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Research Article

Big Data Model of Digital Employees of High-Tech Enterprises under the Background of Digital Transformation

Manhang Li [ID]

School of Public Affairs and Administration, University of Electronic Science and Technology of China, Chengdu 611731, China

Correspondence should be addressed to Manhang Li; 2019160901024@std.uestc.edu.cn

This paper firstly conducts a theoretical analysis on the digital transformation of enterprises. Theories such as Marxism and new institutional economics related to the digital transformation of enterprises are sorted out. Secondly, it conducts an empirical analysis on the digital transformation of high-tech enterprises. This paper summarizes the three major transformation paths of the existing production service digitization, marketing model digitization, and industrial digitization. Based on the data analysis of the questionnaire, this paper summarizes the difficulties of digital transformation of high-tech enterprises, mainly due to the lack of transformation ability, resulting in "cannot transfer"; the lack of self-development conditions and digital transformation, resulting in "will not transfer"; digital transformation lacks full guarantee, resulting in "do not dare to turn." And based on the analytic hierarchy process, the influencing factors of the digital transformation of high-tech enterprises are analyzed, and the relative importance of each factor is obtained.

1. Introduction

With the introduction of new development and new development strategies, China's economic development has undergone tremendous changes. The term "digital economy" was first coined in government work in 2017, and it has had a profound effect on the optimization of the economy by the prosperity of emerging industries such as the digital economy. And accelerating the development of the digital economy and promoting the combination of digital economy have become a hot topic. With the rise of digital technologies such as big data, cloud computing, and artificial intelligence, digital technology has become an important means for modern enterprises to adapt to the changes of the times, implement national strategies, and improve their competitiveness. According to a survey report by IDC on CEOs of 2,000 companies, up to now, 67% of companies regard digital transformation as the core of their corporate strategy, and 70% of China's 1,000. The "2019 Chinese Enterprise Digital Transformation Index Research" published by Accenture on September 10, 2019, shows that China's "ideal digital company" was a measure in 2018, with a comprehensive score of 45, up from 37 in the same period last year, 20%. This shows that China's e-commerce has entered a new stage, and it is also a new digital age [1].

In order to maintain the stable development of enterprises, it is necessary to conform to the development trend of the times and the digital age although many companies regard digital transformation as a strategic focus and have invested in many companies' systems and equipment on the basis of digitalization [2, 3]. However, the "2019 Chinese Enterprise Digital Transformation Index Research" pointed out that although China has achieved a substantial increase in revenue and sales, in terms of digital transformation, only 9 aspects have achieved obvious results, and many companies are still unable to achieve expected goals and effect, facing the difficulty of transformation. How to promote the digital economy of enterprises to achieve higher performance has become an important topic of concern to the industry and theoretical circles. This dissertation takes high-tech companies as the center and discusses their digital transformation. Most of the previous literature on the transformation of high-tech companies has discussed the transformation strategies of high-tech companies from a

macro perspective, but the results are inconsistent with the digital transformation trend of high-tech companies; only a few scholars have focused on the digital transformation of high-tech industries. However, due to the lack of accurate understanding, their digital research mainly focuses on the network. In the digital age, the digital transformation of high-tech industries involves a relatively narrow scope and a relatively shallow level.

2. Overview

2.1. Digital Economics. The "digital economy" was first proposed in 1994, and its meaning is constantly changing. The connotations of various concepts and researches on the digital economy are getting richer and richer. So far, there is no consensus on this issue, whether domestically or in academia. The definition of digital economy in European and American countries is mostly defined from the perspective of industry and products, which focuses on the interaction between technology and people, but the definition of industry is relatively simple in general, involving telecommunications, audio-visual, software, Internet, and other industries [4]. And on this basis, the communication, audio-visual, and other technologies have been deeply analyzed. When China defines the digital economy, what it considers is the entire relevant behavior, that is, the changes that occur on the basis of the occurrence and development of an economic system, that is, the combination of economy and technology. The "G20 Digital Economy Development and Cooperation Initiative" was officially released by China at the 2016 G20 Summit. The initiative focuses on China's ideas in promoting economic growth and strengthening cooperation with other countries. The digital economy is a kind of production factor that uses digital technology as the medium to effectively utilize digital technology to achieve economic optimization and improve efficiency. It is pointed out that the digital economy is the combination of industry and industry with communication as the main content. In the context of the digital economy, digital information is regarded as the main means of production. The new socioeconomic form came into being after the two major development forms of agriculture and industry [5]. Compared with the conventional model, the new economic model has brought a large amount of digitalization of production and operation, and these new means of production are new means of production based on data. In short, the digital economy is a huge economic change. Its combination with modern technology allows enterprises and users to communicate efficiently, so that the circulation of products and services will develop in a more convenient and scientific direction. Through the digital economy, all aspects of each link can be effectively integrated, so as to achieve better development.

