvements in enterprise innovation performance further promote enterprises to obtain greater competitive advantages. In addition, digitalization degree and enterprise size lead to the difference in the impact on enterprise performance. The agent heterogeneity of highly digitized or large-scale enterprises has little negative impact on innovation performance. The cooperation quality of small-scale enterprises or enterprises with digitization levels is important in improving innovation performance.

This study offers the following implications for promoting the digital transformation of manufacturing enterprises:

(1) From the relationship between agent heterogeneity and interaction frequency on enterprise cooperation quality and innovation performance, a negative or inverted U-shaped relationship exists between agent heterogeneity, cooperation quality, and innovation performance. Therefore, enterprises should pay attention to controlling participants' heterogeneity in the value chain to maximize its positive effect. Enterprises should rationally choose partners who have similar strategic goals and business philosophies. Before implementing the cooperation, strategic consistency should be achieved in key areas of cooperation, key digital technology development junctions, and expected goals to ensure its stability and sustainability. On the other hand, enterprises should fully utilize digitalization to improve the knowledge synergy of the agents and form the innovative knowledge network from different sources through digitalization technology to realize knowledge transformation and innovation output quickly. They should realize collaborative learning and digestion of heterogeneous knowledge to improve the efficiency of knowledge acquisition.

(2) Based on the different analyses of factors influencing enterprise innovation performance at different digitalization levels, enterprises should choose the cooperation strategy based on the actual digital development level. On one hand, enterprises with higher digitalization degrees should establish long-term cooperative relationships or innovation ecology with corresponding agents according to cooperation quality and form a collaborative innovation network for the manufacturing value chain. The negative impact of agent heterogeneity should be reduced by establishing long-term, stable relationships. On the other hand, enterprises with low digitalization degrees should use digital technology to facilitate the establishment of effective communication management platforms and digital cooperation management mechanisms with agents to improve the interaction frequency and cooperation quality among agents.

(3) Based on the different analyses of factors influencing the innovation performance of enterprises of different sizes, large enterprises should lead the cooperation. They can carry out collaborative innovation through resource sharing and risk sharing to provide support for the entire digital collaborative value chain of manufacturing enterprises. Synergistic and interactive behaviors play an important role in improving the innovation performance of small enterprises. Small and medium-sized enterprises should actively seek cooperation opportunities, especially with leading digital enterprises in the industry, to quickly acquire the required digital technology and knowledge through high-quality collaborative cooperation and interaction and help enterprises to further digitally transform and upgrade.

This study has some limitations. First, systematic and quantitative data evaluation of agents' related nature and cooperative behavior requires further research. Second, this study only conducts questionnaire surveys, group stability tests, and heterogeneous analyses in industries with a high digital transformation index. A more detailed data analysis is needed for enterprises in industries with low digital transformation degrees.

7. Funding Statement

The authors did not receive specific funding.

CRediT authorship contribution statement

Jing Gao: Writing – original draft, Conceptualization. **Wanfei Zhang:** Validation, Investigation, Data curation. **Tao Guan:** Writing – review & editing, Supervision, Project administration. **Qiuhong Feng:** Visualization, Methodology. **Abbas Mardani:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Angel, M., José, M. V., Manuela, P., & Pilar, D. (2009). Inter-organizational cooperation and environmental change: moderating effects between flexibility and innovation performance. *British Journal of Management, 20*(4), 5370561. https://doi.org/10.1111/j.1467-8551.2008.00605.x

