Digitalization Paths, Heterogeneity And Productivity Growth —A Hidden Classes Linear Mixed Model Approache

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From the perspective of digital transformation trajectory, the Latent Class Linear Mixed Model (LCLMM) was first applied in the field of enterprise management. Based on panel data of 790 small and medium-sized enterprises (SMEs) in China from 2013 to 2022, the internal mechanism of how digital transformation of SMEs affects total factor productivity (TFP) was explored. The research results show: (1) There are three trajectories of digital transformation for SMEs: speed adjustment, steady growth, and rapid growth. (2) Regarding the impact of digital transformation on total factor productivity, the speed adjustment enterprises will suppress its improvement effect, the uniform growth enterprises will exhibit an inverted "U"-shaped relationship, and the rapid growth enterprises can strengthen this promoting effect. (3) The digital transformation of SMEs improves their production efficiency by reducing R&D investment, improving innovation efficiency and shifting the resource structure to non-strategic resources; among them, the differences in R&D investment among different trajectories of SMEs are significant, while there are no differences in the adjustment of the resource structure. The marginal contribution of this study is mainly reflected in three aspects: first, explaining the paradox of digital productivity from the perspective of dynamic trajectories; second, revealing the differential mechanism of innovation capability and resource allocation under different transformation trajectories; third, for the first time, applying the Latent Class Linear Mixed Model to the field of enterprise digital transformation.

Keywords: Computer Network; Digital Transformation Trajectory; Total Factor Productivity; Latent Class Linear Mixed Model; Strategic Resource Structure

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1. Introduction

Small and medium-sized enterprises (SMEs) with a small-scale operation, adaptable organizational structure, short management chain, and fast access to information are key factors for promoting the generation of ideas, job creation, and overall productivity [1, 2]. Nevertheless, owing to limited resources and a relatively low level of risk resistance capability, SMEs are unable to realize long-term and steady growth [3]. As a result of the explosive development of digital technology, digital transformation is often considered one of the most effective ways to enhance productivity and offset resource disadvantages [4]. However, recent researches show that while average levels of digitization across enterprises have been increasing, productivity at individual enterprises is not always improving as a result-and sometimes has even declined-giving birth to a so-called "digital productivity paradox" [5, 6].

It is apparent that there are two opposite views about if digital transformation would influence the productivity or no, some people think that technology adoption-based approach postulates the "Solow Paradox," i.e., early use of digitization may result in temporary loss in productivity due to initial mismatch between new technology and enterprise's legacy capital (assets), as well as increased managerial complexity [5–7]. In contrast, there is an argument stemming from the dynamic capability perspective, which states that digital transformations are considered key heterogeneous resources that can reduce entry costs, promote lifelong education, and optimize resource use to substantially raise productivity in the long run [8, 9].

However, the digitalization process in enterprises is not simply a linear one, but that there are ups and downs with times when things improve or stay the same or, in some cases, get worse. Such shifting paths can be relevant for enterprises' productivity performance, and from the perspective of resource-based theory, a enterprise's current position is the result of all past developments and therefore changes in the historical digital transformation trajectories can be an important determinant for diverging total factor productivity between enterprises [10].

Hence, in this study, we examine an enterprise's digital transformation trajectories and use a Latent Class Linear Mixed Model (LCLMM) to analyze their impact on TFP. To increase the relevance and policy implications of our empirical exercise, this study takes the listed company on the SME board of China's A share stock market for the research object representative data quality, fairly clear lines of governance, and substantial outside regulation, making them applicable to capture the actual dynamics of SMEs in the transformation process and providing lessons learned that can be applied to other developing countries. The innovative contributions of this paper are mainly reflected in three aspects: (1) In terms of research perspective, it breaks through the existing analysis framework that focuses on the static temporal characteristics of digital transformation, and from the perspective of dynamic trajectory, incorporates the historical evolution process of transformation into productivity effect analysis, surpassing the simple system integration of technology adoption and dynamic capability perspectives. Based on the resource-based theory, this study reveals the differential impact of heterogeneity in transformation trajectories on productivity, providing a new theoretical perspective and empirical evidence for explaining the paradox of digital productivity, and filling the gap in this research field from the perspective of dynamic processes. (2) In terms of mechanism analysis, break the paradigm of holistic and homogeneous analysis of the impact of digital transformation on productivity, and deeply identify the differential mechanisms of different transformation paths on enterprise innovation capability and resource allocation. For the first time, it was discovered that there is significant heterogeneity in the adjustment of R&D investment among enterprises with different trajectories, while the adjustment of resource structure follows a unique pattern of consistency. This clarifies the applicable boundaries of the relevant mechanisms in different transformation contexts, making the analysis of digital transformation mechanisms more targeted and refined. (3) In terms of research methodology,
for the first time, the LCLMM has been applied to the field of digital transformation. This is not a simple method transplant, but rather a new modeling hypothesis that incorporates covariates such as enterprise size and considers temporal random effects, taking into account the dynamic and heterogeneous characteristics of digital transformation in SMEs. We have achieved a methodological breakthrough in the digital transformation trajectory from traditional qualitative classification to quantitative and precise identification, providing a new practical paradigm and methodological reference for heterogeneity quantification research in this field.

While most studies focus on the innovative value of digital transformation [2, 11], it is still unclear whether and how digital transformation influences' Esthe TFP. Building on both the technology adoption perspective and the dynamic capabilities perspective, the relationship of digital transformation to TFP could be investigated in two ways: one holds that digital transformation promotes productivity improvement, while the second argues that it can be a potential impediment for productivity growth.

The first line of reasoning adopts the technology adoption perspective, viewing digital transformation as the process through which SMEs invest in and absorb digital technologies [12]. From this standpoint, digital transformation is believed to have a negative effect on enterprises' TFP.

First, SMEs tend to suffer from crowding out digital technology investment. Digital transformation requires huge investments, both for the purchase of technologies and their operation and maintenance costs [5]. Therefore, the transformation activity and regular business operations compete intensely over scarce resources. Digital investment might be crowding-out from other important activities, such as R&D or production [13], thus lowering total production. Digital transformation relies heavily on capital.