2.2. Data Processing. "Digitalization" is an important part of the digital economy. With the passage of time and the continuous innovation of technology, the meaning and external expansion of numbers have become more and more diverse. Digital technology is the integration and optimization of traditional information systems. Through integration and optimization, the operation of enterprises can be improved, and new technologies can be improved through new technologies, so that they can meet the needs of digitalization.

2.3. Digital Conversion. How to carry out digital transformation has become a common concern of both the theoretical and practical circles. Huawei believes that digital transformation is the use of a new generation of digital technologies to build a digital society with full perception, full link, full scene, and full intelligence, thereby reconstructing traditional management and business models. By innovating and reconstructing the way of operation of the enterprise, we can obtain the victory of the enterprise. Kingdee regards digital transformation as the digital transformation of enterprises; that is, enterprises use digital technologies to apply technologies such as the Internet of Things, cloud computing, big data, mobile, and intelligence to enterprises and plan and implement business model transformation, management, and operation transformation. Enterprises and employees bring new digital value enhancement and continuously improve the new core competitiveness of enterprises in the digital economy environment [6].

There are differences in the understanding of "digital transformation" in academic circles. Gemini believes that digital technology is the fundamental improvement of company performance through digital technology and through the use of digital technology to break down the information barriers between various departments, thereby improving the efficiency of company operations. Experts such as Berman believe that the essence of digital transformation is to reconstruct the value of customers and use digital technology to change the way of production and operation, thereby changing the value and operation of traditional manufacturers, thereby promoting their development in the digital age. The main proposition of Wang Hua in China is as follows: digital transformation means that the company's production and services can be realized through digital technology, the company's operations and operations can be combined with digital technology, and the company, customers, and the market can achieve, through comprehensive technological transformation, interaction and communication and constantly promote the comprehensive innovation of the market, business system, and customers, thereby improving operating efficiency.

Based on the above theories and the actual experience of enterprises, the concept of enterprise digital and the innovation of product models and business models accelerate the transformation and upgrading of enterprises through digital means and seek new paths for innovation and development. Big data application, intelligence, and networking are important features of the transformation of the digital economy.

3. Mechanism Analysis of the Driving Force of Digital Transformation of Enterprises

With the development of economy and society, and the continuous progress of the times, emerging industries such as the Internet and e-commerce have emerged as the times require. In the research of emerging fields, the basic principles of Marxism can still be used as the basic theory to build the theoretical logic of related research. Based on the actual national conditions of China, it still has extremely important practical guiding significance to apply the basic principles of Marxism directly or indirectly to the research of economic or social topics in the new era. The pursuit of excess profit is the subjective motivation and fundamental driving force of the digital transformation of enterprises [7]. Marx believed that the productivity of social labor is affected by many factors. With the integration and development of large industry and the digital economy, the creation and accumulation of real wealth depend more on the average level, iteration speed, and application of science and technology in the current society, rather than the simple accumulation of labor time. Therefore, the advancement of digital technology is a key factor in promoting the transformation of social productivity, resulting in changes in the economic form and gradually forming a digital economy.

3.1. Digital Technology Lays a Technical Foundation for the Digital Transformation of Enterprises. The development and progress of digital information technology have laid the necessary technical foundation for enterprises to carry out digital transformation. On the one hand, the advancement of digital information technology can improve the labor productivity of enterprises in digital production. Using Marx's relevant viewpoints for analysis, we can see that the development and application of digital information technology determine the proportion of capital divided into constant and variable parts. However, in the current situation where the nature of society is certain and the speed of development is relatively stable, the accumulation of wealth is closely related to the development of human beings. Therefore, when the production department of the enterprise is reasonably and effectively equipped with digital software and hardware facilities and high-tech talents, the labor productivity of the production department of the enterprise will be greatly improved [8]. In the era of digital economy, as long as a certain department takes the lead in completing digital transformation and realizes the transformation of production methods, "it will inevitably lead to changes in the production methods of other departments." It is worth noting here that, in the process of digital production, digital information technology and the corresponding digital hardware and software facilities "always enter the labor process in their entirety but always only partially enter the value appreciation process." Digital technology and digital production equipment itself do not create value, but they gradually transfer their own value to the digital products they produce or the digital services they provide. In this

sense, digital technology and digital production equipment are a digital component of the value of a product or service.

