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IDENTIFICATION OF THE PATH OF ENTERPRISE DIGITAL TRANSFORMATION ——EVIDENCE FROM CHINESE A-SHARE LISTED COMPANIES

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Abstract: The foundation of high-quality economic development lies in enterprises' innovation in models, businesses, processes and products, and digital transformation is the only way for enterprise innovation. Then, what drives enterprise digital transformation? And what path does it follow? By using the frequency of digital-related vocabulary in the annual reports of listed companies to measure the degree of digital transformation, this paper adopts the structural equation model to analyze the driving role of R&D in digital transformation and explore the path of digital transformation at the same time. It is found that the fixed asset ratio, digital technology and total asset turnover are the key nodes connecting R&D and the generation of data application scenarios. The transformation path with total asset turnover as the node either has an insignificant effect or shows a negative effect, revealing the problem of the disconnection between digital technology and business in the transformation process.
Keywords: Digital transformation; R&D; Digital technology; Data application scenarios; Driving force; Path; Structural equation model

1 INTRODUCTION

Information technology and its application have brought profound changes to China's economic and social development. Today, informatization has entered the PB-level data era. How to integrate massive data into all aspects of human progress is not only an innovative move that the Chinese government should lead, but also a positive action for Chinese enterprises to seek innovation in the face of profound changes in the business environment. Grasping the direction of digitalization, networking and intellectualization, promoting the digitalization of manufacturing, service, agriculture and other industries, transforming traditional industries in an all-round and whole-chain way by using digital technology, and improving total factor productivity are the driving forces for building Chinese modernization[1-2].

Although Chinese enterprises have made certain achievements in digital transformation, there are some common problems in transformation at the enterprise level. The 2019 Research Report on Chinese Enterprise Digital Transformation and Data Application shows that 40% of the surveyed enterprises have implemented digital transformation, among which 80% are not satisfied with the transformation effect. The reasons are as follows: First, the transformation path is unclear. Due to the lack of systematic thinking, enterprises have not set clear strategic goals for digital transformation and carried out comprehensive path planning. Some enterprises simply regard digitalization as the reconstruction or upgrading of IT systems, or only implement transformation in parts of the value chain. For example, digital technology is applied in the production link, but there is a lack of corresponding supporting system design in the marketing and logistics links, and there is a lack of communication between departments. Furthermore, as a complex systematic project, digital transformation will lead to continuous capital investment, however, the return is uncertain and cannot be realized in the short term. Insufficient incentives lead to limited transformation investment and even abandonment halfway. The research results of JD Digits Research Institute show that the actual amount of digital investment of domestic enterprises is low. Nearly 70% of enterprises have transformation investment lower than 3% of annual sales revenue, 42% lower than 1% of annual sales revenue, and only 14% higher than 5% of annual sales revenue[3-4]. In addition, the level of digital technology needs to be improved. Big data, cloud computing and other technologies are far from popular in enterprises. Traditional enterprises cannot convert business information and experience into effective data. Restricted by the low technical level, most enterprises cannot effectively integrate digital technology into existing businesses, resulting in the output of digital transformation being mainly concentrated in limited application scenarios such as precision marketing[5-6].

Exploring the driving factors of enterprise digital transformation is helpful to clarify the transformation path, thus setting long-term action plans, grasping the key nodes of transformation and making continuous efforts. Focusing on the internal of enterprises, we hold that as a systematic innovation activity, digital transformation is driven by R&D. Enterprises integrate digital technology into existing businesses to generate data application scenarios, which transform data, a new production factor, into productivity and realize the value of data. The possible marginal contribution of this study is that, in view of digital transformation being a systematic project, the structural equation model is adopted to explore the transformation path, and it is found that the fixed asset ratio, digital technology and total asset turnover are

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the key nodes connecting R&D and data application scenarios, and five significant paths of R&D affecting the generation of data application scenarios are identified[7-9].

2 THEORETICAL ANALYSIS, RESEARCH HYPOTHESES, DATA AND VARIABLES

2.1 Theoretical Analysis and Research Hypotheses

Any innovation of an enterprise takes R&D as a prerequisite, so digital transformation starts with R&D, and the purpose of digital transformation is to create value by using data. This result relies on digital technology, so the transformation ends with data application scenarios. Digital transformation aims to use digital technology to solve the business pain points and difficulties in enterprise operation, reshape the business model, optimize business processes, design new products and services, and realize the reconstruction and extension of the value chain. R&D is bound to run through the whole process of digital transformation.