Second, SMEs tend to experience a lag effect when adopting digitized technology. SMEs often have limited capability of rapid adoption and integration of digital technology and its value realization, with significant gaps in both technology usage and organizational practices in a direct transition towards digitalization [4]; therefore, SMEs must pay for a more expensive configuration of the use of digital technology [3] and therefore reduce their production efficiency. Furthermore, the persisting digital gap impedes SMEs' adoption of digital technologies in existing production and management processes [14], which leads to a lag in the productivity effects digitalization can generate. Thus, digital transformation can hamper an increase in TFP among SMEs. Based on the above analysis, we propose the following hypotheses:

Hypothesis la: Crowding-out effect and lag effect from digital transformation implementation in SMEs are obstacles to improve TFP.

The second line of thinking considers digital transformation as a process of building an enterprise's dynamic capabilities [11], meaning that enterprises strategically exploit key resources through novel uses of digital technology [15]. Digital transformation increases the ability of an enterprise to orchestrate its resources, thus helping SMEs better coordinate and integrate their resource base, which in turn helps promote the improvement of TFP.

First, digital transformation can facilitate SMEs in improving their innovative capacities and developing a first-mover advantage in terms of technology leadership, thus improving its TFP[16, 17]. First, digital transformation reshapes the organizational identity of SMEs [18], imprinting them with a digital signature that facilitates continuous interaction with actors across networks, including upstream and downstream enterprises, platform enterprises, and government agencies, thus providing SMEs with a gateway to embed themselves into innovation networks[19, 20]. Furthermore, the knowledge embodied in digital technologies is typically standardized and replicable [21], and digitization enables companies to harvest and use such knowledge [22]. The enhancement of their innovative capacity, in turn, enables SMEs to acquire easier lead time advantages and build difficult-to-copy competitive boundaries [23]

Second, digital transformation may help SMEs optimize their resources using digital technology to address information asymmetries, update resource scheduling techniques, and increase redundancy and critical resource utilization rates [24]. The digital transformation of SMEs drives data flow to drive the flow of technology, material, capital, and talent [25]. Thus, SMEs can identify internal data on a large scale at a relatively low cost, facilitate the rapid acquisition of the resources necessary for value creation, and lay the foundation for the effective integration of resources. Digital transformation allows SMEs to expand into areas of new know-how and technologies by reallocating digital, information, and production resources[26].

Thus, digital transformation allows SMEs to optimize and renovate the structure of resources, improve resource availability, and boost TFP. Based on this reasoning, we propose the following hypothesis:

H1b: digital transformation of smes promotes tfp by improving innovation ability and optimizing resource allocation

The apparent contradiction between these two views has some hidden commonalities. According to resource-based theory, competitive advantage is formed by the unique historical development path of enterprises [10, 27]. Therefore, from an overall process-oriented perspective, the historical digital transformation trajectory is the core condition for an organization to build and maintain its competitive advantage.

So should we think that when we integrate the technology adoption perspective and the dynamic capability perspective to form a process perspective, the impact of digital transformation on the TFP of SMEs will inevitably show a "U" relationship? The answer is No. Kopalle (2020) believes that data elements have real-time and potential values [28]. General studies believe that data elements require in-depth integration and analysis to produce utility [29]. However, when the value proposition expression is the main configuration direction, the data elements produce real-time values. Accordingly, even from the perspective of technology adoption, we must be concerned about how digital artifacts have been created when implementing digital transformation. Based on this analysis, we propose the following hypothesis:

Hypothesis 2: The difference in the impact of SMEs 'digital transformation on production efficiency is formed by the different transformation trajectories.

Through a systematic review of existing related research, this article finds that there are three shortcomings in exploring the relationship between digital transformation and TFP of SMEs. This is also the starting point and innovative direction of this study.

(1) In terms of research perspective, existing studies mostly focus on the static temporal characteristics of digital transformation, lacking exploration of dynamic trajectory heterogeneity, and failing to consider the impact of the historical evolution of enterprise digital transformation on productivity, making it difficult to fundamentally explain the micro causes of the "digital productivity paradox". The heterogeneity of the trajectory of digital transformation, as a dynamic manifestation of a company's digital resource accumulation, will inevitably affect its efficiency effect. However, existing research has not yet focused on this core issue.

(2) In terms of mechanism analysis, although there have been studies exploring the nonlinear relationship between digital transformation and production efficiency, the heterogeneity effects of different transformation trajectories have not been identified. There are significant differences in resource base, strategic choices, and organizational change speed among enterprises with different transformation trajectories, and the mechanism by which digital transformation affects productivity is inevitably heterogeneous. Especially, due to stricter resource constraints, the digital transformation trajectory of SMEs presents greater variability and uncertainty, which has not been thoroughly explored in existing research.
(3) In terms of research methods, existing studies mostly use traditional linear regression models and lack quantitative methods that can accurately characterize the heterogeneity of the dynamic trajectory of enterprise transformation. The identification of transformation trajectories lacks scientific and objective rigor.

In response to the shortcomings of the above research, this article intends to improve and explore from the following aspects: (1) examine the heterogeneous impact of digital transformation on the TFP of SMEs under different transformation trajectories, explain the "digital productivity paradox" from a dynamic perspective, and fill the research gap limited to a static perspective; (2) Combining the dimensions of innovation capability and resource allocation, examine the differential mechanism of the impact of digital transformation on productivity under different transformation trajectories, and deepen the understanding of the micro mechanism of the efficiency effect of digital transformation; (3) Using LCLMM to quantitatively identify the trajectory of digital transformation of SMEs, accurately characterizing the heterogeneous characteristics of the transformation trajectory, and filling the gap in existing research on quantitative identification of transformation trajectory.

2. Methods

2.1. Empirical Framework and Data Sources

The empirical section of this study consists of three steps. First, we use the panel fixedeffects model to estimate the net impact of digital transformation on the TFP of SMEs as well as to test the robustness of the results. Second, we apply the LCLMM to identify the heterogeneous evolution trajectories of SMEs' digital transformation and then investigate the differential effect of digital transformation on TFP among different trajectory patterns. Third, we applied a moderated mediation model to uncover the core mechanisms underlying these effects.