On the other hand, the advancement of digital information technology promotes the digitization of collaboration and the specialization of division of labor among various departments of the enterprise, which is conducive to promoting the digital transformation of enterprise organizations. The development of digital information technologies such as the Internet and SG makes collaboration not limited by time and space, which is conducive to expanding the scope of collaboration and greatly improving the efficiency of collaboration [9]. The digital production operation of an enterprise under the technological progress itself is a huge and complex system, which requires a large number of local workers to divide and cooperate. As Marx put it: "Not to mention the new forces arising from the fusion of many forces into one total force, in most productive labor, social contact alone evokes a sense of competition and a peculiar invigoration of energy that elevates everyone. The application of digital information technology provides technical support for expanding the influence of this social contact, promotes the digital and efficient transformation of enterprise organizations, and greatly improves the work efficiency of enterprise workers."

3.2. Participation and Distribution of Data Is a Necessary Condition for Digital Transformation of Enterprises. The reason why nonphysical data can participate in the distribution is that it is gradually capitalized with the development of the digital economy. It has the nature of capital and is also a special kind of capital. Combined with the analysis of the basic principles of Marxism, it can be seen that, in the digital network formed by the application of related, the data generated in the daily use of social media will be transformed into capital through two stages:

First, the commercialization stage: users need to consume a certain amount of physical and mental energy in the process of using social media, and the relevant data generated based on this exists in the form of labor products; when these digital labor products are "exchanged, transferred to use as use value, and use it in the hands of people," it becomes a data commodity; that is, in the market economy, the data generated through digital labor is exchanged for the purpose of profit, and it exists in the form of a commodity.

The second is the capitalization stage: the digital labor that users use various software to generate data in their daily life is unpaid labor and still has the nature of "exploitation." Large-scale Internet companies such as Amazon, based on the volume of their digital business and the advantages of related digital technologies, freely occupy the digital labor of users and the data value they generate [10, 11]. According to the needs of business development, the relevant data generated by the digital labor that they possess for free are extracted, processed through digital technology to form a data group, exchanged, and sold, and their data products are sold, "and most of the money obtained from this are reconverted into capital" and used for the additional

production materials and labor required for the continuous digital development of enterprises, and data commodities are transformed into digital capital. In this process, data exists in the form of capital.

Participation in the distribution of data mainly involves two aspects: on the one hand, data as a factor of production participates in the distribution. According to the relevant theoretical analysis of factor distribution theory, data has become a special production factor, and its distribution principle is determined by social production relations. In a capitalist society, how data is distributed as a factor of production is determined by the owners of the data, the capitalists. In a socialist society, public data resources are shared by the whole people, while nonpublic data resources are distributed by the market under established legal conditions. Another aspect is that data participates in distribution as the final product. In China, the distribution of data products needs to meet the relevant requirements of the basic distribution system, which is mainly determined by the amount of labor paid by the laborers in the process of data collection, analysis, and application.

3.3. Pursuit of Excess Profit Is the Fundamental Driving Force for Digital Transformation of Enterprises. In the digital age, the "labor" expounded by Marx in the labor value theory combines digital information and other modern technologies to form a new form of labor, that is, digital labor. According to the relevant elaboration of labor value theory, digital labor includes concrete labor and abstract labor. A user posts videos, images, comments, etc. in social media. This kind of labor consumption based on a certain purpose constitutes the specific labor of digital labor. The specific content published can meet certain needs of people. Therefore, there is the specific labor of digital labor. The generated data information can create use value for the economy and society; the digital behavior of all users, such as web page search and browsing behavior, has no specific form. Human labor in the general sense forms the abstract labor of digital labor, which is given to commodity producers. The demand information about the size, shape, and function of the designed product can be produced based on the application of related technologies to create value, which reflects the relationship between data producers, information users, and commodity sellers in the social production process in the digital age social relationship. The amount of value of goods produced based on the use of digital technology is determined by the socially necessary labor time [12]. The higher the "development level of science and the degree of its application in craftsmanship" in the field of digital information are, the higher the productivity of digital labor is, and the smaller the value of the digital goods it produces. From the relevant analysis of the theory of surplus value production, it can be seen that, in the early stage of the development of the digital economy, individual entrepreneurs used digital information technology to improve the labor productivity of enterprises and carried out digital production and operation. The labor time consumed by the same

commodity shows that the commodity value produced by individual entrepreneurs based on digital information technology is lower than the social value, thus obtaining excess surplus value. Based on this, the individual production price of the commodity will be lower than the social production price, and enterprises that use digital information technology for digital operations will obtain additional profits that are more than average profits, that is, excess profits. Due to the existence of the law of market competition, the practice of individual entrepreneurs using digital information technology for production and operation to obtain excess profits will be replicated and promoted by other entrepreneurs in their industry, which will eventually attract more enterprises to improve their digital production and operation capabilities and conduct digitalization [13].