Beckman, C. M., & Haunschild, P. R. (2002). Network learning: The effects of partners' heterogeneity of experience on corporate acquisitions. *Administrative Science Quarterly, 47*(1), 92–124. https://doi.org/10.2307/3094892
Benhayoun, L., Ayala, N. F., & Le Dain, M. A. (2021). SMEs innovating in collaborative networks: how does absorptive capacity matter for innovation performance in times of good partnership quality? *Journal of Manufacturing Technology Management, 32*(8), 1578–1598. https://doi.org/10.1108/JMTM-11-2020-0439
Boh, W. F., Huang, C. J., & Wu, A. (2020). Investor experience and innovation performance: The mediating role of external cooperation. *Strategic Management Journal, 41*(1), 124–151. https://doi.org/10.1002/smj.3089
O. Bruyaka. Alliance Partner Diversity and Biotech Firms' Exit. Differing Effects on Dissolution Versus Divestment. Paper presented at the Academy of Management Proceedings, 2008.
Chen, Y. S., Lin, M. M. J., & Chang, C. H. (2009). The positive effects of relationship learning and absorptive capacity on innovation performance and competitive advantage in industrial markets. *Industrial Marketing Management, 38*(2), 152–158. https://doi.org/10.1016/j.indmarman.2008.12.003
Chen, T., Qu, Y. Y., Ren, H., & Guo, Z. P. (2020). The influence of inter-enterprise knowledge heterogeneity on exploratory and exploitative innovation performance: The moderating role of trust and contract. *Sustainability, 12*(14). https://doi.org/10.3390/su12145677
Chen, N., Sun, D., & Chen, J. (2022). Digital Transformation, Labour Share, and Industrial Heterogeneity. *Journal of Innovation & Knowledge, 7*(2), Article 100173. https://doi.org/10.1016/j.jik.2022.100173
Dai, Y., & Hu, M. F. (2016). The effect of industry-university-research partner heterogeneity on collaborative innovation performance: From the perspective of organizational learning. *Higher Education Exploration, 1*, 5–11.
Dan, B., Hu, Z. J., & Li, W. B. (2021). Evolution game model and simulation analysis of multi-value chain members' transcation behavior under supervision of third-party platforms. *Computer Integrated Manufacturing Systems, 27*(11), 3291–3304. https://doi.org/10.13196/j.cims.2021.11.022
Feng, D. L., Hu, M. Z., Zhao, L. D., & Liu, S. (2022). The impact of firm heterogeneity and external factor change on innovation: evidence from the vehicle industry sector. *Sustainability, 14*(11), 6507. https://doi.org/10.3390/SU14116507
Guo, H., Guo, A., & Ma, H. (2022). Inside the black box: how business model innovation contributes to digital start-up performance. *Journal of Innovation & Knowledge, 7*(2), Article 100188. https://doi.org/10.1016/j.jik.2022.100188
Heredia, J., Castillo-Vergara, M., Geldes, C., Carbajal Gamarra, F. M., Flores, A., & Heredia, W. (2022). How do digital capabilities affect firm performance? The mediating role of technological capabilities in the "New Normal". *Journal of Innovation & Knowledge, 7*(2), Article 100171. https://doi.org/10.1016/j.jik.2022.100171
Homburg, C., & Jensen, O. (2007). The thought worlds of marketing and sales: which differences make a difference? *Journal of Marketing, 71*(3), 124–142. https://doi.org/10.1509/jmkg.71.3.124
Huang, S. F., Chen, J., & Liang, L. (2018). How open innovation performance responds to partner heterogeneity in China. *Management Decision, 56*(1), 26–46. https://doi.org/10.1108/MD-04-2017-0452
Huang, S. F., Chen, J., Ye, W. W., & Wang, K. (2019). The effect of external partner heterogeneity on open innovation: The moderating role of the technological regime. *Technology Analysis & Srrategic Management, 31*(5), 593–605. https://doi.org/10.1080/09537325.2018.1529301
Jing, Z., Chi, A. P., & Yoshiki, M. (2015). The impact of hard and soft quality management on quality and innovation performance: An empirical study. *International Journal of Production Economics, 162*, 216–226. https://doi.org/10.1016/j.ijpe.2014.07.006
Laursen, K., & Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. *Strategic Management Journal, 27*, 131–150. https://doi.org/10.1002/smj.507
Lee, Y. M., & Yang, C. (2014). The relationships among network ties, organizational agility, and organizational performance: A study of the flat glass industry in Taiwan. *Journal of Management & Organization, 20*(2), 206–226. https://doi.org/10.1017/jmo.2014.32
Li, R. X., Peng, C., Koo, B., Zhang, G., & Yang, H. (2021). Obtaining sustainable competitive advantage through collaborative dual innovation: Empirical analysis based on mature enterprises in Eastern China. *Technology Analysis & Strategic Management, 33*(6), 685–699. https://doi.org/10.1080/09537325.2020.1839043
Lin, H. Y. (2012). Cross-sector alliances for corporate social responsibility partner heterogeneity moderates environmental strategy outcomes. *Journal of Business Ethics, 110*(2), 219–229. https://doi.org/10.1007/s10551-012-1423-2
Lin, X. F., Zhao, Z. H., & Xia, H. L. (2019). Construction and evaluation of modern service enterprise quality performance evaluation system under O2O mode. *Marketing Research, 11*, 68–73. https://doi.org/10.13999/j.cnki.scyj.2019.11.025
Lyu, C., Peng, C., Yang, H., Li, H., & Gu, X. (2022). Social capital and innovation performance of digital firms: serial mediation effect of cross-border knowledge search and absorptive capacity. *Journal of Innovation & Knowledge, 7*(2), Article 100187. https://doi.org/10.1016/j.jik.2022.100187
Lyytinen, K., Yoo, Y., & Boland, R. J. (2016). Digital product innovation within four classes of innovation networks. *Information Systems Journal, 26*(1), 47–75. https://doi.org/10.1111/isj.12093