The research sample comprises enterprises listed on the SME Board of China's A-share market from 2013 to 2022. The data are from the CSMAR database and China Research Data Services Platform (CNRDS). The data were processed as follows: (1) Firms with ST or *ST status and other abnormally listed companies were excluded, (2) firms in the financial sector were removed, (3) observations with missing data were deleted, and (4) continuous variables were winsorized at the top and bottom 1% to mitigate the influence of outliers.

2.2. Variable Measurement

2.2.1. Dependent Variable: Total Factor Productivity (TFP)

TFP reflects the average output per unit of input across all production factors and represents the overall efficiency with which inputs are transformed into final outputs. Following Ding et al. 's(2024) TFP estimation approach for major industrial enterprises in China [28], we measure firm-level TFP using three methods: fixed effects, ordinary least squares (OLS), and the semi-parametric Levinsohn-Petrin (LP) approach. Based on the CobbDouglas (C-D) production function, the production process of the firm is modeled as follows in Equation (1):

$$\mathrm{Ln}\left(\mathrm{Y}_{\mathrm{i,t}}\right) = \alpha\,\mathrm{Ln}\left(\mathrm{L}_{\mathrm{i,t}}\right) + \beta\,\mathrm{Ln}\left(\mathrm{K}_{\mathrm{i,t}}\right) + \omega_{\mathrm{i,t}} + \varepsilon_{\mathrm{i,t}} \tag{1}$$

In this equation, $\mathrm{Y}_{\mathrm{i,t}}$ is the output of firm i in year t , measured by the firm's operating revenue; $\mathrm{L}_{\mathrm{i,t}}$ and $\mathrm{K}_{\mathrm{i,t}}$ are labor and capital stock, respectively, measured by the number of workers and the net book value of fixed capital of firm i in year t . $\omega_{\mathrm{i,t}}$ is an unobserved TFP to estimate, which is measured by intermediate inputs as proxy variables. Specifically, intermediate inputs equal operating costs, administration costs, and selling expenses minus staff salaries.

2.2.2. Independent Variable: Digital Transformation (DT)

Digital transformation is defined as a process through which companies improve and redesign their current technology, production, and management systems using digital technology such as big data, artificial intelligence (AI), cloud computing, and blockchain. Similar to Ding et al. (2024), we constructed a digital transformation index based on the keyword occurrence rate of big data, artificial intelligence, cloud computing, and blockchain technologies in enterprises' annual reports [28].

2.2.3. Core Mechanism Variable: Digital Transformation Trajectory

Existing research seldom explores the classification of enterprises' digital transformation trajectory, and most classifications of digital transformation tend to focus on the strategic emphasis. Existing studies are mostly qualitative and categorize companies according to the starting point and direction of change during the transition process [30–32]. Digital transformation is a dynamic process. Categorizations based only on discrete-time point observations have the potential to miss the overall transformation "trajectory" [33]. Thus, in this study, we propose a classification of SMEs based on the features of their historical digital transformation trajectories.

The LCLMM combines characteristics from latent class analysis and linear mixed models, enabling the simultaneous identification of latent class membership as well as class-specific change patterns while accounting for within- and between-individual variation [34]. The LCLMM appears to be capable of modelling the underlying structure in a data set, is also able to more accurately model group differences, and is suitable for identifying the possible heterogeneous transformation trajectories of SMEs. Based on the analysis by Mirza et al. (2016) in The Lancet regarding the impact of symptom fluctuation trajectories in patients with depression on the development of Alzheimer's disease [35], as well as the trajectory identification method proposed by Lenon et al. (2018) [36], this paper uses relevant functions in the "lcmm" package of R language [34] to estimate latent digital transformation trajectories for a sample of 790 Chinese SMEs. The model represents the time trajectories of digital transformation over time and considers the random effects of time. To enhance the accuracy of the regression, this study also selects the following variables as covariates: enterprise size (Size), return on assets (ROA), Cash Flow ratio (cash flow), loss indicator (loss), nature of equity (NOE), and years since listing (List Age). Based on the recommended procedure, we fit a model of to 1-7 latent trajectory one after another. As presented in Table 1, according to the principle of the minimum BIC value, we selected the model with three latent trajectories for further analysis [36].

Fig. 1 shows the fitted digital transformation trajectory of SMEs found by our model with a total of three different classes: class 1, Speed Adjustment, Class 2, Steady Growth, and Class 3, Rapid Growth. The Speed Adjustment trajectory is characterized by a rather high starting point in terms of the degree of digitalization, which is higher than others' at the beginning of the conversion process; however, it will not keep pace with them later, and the Steady Growth trajectory is characterized by a comparatively low mean level of digitization that steadily increases over time, but at approximately comparable speeds; the Rapid Growth trajectory is generally characterized by a relatively low initial investment but the highest marginal growth rate.

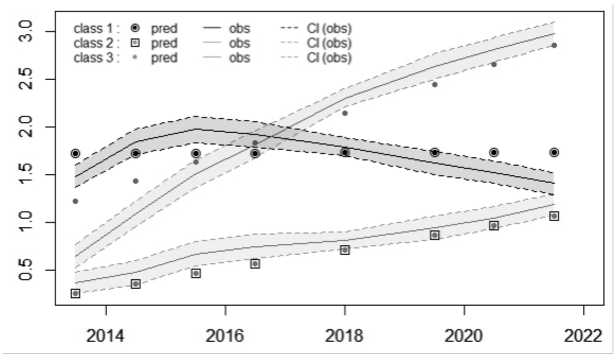

Fig. 1. Digital Transformation Trajectory Class of SMEs

Fig. 1 Alt text: The figure shows three distinct trajectory classes of digital transformation for SMEs from 2014 to 2022: Class 1 (Speed Adjustment Type) starts high but declines after 2016, Class 2 (Steady Growth Type) maintains steady low-level growth, and Class 3 (Rapid Growth Type) starts low but exhibits the steepest upward trend. The figure includes predicted values (markers), observed trajectories (solid lines), and confidence intervals (dashed lines) for each class.