To sum up, the pursuit of excess profit is the fundamental driving force and subjective motivation for enterprises to improve production technology and carry out digital transformation. In the era of digital information, the pursuit of excess profits by various entrepreneurs is conducive to improving the level of labor productivity in society and promoting the pursue more Excessive profits, thus forming a virtuous circle.

4. Big Data Model for Digital Evaluation of High-Tech Enterprises

There are currently three ways to distribute the income of estimating the coefficients of the digital combination: one-way ANOVA, historical simulation, and Monte Carlo simulation.

4.1. The Variance-Covariance Method. This method is one of the most common VaR values and belongs to the parametric method. On this basis, the statistical method is used to predict the income distribution of the digital coefficient, and the historical data are used to estimate it, such as variance and correlation coefficient, thus obtaining an overall under certain credibility. The VaR value of the asset is

$$\text{VaR} = z_\alpha \sigma_p \sqrt{\Delta t}, \tag{1}$$

where σ_p is the standard deviation of the entire portfolio return, z_α is the quantile of level α, and Δt is the holding period. According to the above formula, the VaR value can be obtained only by calculating the variance. The commonly used variance prediction methods include the RiskMetrics method and the GARCH method.

4.1.1. Risk Metrics Method. The RiskMetrics digital control model was launched by the digital management department of JPMorgan in October 1994. It is the world's first quantitative VaR model. Its main idea comes from the exponential moving average method (EWMA), which takes unequal weights on the data in the time series. To simplify the assigned weights, it introduces a parameter λ, called

attenuation factor, whose value is between 0 and 1. For the estimation of λ, the principle of root mean square error (RMSE) is usually used; that is, the value of λ that minimizes the root mean square error of the prediction is selected:

$$\sigma_t^2 = (1 - \lambda) \sum_{i=1}^{\infty} \lambda^i r_{t-i}^2. \qquad (2)$$

The exponential moving average method estimates the standard deviation of returns. The variance estimation formula can be written in an iterative form, which will help the use of computers process huge data. RiskMetrics based on the normal method has some drawbacks: it relies on the normality of position returns and is a partial method and a thoroughly linear method, while being computationally cumbersome.

4.1.2. GARCH Class Methods.

The 2003 Nobel Laureate in Economics Robert Engle first introduced the ARCH model in 1982 to model variance. In 1987, Bollerslev extended the autoregressive conditional heteroscedasticity (ARCH) model and developed it into a generalized ARCH model, namely, the general autoregressive conditional heteroscedasticity (GARCH) model. Over the years, GARCH models have become a large family of many different types. A large number of empirical studies have shown that GARCH-type models have the characteristics of good description of financial time series, that is, the ability to deal with the time-varying and thick-tailed distribution of variance.

$$r_t = \mu + \varepsilon_t, \qquad (3)$$

where μ is the unconditional mean and ε_t is the disturbance term. The conditional variance equation of GARCH-like models provides a simple analytical form for the stochastic volatility process in financial return data. The GARCH (p, q) model predicts volatility as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + L + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + L + \beta_p \sigma_{t-p}^2$$
$$\cdot \left(\omega > 0, \alpha_1, L, \alpha_p \geq 0, \beta_1, L, \beta_p \geq 0 \right). \qquad (4)$$

The choice of the conditional variance equation and the assumption of the independent and identical distribution of the residuals are two key factors. With the application of GARCH-type models in the financial field, two obvious problems have gradually emerged in general GARCH-type models: first, the nonnegativity constraints on coefficient parameters are too strong, which excessively restricts the dynamics of conditional variance. Second, the conditional variance σ_t in GARCH-like models is a symmetric function of ε_t, which depends only on the magnitude of ε_t and not on its sign. Obviously, this is not true because interest rate movements in financial markets have a leverage effect, and the rise and fall of stocks will have an uneven impact, and the fall of stocks will have a greater impact on subsequent volatility. This means that the preferred mode handles both positive and negative types of residuals in an asymmetric manner.

4.2. Historical Simulation Method.

By analyzing the frequency of portfolio income in a certain period, the method finds the historical rate of return and the current minimum rate of return of the index within a certain confidence interval [14]. The model does not need to assume the statistical distribution of various market factors and can fully reflect the real changes of various market factors, so that it can solve the problem of abnormal distribution. The simulation algorithm is easy to implement and suitable for various types of positions and digital calculations in various markets. However, because this model assumes that future market factors and past historical changes are exactly the same, which is inconsistent with the real financial market, especially in the recent large-scale range, past data cannot be used to predict future stock markets and make accurate expectations, so historical simulation techniques are employed without any warning of unforeseen numbers. In addition, it is difficult to meet the above requirements because of the many specific data required for historical allocation of portfolio returns.