First, in the stage of market research and product and service design, digital technology is used for R&D to develop more efficient schemes to understand consumer needs and provide solutions to meet the diversified needs of consumers[10]. Second, in the production stage, digital technology is applied to R&D of intelligent manufacturing to realize flexible production that effectively meets the personalized needs of consumers. Third, in the after-sales stage, digital technology is used to develop intelligent applications for monitoring, sorting out and analyzing data in product use and feeding back to the background, build a full life cycle service system and improve product added value. Fourth, in the process of product and service iteration and upgrading, digital technology is used to develop platforms for consumers to directly participate in product design.

As a systematic project, the logic of digital transformation is that enterprise value creation is driven by R&D, elements are integrated through the formation of assets, elements change their forms in circulation, products and services are output, and value appreciation is realized through sales. With the increase of R&D intensity, fixed assets are formed. Under the background of the digital economy, the factor attribute of data is becoming increasingly obvious. To adapt to the factorization of data, fixed assets have opened up the application space of digital technology. For example, in the past 20 years, the process optimization of China's manufacturing industry has been realized from scratch on the one hand by introducing foreign CAPP (Computer Aided Process Planning) systems; on the other hand, it has committed to cultivating local experts to achieve technological independence, and now it has embarked on the road of data intelligence. In the era of intelligent manufacturing, the circulation of elements also includes data elements. For example, in the intelligent quality inspection scenario, deep learning combined with image processing algorithms for data collection, annotation, training and algorithm model tuning improves the detection accuracy and reduces the missed detection rate.

Production and marketing collaborative flexible manufacturing is a typical application scenario where digitalization runs through the whole process of enterprise operation. By using MRP (Material Requirements Planning), material requirements are refined, processes are carefully designed, equipment operation is matched with personnel needs, plan results are visualized, and departmental plan coordination is promoted. MES (Manufacturing Execution System) is linked with MRP for rolling planning, and capacity demand and bottleneck processes are estimated by predicting orders[11].

Therefore, we put forward the following hypotheses:

H1: R&D affects the generation of data application scenarios through multiple paths.

H2: The increase of R&D intensity promotes the generation of data application scenarios through the path including the digital technology node.

2.2 Data Sources

We select the data of 3,082 Chinese A-share listed companies from 2007 to 2020 as the original research sample. Considering the rapid development of financial technology and the financial support required for enterprise digital transformation, the sample includes financial enterprises. To reduce the impact of extreme cases on empirical analysis, all continuous variables are winsorized at the 1% level on both sides. Enterprise operation and financial data are from the CSMAR database, and annual reports are from the official websites of the Shanghai and Shenzhen Stock Exchanges.

2.3 Variable Setting

2.3.1 Dependent variable

Enterprise digital transformation: ditechapp (data application scenarios)

We use the word frequency of digital transformation-related vocabulary in the company's annual report as a proxy variable for the willingness and degree of digital transformation. Considering the dilemma of the disconnection between IT and business in the process of digital transformation, we divide digital transformation into two dimensions: digital technology application and data application scenario generation. Digital technology application is the means, and data application scenario generation is the purpose, both of which are indispensable. Without digital technology, application scenarios are castles in the air, and if digital technology fails to create scenarios for existing businesses to realize data value, the transformation will have no way out. Specifically, the digital technology vocabulary including artificial intelligence, blockchain, cloud computing and big data in the enterprise's annual report is summed up to generate digital technology (ditech), and the data application scenario vocabulary such as intelligent manufacturing, intelligent energy, digital marketing and quantitative investment is summed up to generate application scenarios (ditechapp)[12].

2.3.2 Core explanatory variable

R&D intensity (R&D)

We use the logarithm of the ratio of enterprise R&D investment to operating income to measure R&D intensity (Yang Bingxin & Chen Gengfei, 2019). Since digital technology is the means for the generation of data application scenarios, digital technology is also used as an explanatory variable of data application scenarios.