Upon further observation of Fig. 1, based on the fitting results of the digital transformation trajectory, a quantitative analysis was conducted on the dynamic characteristics and inter group evolutionary differences of the three types of trajectories. The results showed that:

(1) Difference in average annual growth rate: The average annual growth rate of the digital transformation index for speed adjustment enterprises (Class1) from 2013 to 2022 is −2.1%, showing a slight and sustained downward trend, consistent with the high level of transformation at the beginning of this type of enterprise and the inability to continue to follow up in the future; The average annual growth rate of steady growth enterprises (Class2) is 8.3%, maintaining a stable low-speed growth with no obvious inflection point in the trajectory curve; The average annual growth rate of rapid growth enterprises (Class3) is 19.7%, much higher than the other two types of enterprises, and the growth rate shows a slight upward trend year by year, reflecting the marginal growth characteristics.

(2) Characteristics of Transformation Turning Point: The transformation turning point of Class 1 appeared in 2016, with slight fluctuations in the digital transformation index before 2016 and a continuous decline after 2016; The turning point for the transformation of Class 3 occurred in 2018, with low-speed growth before 2018 and high-speed growth after 2018, which coincides with the popularization and application of digital technology in SMEs; Class 2 have no obvious turning point for transformation and have main-

Table 1. Model Fit Comparison for Latent Trajectory Models with Varying Class Numbers

Pre-specified Trajectories	Number of Latent	BIC	AIC	Maximum	log-likelihood
1			25383.13	25349.06	-12667.5
2			25113.54	25025.92	-12495
3			24959.01	24817.84	-12379.9
4			25718.22	25523.5	-12721.7
5			28060.62	27812.35	-13855.2
6			27654.93	27353.11	-13614.6
7			28945.94	28590.58	-14222.3

tained linear uniform growth from 2013 to 2022.

(3) Evolution trend of inter group gap: From 2013 to 2016, there was a relatively small gap in the level of digital transformation among the three types of trajectory enterprises; After 2016, the gap between groups continued to widen, with the gap between rapid growth and speed adjustment enterprises widening the most significantly in 2022. This indicates that the "digital divide" of digital transformation for SMEs continues to deepen over time, further confirming the dynamic evolution characteristics of the heterogeneity of digital transformation trajectories and providing a basis for explaining the heterogeneity of productivity effects at the trajectory evolution level.

2.2.4. *Control Variables*

To further improve the precision of the regression results in this study, we add other control variables, such as operating revenue growth rate (Growth), administrative cost ratio (Mfee), Big Four audit dummy variable (Big4), number of directors (Board), accounts receivable ratio (REC), ownership concentration of the top ten owners (Top10), and book-tomarket ratio (BM).

2.3. Regression Models and the Method

This article constructs the following regression models to test the three hypotheses proposed:

$$\mathrm{TFP_{it}} = \alpha + \beta_1 \mathrm{DT_{it}} + \beta_2 \text{ Controls } + \text{ Firm } + \text{ Year } + \epsilon_{\mathrm{it}} \tag{2}$$

$$\begin{aligned} \mathrm{TFP}_{it} &= \alpha + \beta_1 \mathrm{DT}_{it} + \beta_2 \mathrm{Class}_n \\ &+ \beta_3 \left(\mathrm{Class} \times \mathrm{DT}_{it} \right) + \beta_4 \mathrm{Controls} \\ &+ \mathrm{Firm} + \mathrm{Year} + \varepsilon_{it} \end{aligned} \tag{3}$$

Equation (2) examines the effect of digital transformation on TFP. In this specification, TFPi, t denotes the TFP of SMEs and DTi, t measures the level of digital transformation. A significantly positive estimate of β_1 indicates that digital transformation effectively enhances SMEs' TFP; otherwise, a negative or insignificant coefficient would suggest. Controls represent a vector of control variables, firm denotes individual-fixed effects, and year captures time-fixed effects, which control for time-invariant firm characteristics and macro-level influences, such as policy changes and business cycle fluctuations. ϵ is the random error term.

Equation (3) tests whether the differences in digital transformation trajectory classes moderate the effect of digital transformation on TFP. The dummy variable class $(n = 1 - 3)$ identifies each trajectory class. A significantly positive estimate of β_3 on the interaction term indicates that within the corresponding trajectory class, digital transformation more strongly promotes the TFP of SMEs.

3. Results and discussion

3.1. Basic Empirical Results and Analysis

3.1.1. *Regression Results*

This subsection explores the effects of digital transformation on SMEs' TFP. First, we estimated the aggregate effect of digital transformation on TFP, followed by an analysis of the heterogeneous effects across different digital transformation trajectories.

Using the "lfe" package in R language, and based on the results from F-test and Hausman test, we select a fixed-effect model to estimate. Table 2 reports the linear estimation results of digital transformation on SMEs' TFP. In Columns (1) without control variables and (2) with them, the coefficient estimates of the main explanatory variable DT are significantly positive. Table 2 reports the linear estimation results of digital transformation on SMEs' TFP. In Columns (1) without control variables and (2) with them, the coefficient estimates of the main explanatory variable DT are significantly positive. This implies that the higher the level of SMEs' digital transformation, the better the effect of TFP and preliminarily verifies the hypothesis that digital transformation promotes TFP.

Table 2. The Impact of Digital Transformation on the Total Factor Productivity of SMEs

	(1)	(2)	(3)	(4)
	TFP	TFP	TFP OLS	TFP FE
DT	0.028***	0.022***	0.039***	0.022**
	(0.009)	(0.008)	(0.010)	(0.010)
Growth		0.024**	0.024**	0.024**
		(0.010)	(0.010)	(0.010)
Mfee		-4.060***	-4.060***	-4.061***
		(0.403)	(0.402)	(0.403)
Big4		0.556***	0.556***	0.556***
		(0.178)	(0.177)	(0.178)
Board		0.189**	0.188**	0.189**
		(0.094)	(0.094)	(0.094)
REC		0.693***	0.678***	0.693*** (0.243)
		(0.243)	(0.244)	(0.243)
TOP10		0.514***	0.517***	0.513***
		(0.174)	(0.174)	(0.174)
BM		0.070**	0.070**	0.070**
		(0.030)	(0.031)	(0.030)
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes
N	5599	5581	5581	5581
R^2	0.004	0.226	0.229	0.226

Note: Cluster-robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The same notation applies to all the subsequent tables.

3.2. Endogeneity Concerns and Robustness Checks

3.2.1. *Omitted Variable*

In the baseline regression model, there is a possibility that some unobserved time-varying factors are embedded in the error term. These factors may be correlated not only with the Digital Transformation of SMEs, but also with their TFP, which could bias the coefficient estimates. To mitigate this issue, the model is further refined by incorporating interaction fixed effects for province × time and industry × time to capture and control such potentially timevarying unobservables.