4.3. Monte Carlo Simulation.

Return on assets or market factor returns are not derived from historical observations, but we use tools to generate a huge amount of possible random data that conform to historical distributions, thereby constructing a portfolio, possible gain or loss, and then get an estimate of the digitized value at a given confidence level [15]. This method is extremely efficient and flexible because it does not require normality assumptions about the distribution of asset values, can be used for arbitrarily distributed return assumptions, does not require linear relationships between digitized factors, and also applies to variance changes with time, when the distribution is tail, in extreme value scenarios, and other special situations. However, the process used to generate data in the simulation process is random, which makes it subject to a certain degree, and this method has a large amount of calculation, a long calculation time, and is more complicated than other methods.

5. VaR Measurement Analysis of Market Digitization of Small- and Medium-Sized Private Enterprises

By processing the closing prices of 423 small- and medium-sized private listed companies from January 4, 2016, to December 31, 2020, a logarithmic daily rate of return sequence containing 1215 data was obtained.

5.1. Basic Statistical Data Analysis.

The normality test of financial time series can generally be tested by calculating the mean, skewness, kurtosis, and Jarque–Bera statistics. The daily rate of return was analyzed using EViews software to obtain the histogram and descriptive statistics of the logarithmic daily rate of return series (Figure 1).

From the chart, we can see that the deviation value of the portfolio is above 0, and the distribution is positive, indicating that there is a right tail in the return distribution.
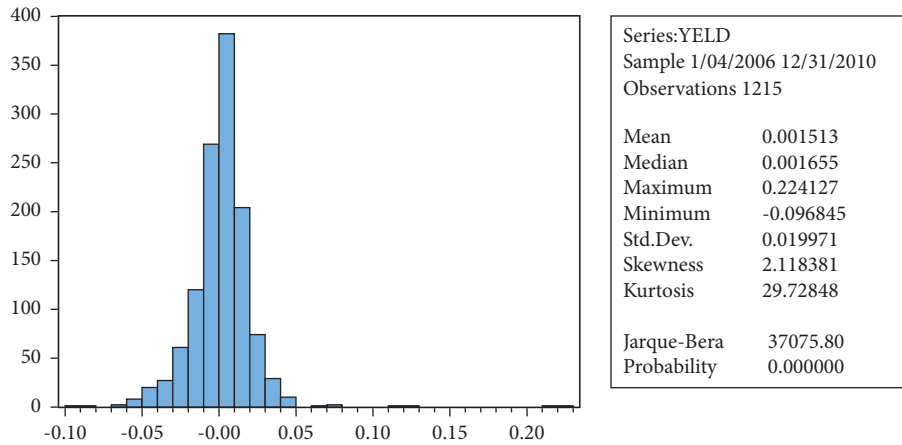
FIGURE 1: Descriptive statistics of log daily returns and their histograms.
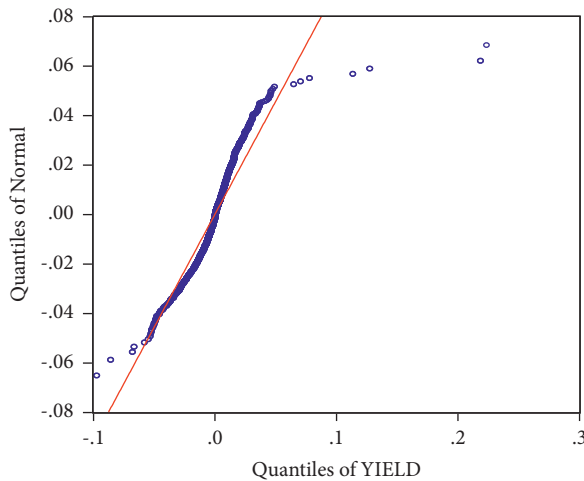

FIGURE 2: QQ plot of log daily returns.

FIGURE 3: Logarithmic daily return time series chart.

Kurtosis is used to describe this type of steep slope, which is much higher than the normal 3 peaks, which means that the frequency distribution is much more dense than normal. The Jarque–Bera statistic is used to detect the normal distribution of a series, and the threshold for 5% significance of this statistic is 5.99 under the assumption that the condition is 2. The value of the Jarque–Bera standard test statistic here is above the threshold of 5.99, which, in terms of the probability of the JB statistic, shows that a 0 assumption negates a normal distribution. The average return is not too far from zero, and it is also insignificant compared to the standard deviation. It is clear from the curve that there is a sharp rear tail in the distribution of returns. The average daily returns of small- and medium-sized board stocks show abnormal characteristics.

In addition, the QQ chart can more directly detect the normal distribution of returns (Figure 2).