2.3.3 Control variables

To reveal how the change of R&D intensity affects digital transformation while maintaining the simplicity of the model, we only introduce the internal characteristics of enterprises as control variables, including (1) aggregate indicators—asset scale (asset), operating income (oi), net cash flow from operating activities (cf), all taking logarithms; (2) financial ratios—asset-liability ratio (dtar), capital intensity (ci), total asset turnover (ato), return on total assets (roa), financial leverage (dfl), operating leverage (dol); (3) ownership structure indicator—ownership concentration (oc), the ratio of the shareholding ratio of the largest shareholder to the shareholding ratio of the top ten shareholders). The statistical characteristics of the variables are shown in Table 1.

Table 1 Descriptive Statistics of Variables

Variable	Obs	Mean	Std.Dev	Min	Max
ditech	10604	8.486	20.890	0	466
ditechapp	10604	8.320	17.647	0	422
R&D	10604	1.156	1.258	-3.219	3.356
asset	10640	22.165	1.299	19.833	26.181
oi	10564	21.395	1.435	18.701	25.477
cf	10604	19.162	1.615	15.081	23.539
dtar	10604	0.402	0.257	0.008	11.386
ci	10603	6.667	298.716	0.088	2508.44
ato	10603	0.655	0.491	0.00004	12.373
roa	10604	0.052	0.099	-1.872	4.489
dfl	9516	1.352	1.897	-17.953	69.266
dol	9579	1.636	3.041	1.003	243.914
oc	10604	0.560	0.186	0.197	0.945

3 MODEL CONSTRUCTION, TEST AND REGRESSION RESULTS

Based on the theoretical analysis above, we speculate that the fixed asset ratio, digital technology and total asset turnover are the key nodes of enterprise internal digital transformation. All three directly connect R&D and data application scenarios. As a direct result of R&D, the fixed asset ratio points to data application scenarios through digital technology and total asset turnover respectively. As a kind of productivity, digital technology inhibits or promotes the circulation of elements and exerts an impact on data application scenarios through the intermediary of circulation efficiency. Therefore, enterprise internal digital transformation has the characteristics of multiple intermediaries. Inspired by the research on the impact of digital transformation on enterprise financial performance (Bai Fuping et al., 2022), we use the structural equation model to depict the multiple intermediary effects. Figure 1 shows the transformation path[13-16].

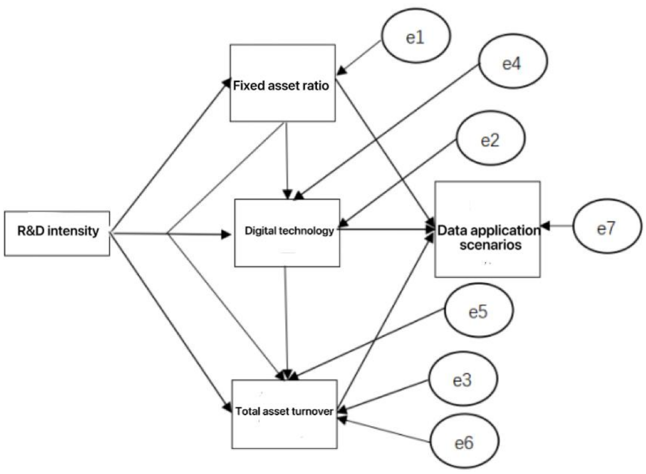

Figure 1 Path of Enterprise Internal Digital Transformation

The purpose of model test is to test the fitting degree between the constructed model and the sample data. Since the model uses panel data and the number of cross-sections is much larger than the number of years, the robust standard error of individual clustering (i.e., each listed company as a cluster) is used for fitting, so only SRMR (Standardized Root Mean Square Residual) is valid. Under the full sample and continuous transformation sample, the value is 0.000. According to the rule of SRMR ≤ 0.08, it can be considered that the enterprise internal digital transformation path model well fits the multiple intermediary effects existing in the process from R&D to data application scenarios.

Bootstrap is used to estimate the path effects for the full sample and the continuous transformation sample (i.e., the sample where digital technology and digital scenarios are greater than zero in each year) respectively. Table 2 shows the estimation results of the full sample, and Table 3 shows the estimation results of the continuous transformation sample.