Columns (1) and (2) of Table 3 report the regression results that control for province × time fixed effects and industry × time fixed effects, respectively, while Column (3) presents the results that control for province × industry × time fixed effects simultaneously. In all specifications, the estimated coefficient of the Digital Transformation variable remains significantly positive, indicating that the positive effect of digital transformation on Total Factor Productivity holds, even after accounting for systematic changes in the external environment.

3.2.2. *Sample Deviation*

To address potential endogeneity arising from self-selection bias, this study treats enterprise-level Digital Transformation as a quasi-natural experiment and adopts Propensity Score Matching combined with a difference-in-differences (PSM-DID) approach to examine its impact on innovation output. In Table 4, a binary variable, DT_treat, is used to indicate whether a firm has undergone digital transformation. DT_treat takes the value of 1 if the firm implements digital transformation in the current or subsequent years and 0 otherwise. The coefficient of the interaction term DT × DT_treat captures the effect of post-transformation digitalization levels on TFP.

There was no difference in any of the covariates before or after propensity score matching between the treated and control groups, suggesting good matching quality. The estimated results in Column (1) of Table 4 show that the coefficients of the dummy variables and cross terms are positive at the 5% significance level, which confirms the positive impact of enterprise digital transformation on innovation output. Columns (2) and (3) show similar results under alternative matching techniques, where the interaction term is always positive and significant at the 5% level.

3.2.3. *Reverse Causality*

In this paper, digital transformation is regarded as an effective means to facilitate the flow of resources and optimize management processes, thereby enhancing the total factor productivity of enterprises. However, this productivity improvement might also serve as a driving force for enterprises to promote digital transformation, thus introducing the possibility of a reverse causal relationship. To address this issue, we adopt two strategies: one is to conduct lagging processing on the explanatory variables and the other is to employ the instrumental variable method.

Table 3. Regression Results with Interaction Fixed Effects

	(1)	(2)	(3)
	TFP		
DT	0.059***	0.063***	0.059**
	(0.017)	(0.015)	(0.017)
Control	Yes	Yes	Yes
Fixed Effects	province × time	industry × time	province × industry × time
N	5581	5581	5581
R^2	0.344	0.327	0.317

Table 4. PSM-DID Regression Results

	(1)	(2)	(3)
	TFP	TFP	TFP
	Nearest Neighbor	Optimal Full	Subclassification
DT_treat	0.072*	0.0121**	0.038
	(0.045)	(0.057)	(0.074)
DT* DT_treat	0.057***	0.055**	0.023**
	(0.019)	(0.026)	(0.009)
Control	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes
N	1026	1141	4252
R^2	0.054	0.067	0.061

(1) Lagged Explanatory Variables: The Digital Transformation index (DT) is lagged by one and two periods, respectively, and regressed on TFP. According to Columns (1) and (2) of Table 5, the estimated coefficients remain significantly positive even when lagged values are used. This indicates that the positive effect of SMEs' digital transformation on Total Factor Productivity is robust to concerns regarding reverse causality.

Instrumental Variable: To further address the potential issue of reverse causality, this study employs an instrumental variable (IV) strategy. Following the methodology of Yuan Chun (2021) and others, the average level of Digital Transformation across region-industry-year groups (DT_iv) and its interaction with the number of post offices in each prefecture-level city in 1984 (Y1984) were used as instrumental variables.

The historical mode of communication in a firm's city is likely to influence its adoption and use of digital technologies during the sample period through factors such as technological familiarity, infrastructure availability, and societal preferences. This satisfies the relevance condition for the instrument selection. At the same time, given that postal services in 1984 were primarily used for public communication and not directly related to firms' technological innovation activities during the sample period, the exogeneity condition was also met.

Additionally, since the post-office data are cross-sectional and cannot be directly used as panel instruments, the interaction term between the number of post-offices per million people in 1984 and the region-industry-year average of digital transformation is constructed as the instrumental variable for firm-level digitalization.

The results are reported in the corresponding Table 6. Columns (1) and (2) present the firststage regression results, whereas Columns (3) and (4) report the second-stage regression results. The findings confirm that even after using the constructed instruments to address endogeneity concerns, the baseline conclusion regarding the positive impact of digital transformation on TFP remains robust.

3.2.4. Multiple Robustness Checks

On the basis of endogeneity testing in Tables 3 to 6,, this paper conducts robustness multiple validation from the following three aspects to further verify the reliability of the research conclusions.

(1) Consistency verification of core coefficients: Comparing the coefficients of the core variable "Digital Transformation (DCG)" in Table 3 (province industry fixed effects), Table 4 (PSM-DID), Table 5 (lagged explanatory variables), and Table 6 (instrumental variable method), it was found that the coefficient values were $0.059, 0.057, 0.018/0.012$, and $0.060/0.075$, respectively, all of which were significantly positive at the 1% or 5% level. The direction of the coefficients was completely consistent, and although the coefficient size was slightly adjusted due to different testing methods, it was generally within a reasonable range of

Table 5. Regression Results with Lagged Explanatory Variables

	(1)	(2)	(3)
	TFP	TFP	TFP
DT_lag1	0.018** (0.007)		
DT_lag2		0.012** (0.007)	
DT			0.022*** (0.008)
Control	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes
N	4935	4181	5581
R^2	0.245	0.249	0.091

Table 6. Regression Results Using the Instrumental Variable

	(1)	(2)	(3)	(4)
	DT	DT	TFP	TFP
DT_iv	0.957*** (0.037)			
Y1984 × DT_iv		0.011*** (0.001)		
DT(fit)			0.060** (0.029)	0.075** (0.037)
Control	Yes	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes
N	5581	5581	5581	5581
R^2	0.144	0.111	0.218	0.210

0.012-0.075. This indicates that after alleviating different types of endogeneity problems, the positive promotion effect of digital transformation on TFP always holds, and the core conclusion has coefficient consistency.