The QQ plot compares the quantiles of a sample with the quantiles of a normal distribution. If the return distribution of the index is a normal distribution, then it should be a straight line on the QQ chart, and it can be seen from the figure that the line is a curve rather than a straight line, so the
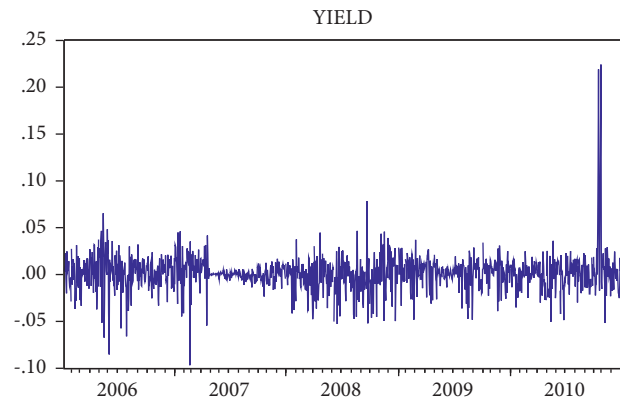
distribution of the logarithmic daily return series is not a normal distribution. In addition, looking at the time series of the logarithmic-day yield series in Figure 3, we can see that there is a clustering effect in yield fluctuations. The QQ plot also shows that this thick-tailedness is asymmetric.

5.2. Stationarity Test. The ADF method controls for higher-order serial correlations by adding a lagged difference of the dependent variable y_t to the right-hand side of the regression equation, as shown in Figure 4.

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + u_t, t = 1, 2, \ldots, T, \tag{5}$$

$$\Delta y_t = \gamma y_{t-1} + \alpha + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + u_t, t = 1, 2, \ldots, T, \tag{6}$$

$$\Delta y_t = \gamma y_{t-1} + \alpha + \delta t + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + u_t, t = 1, 2, \ldots, T. \tag{7}$$

5.3. ADF Inspection. Model (7) is a time variable, which represents a certain trend of the time series over time. The null hypotheses are all H0: $\gamma = 0$; that is, there is a root of unity
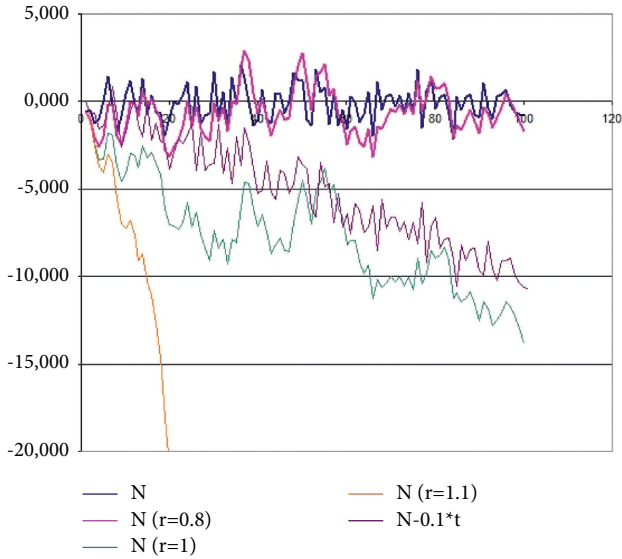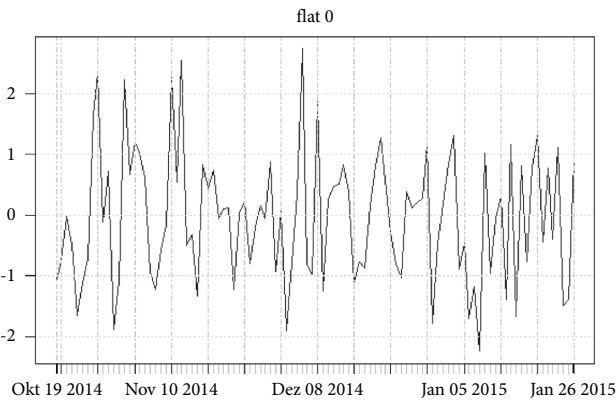
FIGURE 4: Stationarity test.

FIGURE 5: ADF test.

TABLE 1: ADF test.

Null hypothesis: Yield has a unit root		
Lag Length: 0 (fixed)	t-statistic	Prob.*
ADF test statistic	−29.73025	0.0000
1% level	−3.435523	
5% level	−2.863712	
10% level	−2.567977	
Akaike Info criterion	−5.0105 Schwarz criterion	−5.00209

(Figure 5). The difference between model (7) and the other two models is whether it contains constant term and trend term. The actual test starts with model (7), then (5), (6): when to reject the null hypothesis, that is, the original sequence does not have a unit root and is a stationary sequence, and when to stop testing. Otherwise, continue to check until (5) is completed. The results shown in the table were obtained under the principle of minimum AIC and SC (Table 1).