Mao, C. F., Yu, X. Y., Zhou, Q., Harms, R., & Fang, G. (2020). Knowledge growth in university-industry innovation networks-results from a simulation study. *Technological Forecasting and Social Change, 151*, 119746. https://doi.org/10.1016/j.techfore.2019.119746
M. Matarazzo, L. Penco, G. Profumo, R. Digital Transformation and Customer Value Creation in Made in Italy SMEs: A Dynamic Capabilities Perspective, Journal of Business Research, 123(2021), pp. 642-656, DOI: 10.1016/j.jbusres.2020.10.033.
Nguyen, H., Onofrei, G., Akbari, M., & McClelland, R. (2022). Enhancing quality and innovation performance: The role of supplier communication and knowledge development. *Total Quality Management & Business Excellence, 33*(3–4), 410–433. https://doi.org/10.1080/14783363.2020.1858711
Nwankpa, J. K., & Merhout, J. W. (2020). Exploring the effect of digital investment on IT innovation. *Sustainability, 12*(18). https://doi.org/10.3390/su12187374
Park, S. H. (1994). Intersectoral Relationships between Manufacturing and Services: New Evidence from Selected, Pacific Basin Countries. *ASEAN Economic Bulletin, 10*(3), 245–263.
Parker, G. G., & Van Alstyne, M. W. (2016). Two-sided network effects: a theory of information product design. *Management Science, 51*(10), 1494–1504. https://doi.org/10.1287/mnsc.1050.0400
Parkhe, A. (1991). Interfirm diversity, organizational learning, and longevity in global strategic alliances. *Journal of International Business Studies, 22*(4), 579–601. https://doi.org/10.1057/palgrave.jibs.8490315
Pascal, B., Christophe, B., & Sudipta, S. (2011). Strict Nash networks and partner heterogeneity. *International Journal of Game Theory, 40*(3), 515–525. https://doi.org/10.1007/s00182-010-0252-8
Phillips, T. B., Lawrence, & Hardy. (2000). , Inter-organizational collaboration and the dynamics of institutionalfields. *Journal of Management Studies, 37*(1), 23–44. https://doi.org/10.1111/1467-6486.00171
Roszkowska, D. (2017). External knowledge sourcing and innovation processes in modern economic environment. *International Journal of Management and Economics, 53*(2), 39–56.
Sahut, J. M., Dana, L. P., Laroche, M., & Innovations, D. (2020). Impacts on marketing, value chain and business models: an introduction. *Canadian Journal of Administrative Sciences-Revue Canadienne DES Sciences DE Ladministration, 37*(1), 61–67.
Saura, J. R. (2021). Using data sciences in digital marketing: framework, methods, and performance metrics. *Journal of Innovation & Knowledge, 6*(2), 92–102. https://doi.org/10.1016/j.jik.2020.08.001
Skare, M., & Ribeiro Soriano, D. (2021). How globalization is changing digital technology adoption: An international perspective. *Journal of Innovation & Knowledge, 6*(4), 222–233. https://doi.org/10.1016/j.jik.2021.04.001
Song, J. (2016). Innovation ecosystem: impact of interactive patterns, member location and member heterogeneity on cooperative innovation performance. *Innovation-Management Policy & Practice, 18*(1), 13–29. https://doi.org/10.1080/14479338.2016.1165624
Song, J., Chen, J. H., & Sun, Y. L. (2015). Impact of network competence on cooperative innovation performance in different regional culture. *Management Review, 27*(5), 35–42. https://doi.org/10.14120/j.cnki.cn11-5057/f.2015.02.004
Teece, D. J. (2018). Profiting from innovation in the digital economy: enabling technologies, standards, and licensing models in the wireless world. *Research Policy, 47*(8), 1367–1387. https://doi.org/10.1016/j.respol.2017.01.015
Usai, A., Fiano, F., Petruzzelli, A. M., Paoloni, P., et al. (2021). *Unveiling the Impact of the Adoption of Digital Technologies on Firms' Innovation Performance, 133*, 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035
von Raesfeld, A., Geurts, P., & Jansen, M. (2012). When is a network a nexus for innovation? A study of public nanotechnology R&D projects in the Netherlands. *Industrial Marketing Management, 41*(5), 752–758. https://doi.org/10.1016/j.indmarman.2012.06.009
Wang, P. (2021). Connecting the parts with the whole: Toward an information ecology theory of digitalinnovation ecosystems. *MIS Quarterly, 45*(1), 397–422. https://doi.org/10.25300/MISQ/2021/15864
Yue, H., Zhang, Z. Y., & Zhu, H. N. (2018). Innovation partner heterogeneity, dual organization learning and open innovation performance. *Chinese Journal of Management, 15*(1), 48–56. https://doi.org/10.3969/j.issn.1672-884x.2018.01.006
Zhou, F., & Gu, X. (2019). Fuzzy impact of quality management on organizational innovation performance. *ResearchGate, 37*(9), 1–9. https://doi.org/10.3233/JIFS-179112

Jing Gao, doctor, Professor, Department of School of Economics and Management Harbin University of Science and Technology Harbin. Research direction: digital innovation and enterprise strategic decision-making.

Tao Guan (Corresponding author), doctor, associate professor, Harbin Institute of technology, School of economics and management. Research interests: information economics, financial instruments.

Qiuhong Feng, School of Economics and Management Harbin University of Science and Technology Harbin, graduate student, the research direction is Green innovation ecosystem.

Wanfei Zhang, School of Economics and Management Harbin University of Science and Technology Harbin, graduate student, the research direction is digital innovation.

Abbas Mardani, Ph.D. and postdoc, he is graduated in the field of operation management from Universiti Teknologi Malaysia (UTM); his master and bachelor's degrees were in industrial management (operation and production management), he has been a postdoc, researcher, and assistant professor at the University of South Florida (USF) and Universiti Teknologi Malaysia (UTM).