(2) Complementary verification of testing methods: Table 3 used a fixed effects model to control for time-varying omitted variables, Table 4 used PSM-DID to alleviate self selection bias, Table 5 used lagged variables to alleviate reverse causality, and Table 6 used instrumental variable method to further address the problem of reverse causality. The four methods were tested for different sources of endogeneity and all verified the robustness of the core conclusions, forming a comprehensive endogeneity mitigation system of "omitted variables sample bias - reverse causality". The testing methods complemented and confirmed each other, making the empirical results more convincing.

(3) Sample interval robustness verification: Based on the regression results of lagged explanatory variables in Table 5, the core coefficients of first-order lag (DCG_lag1, sample size 4935), second-order lag (DCG_lag2, sample size 4181), and baseline regression (DCG, sample size 6393) were compared. It was found that all three were significantly positive at the 5% level, and the coefficient values slightly decreased with the increase of lag order, but remained significant, indicating that even if the sample time interval was shortened, the positive effect of digital transformation on TFP still existed stably. The research conclusion has sample interval robustness.

3.3. Heterogeneity Analysis Based on Digital Transformation Trajectory Classes

According to Hypothesis 2, the efficiency paradox of SMEs' digital transformation is caused by the differences in their transformation trajectories. To test this mechanism, we produce dummy variables for the types of digital transformation trajectories divided in section 3.2.3, and verify the impact of digital transformation on enterprise efficiency under different transformation trajectories.

Columns (2)-(4) of Table 7 report the impact of the three types of digital transformation trajectories on total factor productivity. Among them, the speed adjustment type significantly reduces the promotion effect of digital transformation on TFP, while the effect of the steady growth type is not obvious, while the rapid growth type significantly enhances the promotion effect of digital transformation on TFP. The insignificant result for the steady growth trajectory class could also be related to the fact that it is similar in terms of the distributional properties as the whole sample, or even to the fact that, for those companies, the relation of digital transformation with TFP may be non-linear. To verify this conjecture, the samples with steady growth were treated separately, the quadratic term of digital transformation was added, and its relationship with the sample population was compared. Columns (5)-(6) report the results of adding quadratic terms to the overall sample and the sample with a steady growth pattern. We find that there is no nonlinearity in the whole sample, while enterprises along the steady growth trajectory class show a negative-U relation between digital transformation and TFP, which is in line with the Solow Paradox.

A comparison of the impact of digital transformation on TFP between the three digital transformation trajectory classes indicates that companies with trajectories in the speed adjustment trajectory class have a lower ability to leverage digital components than those with steady growth and rapid growth trajectory classes. This gap might be due to some degree of difference in the level of digitalization, but at its core, it indicates that constant organizational and/or strategic shifts are detrimental for enterprises [37]. Admittedly, organizations are not in an absolute static or stable state, but in continuous motion [38]. However, a relatively stable strategy, that is, maintaining the digital transformation strategy, is easier for employees to adapt and support. Therefore, compared with enterprises with steady growth and rapid growth, the "change frequently" presented by speed adjustment enterprises will make the digital transformation of enterprises hinder the improvement of their efficiency.

Comparing the steady growth enterprises with the other two types of enterprises, we find that the Solow paradox arises in the steady growth enterprises; that is, with the deepening of digitalization, the TFP of enterprises is reduced. Therefore, although early digital technology has improved the efficiency of SMEs, with the upgrading of technology, the low speed of change makes the digital facilities invested by small and medium-sized enterprises fall behind the general digital technology in society, which makes it difficult to realize the smooth exchange of social network resources, resulting in the reduction of total factor.

Based on the regression results in Table 7, the coefficient difference test method was further used to perform pairwise tests on the interaction coefficients of the speed adjustment type(DCG*Class1), steady growth type (DCG*Class2), and rapid growth type (DCG*Class3), and to verify the differences between the quadratic coefficients of the steady growth type and the linear coefficients of the other two types of trajectories. The results showed that the inter group difference between the coefficient of the speed adjustment type interaction term (-0.050) and the coefficient of the rapid growth type interaction term (0.040) was significant at the 1% level ($\chi^2 = 18.63, \mathrm{p} < 0.001$); The inter group difference between the coefficient of the speed adjustment type interaction term (-0.050) and the coefficient of the steady growth type interaction term (0.004) is significant at the 5% level ($\chi^2 = 5.27, \mathrm{p} < 0.022$); The inter group difference in the coefficient of the steady growth type interaction term (0.004) and the coefficient of the rapid growth type interaction term (0.040) is significant at the 10% level $\left(\chi^2 = 3.89, \mathrm{p} < 0.048\right)$. At the same time, the intergroup differences in the quadratic coefficient of steady growth type (-0.022) and the linear coefficients of speed adjustment and rapid growth are significant at the 5% level, indicating that the impact of the three types of transformation trajectories on TFP not only varies in direction and magnitude, but also has significant intergroup differences at the statistical level. This further confirms the differential impact of heterogeneity in digital transformation trajectories on productivity effects and confirms Hypothesis 2.

In summary, the empirical results in Table 7 validate and further refine the mechanism by which digital transformation impacts the TFP of SMEs with various historical digital transformation trajectory classes. For SMEs in the speed adjustment trajectory class, organizational change barriers hinder the positive effect of digital transformation on TFP, while for SMEs belonging to the steady growth trajectory class, the relationship between digital transformation and TFP is followed by an inverted U-shaped curve. For SMEs belonging to the rapid growth trajectory class, digital transformation has much more weight in enhancing the effect on TFP positively. The bottom line shows that, regardless of the trajectory class, digital transformation contributes to improving production efficiency.

3.4. Extended Results Empirical Analysis Based on Digital Transformation Trajectories

3.4.1. Heterogeneous Impact on Innovation Capability Enhancement

According to H1b, the digital transformation plays an important role in improving innovation capability.