From the test results, at the three significance levels of 1%, 5%, and 10%, the critical values of the unit root test are −3.435523, −2.863712, and −2.567977, the hypothesis $H0$
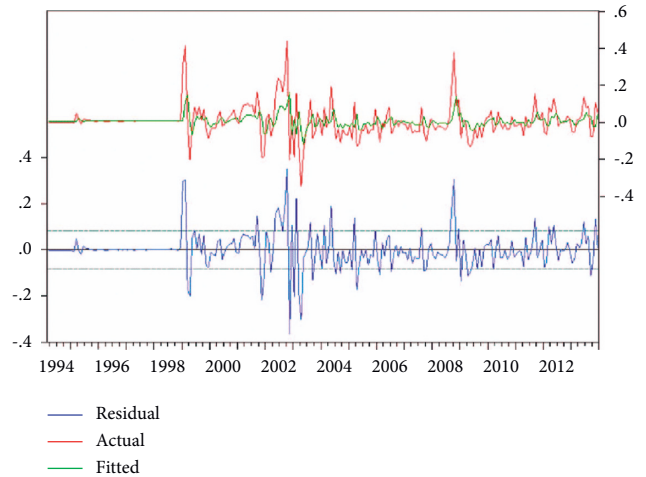

FIGURE 6: ARCH effect test.

TABLE 2: ARCH-LM test.

F-statistic	46.35092	Probability	0.00000
Obs ∗ R-squared	133.56369	Probability	0.00000

indicates that the difference series of daily returns does not have a unit root, and the logarithmic daily returns are stationary series.

5.4. ARCH Effect Test. In 1982, Engle proposed the Lagrangian multiplier test, namely, the LM test, to test whether there is an ARCH effect in the residual sequence. This particular specification of autoregressive conditional heteroskedasticity is due to the discovery that, in many financial time series, the magnitude of the residuals is related to the most recent residual value. The LM test statistic was calculated by an auxiliary test regression (Figure 6). There is no ARCH effect in the residual sequence up to the p-order, and the following regression is required:

$$u_t^2 = \beta_0 + \left(\sum_{s=1}^{p} \beta_s u_{t-s}^2 \right) + \varepsilon_t, \tag{8}$$

where u_t is the residual. This formula represents a regression of the residual squared u_t^2 on a constant and lag u_{t-s}^2 up to the p-order residual squared. This test regression has two statistics:

(1) The F statistic is an omitted variable test for the joint significance of the lags of all squared residuals;

(2) The $T * R2$ statistic is Engle's LM test statistic, T is the number of observations, and $R2$ is the regression test. The exact finite-sample distribution of the F statistic under the null hypothesis is unknown, but the LM statistic is in general asymptotically subject to the $\chi^2_{(p)}$ distribution.

Table 2 is the test result of ARCH-LM, and the result shows that the P value is zero, rejecting the null hypothesis. This indicates that the residual series has an

ARCH effect; the residual squared correlation plot shows that the Q statistic of the residual squared series is significant, which also indicates that the residual series has an ARCH effect.

6. Discussion of Results

As an important part of developing the digital economy and an important part of China's digital strategy, the digital transformation of enterprises is of great significance to boosting the Chinese economy. Based on the data of high-tech listed companies from 2016 to 2020, this paper studies the impact of digital transformation on enterprise performance from multiple perspectives such as dynamic effects and heterogeneity and studies the mediation of its impact. Finally, robustness and endogeneity tests were carried out. This paper mainly draws the following conclusions: first, digital transformation can effectively improve enterprise performance and can continue to improve enterprise performance for a long time, and the effect is more obvious in enterprises with a high degree of digital transformation. Second, considering that differences in the company's own attributes and macro-environmental conditions may have different effects on corporate performance, we empirically test the impact of digital transformation on the effects of digital transformation from a micro perspective (property nature, corporate age) and a macro perspective impact on business performance [16]. It is found that, compared with non-state-owned enterprises, digital transformation can significantly improve enterprise performance in state-owned enterprises, but for non-state-owned enterprises, it does not play a boosting role; from the perspective of enterprise age, digital transformation can effectively improve enterprise performance, but compared with young enterprises, mature enterprises have better performance improvement effect; from the perspective of macroeconomic environment, no matter the macroeconomic environment is good or bad, digital transformation can improve enterprise performance, but the performance improvement effect is more effective when the environment is good for obvious reasons; digital transformation can improve business performance as far as the financial cycle is concerned, but it works better in a bull market [17]. Third, from the perspective of the transmission mediation path, operating costs and labor productivity have a partial mediating effect in the relationship between digital transformation and corporate performance; that is, digital transformation improves corporate performance by reducing operating costs and improving labor productivity. Fourth, considering that the impact of digital transformation on enterprise performance is inseparable from government support, we further embedded government governance elements to study the paradigm of "digital transformation and enterprise performance." The policy effect exerted is inefficient, while the government focuses on refined governance in the micro-field; that is, the policy effect exerted in the form of targeted subsidies is extremely efficient.