Table 2 Path Effects: Full Sample

Path	Standardized Coefficient
R&D intensity → Fixed asset ratio	-0.016***
Fixed asset ratio → Application scenarios	-18.709***
R&D intensity → Digital technology	3.920***
Digital technology → Application scenarios	0.174***
R&D intensity → Total asset turnover	-0.070***
Total asset turnover → Application scenarios	4.932***
Fixed asset ratio → Digital technology	-25.511***
Digital technology → Total asset turnover	0.0002
Fixed asset ratio → Total asset turnover	-0.323***
R&D intensity → Fixed asset ratio → Application scenarios	0.300***
R&D intensity → Digital technology → Application scenarios	0.682***
R&D intensity → Total asset turnover → Application scenarios	-0.344***
R&D intensity → Fixed asset ratio → Digital technology → Application scenarios	0.071***
R&D intensity → Fixed asset ratio → Digital technology → Total asset turnover → Application scenarios	0.0004
R&D intensity → Digital technology → Total asset turnover → Application scenarios	0.004
R&D intensity → Fixed asset ratio → Total asset turnover → Application scenarios	0.026**
Total effect	0.852***
Direct effect	0.112

Note: ***, ** indicate significance levels of 1% and 5% respectively.

Table 2 shows that under the full sample, R&D intensity acts on data application scenarios through seven paths, so H1 is valid. Among the seven paths, the intermediary effects of the two paths including digital technology → total asset turnover are insignificant, and the other five are significant. However, the path with total asset turnover as the intermediary between R&D intensity and data application scenarios shows a significant negative effect. Specifically, R&D intensity has a positive effect on digital technology, and digital technology has a positive effect on application scenarios, so H2 is valid. However, R&D intensity has a negative effect on fixed asset ratio and total asset turnover, fixed asset ratio has a negative effect on application scenarios, digital technology and total asset turnover, and total asset turnover has a positive effect on application scenarios, all of which are significant. Digital technology shows a very weak positive effect on total asset turnover, which is not significant.

Table 3 Path Effects: Continuous Transformation Sample

Path	Standardized Coefficient
R&D intensity → Fixed asset ratio	-0.022***
Fixed asset ratio → Application scenarios	-24.675***
R&D intensity → Digital technology	5.612***
Digital technology → Application scenarios	0.155***
R&D intensity → Total asset turnover	-0.099***
Total asset turnover → Application scenarios	10.556***
Fixed asset ratio → Digital technology	-37.844***
Digital technology → Total asset turnover	0.0003
Fixed asset ratio → Total asset turnover	-0.483***
R&D intensity → Fixed asset ratio → Application scenarios	0.531***
R&D intensity → Digital technology → Application scenarios	0.870***
R&D intensity → Total asset turnover → Application scenarios	-1.047***
R&D intensity → Fixed asset ratio → Digital technology → Application scenarios	0.126***
R&D intensity → Fixed asset ratio → Digital technology → Total asset turnover → Application scenarios	0.002
R&D intensity → Digital technology → Total asset turnover → Application scenarios	0.017
R&D intensity → Fixed asset ratio → Total asset turnover → Application scenarios	0.110***
Total effect	1.765***
Direct effect	1.155***

Note: *** indicates a significance level of 1%.

Table 3 shows that the estimation results of the continuous transformation sample and the full sample are almost completely consistent in terms of the direction and significance of the effects, except for: (1) the direct effect of the continuous transformation sample is also significant; (2) for the path of R&D intensity → fixed asset ratio → total asset turnover → application scenarios, the continuous transformation sample passes the 1% significance test, while the full sample passes the 5% significance test.
According to the regression results, both H1 and H2 are valid.

4 CONCLUSIONS AND IMPLICATIONS

This paper employs a Structural Equation Model on data from 3,082 Chinese A-share listed companies to explore the driving path of digital transformation, verifying that R&D intensity influences data application scenarios through multiple intermediaries including fixed asset ratio, digital technology, and total asset turnover. Empirical results highlight a substantial workload by identifying that the path via total asset turnover exhibits a significant negative effect, thereby revealing the critical "disconnection between technology and business" where digital R&D fails to effectively empower existing operations. Practical application requires enterprises to prioritize accuracy over speed by establishing efficient communication mechanisms and data-driven business loops to bridge this gap, while future research should focus on the heterogeneity of transformation paths across different industries and combine quantitative analysis with case studies to further dissect the dynamic micro-evolution of the transformation process.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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