First, for innovation efficiency, this paper obtains the enterprise R&D costs and patent count from the CNRDS database, takes the natural logarithm of R&D costs as the innovation input variable, and the natural logarithm of patent count as the innovation output variable, and uses the DEA method to calculate the enterprise innovation efficiency (Leff) with the help of the R language "deaR" package. The larger the value, the higher is the enterprise

Table 7. Mechanism Analysis of Digital Transformation Trajectory Classes

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP					
DT	0.022^{***} (0.008)	0.039^{***} (0.010)	0.022^{**} (0.010)	0.001 (0.010)	0.023 (0.018)	0.070^{***} (0.026)
DT*Class1		-0.050*** (0.158)				
DT*Class2			0.004 (0.019)			
DT*Class3				0.040*** (0.016)		
DT^2					-0.001 (0.004)	-0.022** (0.013)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	5581	5581	5581	5581	5581	1760
R^2	0.226	0.229	0.226	0.225	0.225	0.229

innovation efficiency. Column (1) of Table 8 includes innovation efficiency in the interactive regression of digital transformation and verifies the effect of innovation efficiency on the promotion of SMEs' TFP by digital transformation. The results show that the main effect is stronger when the innovation efficiency is higher, which means that digital transformation improves the innovation ability of enterprises and promotes the improvement of TFP.

Second, this study further analyzes the effect of innovation input and obtains the number of enterprise R&D personnel and expenses from the CNRDS database to represent the enterprise's input in innovation resources, denoted as RD1 and RD2, respectively. The larger the value, the higher the enterprise's innovation input. Columns (2)-(3) of Table 8 add the interactive regression between innovation investment and digital transformation, verifying the effects of innovation personnel input and innovation capital input on the promotion of SMEs' TFP by digital transformation. The results show negative moderation effects, suggesting a greater beneficial effect of digital transformation on TFP in sectors with less innovation input.

This implies that digital transformation lowers the innovation input quantity needed to increase productivity more strongly for enterprises with comparatively less innovation expenditure (or staff). This result is in line with Radicic (2023), who studied the impact of digitalization on technological innovation for German SMEs [2]

On this basis, this study also tests the role of improving innovation ability on different tracks. Columns (4) to (7) in Table 8 report the results of the significance test. Among them, speed adjustment enterprises reduce the investment of R&D personnel; steady growth enterprises improve innovation efficiency, but do not reduce R&D investment; and rapid growth enterprises reduce the expenditure of R&D personnel and R&D funds at the same time.

3.4.2. Heterogeneous Effects of Resource Allocation Optimization

According to Hypothesis1b, the digital transformation of SMEs improves TFP by optimizing resource allocation. To test this mechanism, we look for proxy variables from the two aspects of static strategic resource allocation and dynamic strategic resource update to represent the strength of resource allocation optimization.

First, regarding static strategic resource allocation, this study follows the approach of Crossland (2014) [39] and obtains financial statement data from the CNRDS. Four secondary indicators are selected to construct a composite measure of firms' strategic resource allocation (Res): (1) Advertising intensity (advertising expenditure/ sales revenue); (2) R&D intensity (R&D expenditure / sales revenue); (3) capital equipment novelty (net value of fixed assets / gross value of fixed assets); (4) capital input intensity (fixed assets / number of employees). A higher Res value indicates greater strategic input at the resource level.

To test whether static strategic resource allocation serves as a mediating mechanism between digital transformation and TFP in SMEs, we applied a three-step approach. Column (1) of Table 9 reports the effect of digital transformation on TFP; Column (2) reports the effect of digital transformation on Res; and Column (3) reports the effect of Res on TFP. The results show that digital transformation enhances TFP by reducing static strategic resource allocation in SMEs.

Second, for dynamic strategic resource updates, we mainly refer to the methods of Crossland (2014) [39] and others to calculate the novelty of the resource allocation. First, we calculate the absolute value of the difference between the four indicators of strategic resource allocation in

Table 8. Mechanism Test of Innovation Capability Enhancement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DT	0.016*	0.007	0.010	-0.014	0.032**	0.015	0.017
	(0.009)	(0.008)	(0.008)	(0.016)	(0.016)	(0.012)	(0.014)
Ieff	0.811***				0.921***		
	(0.127)				(0.273)		
RD1		0.001***		0.001***		0.001***	0.001***
		(0.001)		(0.001)		(0.001)	(0.001)
RD2			0.001***				
			(0.001)				
Ieff*DT	0.125**				0.401**		
	(0.057)				(0.173)		
RD1*DT		-0.001***		-0.001*		-0.002*	
		(0.001)		(0.001)		(0.001)	
RD2*DT			-0.001***				-0.001**
			(0.001)				(0.001)
Sample	Full	Full	Full	Speed-Adjustment	Steady Growth	Rapid Growth	Rapid Growth
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5146	4383	5451	1314	1641	1631	2027
R^2	0.094	0.134	0.186	0.187	0.186	0.091	0.172

t year and the $t-1$ year, then we take the absolute value as the natural logarithm, standardize the four indicators, add them to build a separate indicator, make the difference between this indicator and the average value of the same year and the same industry, and finally build a separate indicator to measure the novelty of resource allocation (Res_N). The higher Res_N value, the timelier the enterprise updates its strategic resource structure.

To verify the mediating mechanism of strategic resource update in the relationship between the digital transformation of SMEs and total factor productivity, a "three-step method" was adopted for the test: Column (1) of Table 10 shows the impact of the digital transformation of SMEs on TFP, Column (2) shows the impact of the digital transformation of SMEs on strategic resource update, and Column (3) shows the impact of strategic resource update of SMEs on TFP. It can be seen that the digital transformation of SMEs enhances TFP by reducing strategic resource update.

An analysis of the digital transformation trajectory class reveals that the effect of digital transformation is insignificant on resource allocation optimization for all individual classes, suggesting that resource allocation optimization does not act as a mediator variable for any trajectory, and that the effect is consistent between trajectory classes. Mathematically speaking, after classification according to the digital transformation trajectory, the digital transformation degree of each group is relatively close, and the variability is small; however, the effect of resource allocation optimization does not differ in each trajectory, and its numerical distribution does not change with the change in trajectory, resulting in a situation in which the overall effect is significant, but the sub-trajectory is not significant.