This research provides important practical implications for exploring new driving forces for improving corporate performance and thus promoting the high-speed and high-quality development of the digital economy: first, to promote enterprises to actively promote digital transformation, drive flexible production, intelligent manufacturing, and digital management and sales. Promote the value of data, accelerate the deep integration and integration of new-generation technologies such as big data, cloud computing, Internet of Things, and 5G with enterprises, promote cloudification and integration of core systems, and continuously promote enterprises to digitalize transformation of modern business models. Strengthen the interconnection of data, knowledge, and services between enterprises, tap synergies between enterprises, promote the online, intelligent, and digitalization of commercial trade, realize the rapid matching of data and services, and improve the agility to respond to changes in business needs. Customers provide personalized customized services to form a digital ecological cluster that "gets what they need, mutual benefit and win-win," so as to improve corporate performance. For example, home appliance companies can use the smart TV terminals sold by the company as the basis to develop third-party businesses, such as cooperating with Internet companies to collect statistics and data on users' use of watching videos, music, education, games, and other content services, conducting in-depth analysis of these data, and using public services and other means to spread brands to users and gradually form a ten million-level user platform and realize the development model of "user + terminal." In addition, we should also pay attention to the digital transformation of non-state-owned enterprises and young enterprises, promote small-scale enterprises to go to the cloud platform, improve the external economic environment of enterprises, and promote the sustainable development of all-round overall digital economic benefits. Second, help enterprises to improve labor production efficiency through digital transformation and promote the quality and efficiency of digital transformation. In-depth mining, collection, and analysis of enterprise internal data information such as enterprise equipment, personnel, and logistics focus on analyzing this data information and classify and refine it. Identify possible integrated processes and steps that can be omitted and rationally use data core resources to promote intelligent, digital, and networked reforms in the manufacturing industry and promote enterprise innovation [18]. Promote the coordinated development of upstream and downstream enterprises in the industry chain and increase the added value of products based on the transformation needs of key business scenarios [19–21]. For example, companies can rely on the company's procurement channels, distribution systems, and terminal network advantages and use digital technology to eliminate information between upstream and downstream enterprises in the supply chain. Asymmetric tangerine is innovating the supply chain service model and improving the circulation efficiency of the supply chain; on the other hand, it extensively collects and stores consumer group information and conducts in-depth analysis to form

customer portraits and implement precise marketing, thereby improving labor production efficiency, reducing operating costs, management costs, and investment costs, and improving enterprise performance and sustainable competitiveness, based on long-term development [22–28]. Finally, strengthen government governance, and distribute government subsidies in a reasonable and targeted manner. As an important driving force for enterprises' digital transformation, the government must give full play to the "promising government" effect. Relying on ABCD technology to promote government digital management, establish a professional information consulting platform, technical guidance platform, etc., to achieve efficient, active, precise, and flexible government governance, formulate a digital governance system that matches the digital economy, and give full play to the market role of resource optimization and allocation in digital transformation, creating a good external ecological environment for digital transformation and improving the efficiency of government digital services [29–33]. Strengthen the construction of infrastructure, optimize the industrial structure, form a digital development strategy, actively introduce relevant policies to provide technical support for the digital transformation of enterprises, and provide targeted financial support for the transformation of enterprises, so as to alleviate the financial difficulties faced by enterprises. In addition, attach importance to the protection and open sharing of data, break down digital barriers, and appropriately and reasonably open part of the data resources for commercial purposes within the scope of government monitoring to reputable companies, reducing the difficulty and cost of data collection. Improve the level of communication and interaction between government and enterprises, understand the actual difficulties of enterprises, and help them get out of the predicament.

7. Conclusion

Digital transformation is the all-round reshaping of internal and external processes, production methods, and management methods of enterprises in the digital economy era in the face of big data, Internet of Things, cloud computing, 5G, and other information technologies. There are many intermediary paths for corporate performance, and the current research on the impact of the digital transformation of physical enterprises on performance from the perspective of the digital economy mainly studies such as communication and collaboration costs and investment costs, agency costs, logistics costs, research, and development costs. Regarding the intermediary path in terms of cost, relatively, this paper mainly reveals the intermediary path that digital transformation affects enterprise performance, such as reducing costs and improving labor productivity, and then enriches and improves the mediation path in the paradigm of digital transformation and enterprise performance in this field.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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