Furthermore, this may also reveal that digital transformation has a fundamental effect of "resource release" or "efficiency reconstruction" at the micro enterprise level. Regardless of whether enterprises adopt a radical, uniform, or fluctuating pace of transformation, digital technology, as a general-purpose technology, may reduce their dependence on certain traditional and extensive strategic resources (such as excessive advertising and redundant fixed assets) through process automation, information transparency, decision dataization, and other means, thereby releasing and reallocating scarce resources to more core production activities. This mechanism of "cutting costs and increasing efficiency" may be relatively independent of the strategic pace of enterprise transformation and become a common

Table 9. Mechanism Test of Strategic Resource Allocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TFP	Res	TFP	Res	TFP	Res	TFP	Res	TFP
DT	0.021*** (0.008)	-0.033** (0.018)	0.021** (0.008)	-0.007 (0.033)	-0.016 (0.014)	-0.038 (0.049)	0.026* (0.014)	-0.022 (0.031)	0.021* (0.011)
Res			-0.032*** (0.005)		-0.029* (0.012)		-0.036*** (0.008)		-0.043*** (0.008)
Sample	Full	Full	Full	Speed-Adjustment	Speed-Adjustment	Steady-Growth	Steady-Growth	Rapid-Growth	Rapid-Growth
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5581	5803	5549	1765	1706	1847	1748	2157	2059
R^2	0.226	0.015	0.233	0.024	0.297	0.024	0.242	0.017	0.281

Table 10. Mechanism Test of Strategic Resource Reconfiguration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TFP	Res_N	TFP	Res	TFP	Res	TFP	Res	TFP
DT	0.021*** (0.008)	-0.035** (0.018)	0.021** (0.008)	-0.008 (0.032)	-0.016 (0.014)	-0.049 (0.047)	0.025* (0.014)	-0.022 (0.031)	0.021* (0.011)
Res_N			-0.026*** (0.017)		-0.019* (0.011)		-0.037*** (0.008)		-0.035*** (0.007)
Sample	Full	Full	Full	Speed-Adjustment	Speed-Adjustment	Steady-Growth	Steady-Growth	Rapid-Growth	Rapid-Growth
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual/Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5581	5803	5549	1765	1706	1847	1748	2157	2059
R^2	0.226	0.014	0.233	0.024	0.293	0.027	0.242	0.014	0.276

path for digital transformation to enhance productivity. This provides a new perspective for understanding the underlying logic of the value of digital transformation.

In summary, the findings reported in Table 9 and Table 10 empirically verify and explain the mechanism by which resource allocation optimization affects the impact of digital transformation on TFP for SMEs. Digital transformation decreases the strategic resource structure and strategic resource update frequency for SMEs. With the advancement of digital transformation, SMEs' strategic resources gradually become substituted with digital resources, so that enterprises can focus more on the production side and thus raise TFP.

4. Conclusion

4.1. Conclusion

At present, the digital economy has become an important driving force to promote China's economy from quantitative to qualitative change and from large to strong. Digital transformation, as the microfoundation of the digital economy, is an important force in promoting the development of SMEs. However, owing to different research perspectives, there is still no consensus on whether digital transformation enhances a firm's productivity. Using panel data from 790 Chinese SMEs in the time window of 2013-2022, our work tackles the problem from the viewpoint of digital transformation trajectories and integrates the ideas of resource-based theory and organizational change theory. It also deepens our knowledge of how SMEs use digital technology to improve TFP and achieve high-quality development, which can be summarized in three points:
(1) In the basic regression, we find that digital transformation has a significant positive impact on the improvement of total factor productivity of SMEs, which is still true after the endogenous and robustness tests.
(2) Heterogeneity analysis shows how the three typical digital transformation trajectory classes have different impacts on SMEs. We found that for the speed-adjustment trajectory class, the productivity-enhancing effect of digital transformation weakens. For the steady growth trajectory class, the relationship between digital transformation and TFP showed an inverse U-shaped pattern. On the other hand, the digital transformation of rapidly growing SMEs significantly enhanced the promotion of TFP.
(3) Additional empirics show that digital transformation boosts the TFP of SMEs by lowering R&D input, increasing innovation productivity, and changing resource composition: enterprises along the speed adjustment trajectory class decreased their R&D personnel input; those on the steady growth trajectory class increased innovation efficiency, but did not decrease R&D input; and those on the rapid growth trajectory class decreased both people and money R&D input. In terms of resource structure adjustment, the digital transformation of SMEs has promoted the improvement of TFP by inclining toward non-strategic resources, and the effect of resource allocation optimization is consistent in enterprises with different trajectories.

4.2. Managerial Implications and Policy Recommendations

(1) SMEs located in the speed adjustment trajectory class must be cautious about the possible negative influence of digital transformation toward TFP. They should not adopt a radical strategy for transformation because it may lead to a waste of resources and decline in productivity. They should pursue an appropriate balance between the pace and quality of transformation, and be prepared for adaptive approaches that ensure that digital transformation and productivity improvement complement each other.
(2) SMEs located in the steady growth trajectory class should focus on the inverted Ushaped relationship between digitalization and TFP. They are advised not to rely too much on digitalization while ignoring other production factors; they must optimize their resource allocation and preserve the stability and constancy of R&D input. Enterprises should focus on improving innovation efficiency to ensure that digital transformation and production efficiency can be carried out simultaneously. Enterprises must be encouraged to plan a strategy for the future that will specify exactly what digitalization means and how it can be achieved. Accelerate in a deliberate manner consistent with high-quality productivity growth, but avoid blind acceleration and enter the U-shaped curve descent stage.
(3) SMEs located in the rapid growth trajectory class should fully utilize the positive impact of digital transformation on production efficiency while emphasizing the optimization of resource structure and the rationalization of research and development investment.

Enterprises should implement refined management, reduce unnecessary R&D expenses, and maintain innovation momentum to ensure the sustained synergistic effect of digital transformation and production efficiency improvement. Enterprises should have available resources that can be quickly redeployed according to current situations, new opportunities, or new objectives. This would help ensure a virtuous circle between digital transformation and productivity growth.

Finally, as this study identified three trajectories of digital transformation and their differentiated impacts, it naturally raises a forward-looking question: what factors determine enterprises to embark on different transformation paths? We believe that future research can further explore the initial resource endowment of enterprises (such as digital talent reserves, financial redundancy), characteristics of senior management teams (such as digital cognition, risk preference), external network relationships (such as connections with digital platforms and leading enterprises), institutional environment, and how they shape the rhythm and trajectory of enterprise digital transformation. This will help us to have a more comprehensive understanding of the complete dynamic process of enterprise digital transformation from "antecedents" to "paths" and then to "outcomes", providing more detailed guidance for theoretical construction and management practice.

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