Journal of Contemporary Economics and Management

jcem.pol-aca.com

Article

Promoting Firm Growth Performance Through Digital Finance: Empirical Insights from Chinese Manufacturing Enterprises

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Citation:

Abstract: Digital financial tools have emerged as essential for enterprises, playing a pivotal role in alleviating financing constraints, improving resource allocation efficiency, and transforming innovation and development patterns. However, there is limited research on how digital finance (DF) affects a company's growth performance. This article develops a theoretical framework of "digital finance-entrepreneurial opportunities-inefficient investment-firm growth performance" based on the resource-based view. Using data from a survey of 302 Chinese manufacturing enterprises, it examines the moderating role of big data analysis capabilities. The results showed that: (1) DF has a positive effect on enterprise growth performance; (2) Entrepreneurial opportunities and inefficient investment mediate the relationship between DF and growth; and (3) Big data analytics capabilities strengthen the positive impact of DF on entrepreneurial opportunities and increase its negative effect on inefficient investment. This research provides insights into how variables are measured and explores mechanisms within the realms of DF and entrepreneurial opportunities. It broadens the application of DF, entrepreneurial opportunities, and inefficient investment in the context of enterprise growth. Additionally, it aims to offer valuable decision-making guidance for enterprises striving to improve their growth outcomes.

Keywords: Digital finance; Entrepreneurial opportunities; Inefficient investment; Firm growth performance; Big data analytics capabilities.

1. Introduction

Digital technology has a profound impact on customer behavior, organization, market, and business model (Plekhanov et al., 2023), making the competitive environment in which enterprises grow more volatile and complex. This transformation requires enterprises to dynamically and efficiently integrate and utilize resources to gain competitive advantages, enhance overall performance (Savino & Shafiq, 2018), and achieve sustainable growth. However, many enterprises, especially small and medium-sized enterprises, have disadvantages in resource acquisition and allocation due to factors such as opaque information, lack of transaction history, and high failure risk (Abdulsaleh & Worthington, 2013), making it challenging to meet their financing needs in the process of growth. Financial innovation can alleviate the financing constraints caused by traditional financial exclusion, avoid the stagnation of enterprise development, and promote its innovation (Laeven et al., 2015).

In recent years, with the ongoing integration of emerging technologies like big data, cloud computing, blockchain, and conventional finance, digital finance (DF) has emerged and grown rapidly (Tang et al., 2022). For conventional finance, this brings unprecedented business opportunities (Gomber et al., 2017b). In short, DF is to provide individuals or enterprises with products, services, technologies, and infrastructure related to payment, savings, and loans through Internet platforms (Ozili, 2018). With the help of technologies such as big data and the Internet, DF makes up for the shortcomings of the conventional financial system, and provides new solutions to ease the economic constraints of enterprises, optimize resource allocation, and reduce financing costs (Andriushchenko et al., 2020; M. Li et al., 2023), which eventually brings new development opportunities to enterprises (Y. Li et al., 2023). Therefore, in the digital economy environment, enterprises can promote their growth performance through DF. Although the current research on DF has achieved fruitful results and affirmed its positive significance to the growth of enterprises, there are still some limitations. The present study aims to address these gaps by exploring the following aspects:

Firstly, this study examines the impact mechanism of DF on firm growth performance (FGP) using empirical data. A recent study by Hossain and Sultana (2024) found that DF has caused a paradigm shift in business strategy, innovation, financing, and management capabilities worldwide. As an essential branch of the digital economy, researchers have conducted extensive studies on DF. The previous research on the impact of DF on enterprise activities focuses on digital transformation (Luo, 2022), green innovation (Cao et al., 2021), financial performance (Wu & Huang, 2022), and high-quality development (Lee et al., 2023). However, there is a lack of research on how DF affects FGP. Since DF plays a vital role in promoting enterprise development and enhancing performance, this study further investigates the relationship between them using survey data from enterprises, helping to fill gaps in the current research system.

Secondly, from the perspectives of the resource-based view (RBV), this study identified two mediating mechanisms through which DF promotes FGP: increasing entrepreneurial opportunities (EO) and reducing inefficient investment (II). Existing research shows that DF can enhance business performance and foster innovation by changing financial structures, easing restrictions on corporate financing, and supporting the development of financial-related businesses (Lin et al., 2023; Liu et al., 2023; Peng et al., 2023). However, there are few studies specifically studying the mediating mechanisms between DF and FGP. DF can help companies improve their ability to discover and integrate resources, which may initially influence their EO and II, subsequently impacting their growth performance. This study empirically tests the mediating roles of EO and II, adding to the existing research in related fields.

Finally, this study discovers that the big data analytics capabilities (BDAC) can strengthen the impact of DF on FGP. Conventional storage and computing technologies are difficult to calculate and analyze the massive data generated in the digital environment (Sandhu, 2021). In contrast, BDAC can help enterprises process a large amount of available data to identify market opportunities and predict customer needs (Akter et al., 2016; Hao et al., 2019) and assist managers in making key decisions (Shamim et al., 2019). From the lenses of RBV, BDAC can help enterprises identify and evaluate effective resources in DF activities (Mikalef et al., 2018), improve the efficiency of enterprises' use of internal and external resources (Gupta et al., 2020), further enhance the improvement of resource search and integration ability brought by DF to enterprises, and expand the impact of DF on FGP. This study tests the moderating role of BDAC in the model and expands the application of RBV in the field of DF.

Therefore, this paper evaluates the potential relationship between DF and FGP, establishes the theoretical framework of " DF- BDAC- EO/II- FGP ", and discusses the impact mechanism of DF on FGP and the mediating effect of EO and II based on the theoretical perspectives of RBV. This study will provide significant theoretical value and practical significance for the research of DF, EO, II, and FGP, and other related fields.

2. Theory and Hypotheses

2.1 Resource-based View (RBV)

According to the RBV, there is a close relationship between the resource endowment and performance growth of enterprises (Russo & Fouts, 1997). Due to the heterogeneity and rarity of enterprise resources, it is not easy to be imitated and copied by competitors. Integrating heterogeneous resources can help enterprises establish unique competitive advantages and further improve their performance (Newbert, 2008). The growth of a company involves discovering new market opportunities, and enterprises need to change and use existing unique resources to match and capture these opportunities (Lockett et al., 2009). If resources exhibit complementarity (Harrison et al., 1991), correlation (Dierickx & Cool, 1989), or shared expertise (Lippman & Rumelt, 2003), their integration can generate greater value.

Besides, resources have multiple functions and apply to many different markets. Among them, physical resources are easily exhausted. The use in one market will affect the use in another market, so it is essential to put resources in the right place (Lockett et al., 2009).

The core of the RBV is to optimize the resource utilization efficiency of enterprises to improve their overall performance. Rational resource allocation is the key for enterprises to obtain a competitive advantage (Helfat & Martin, 2015). From the perspective of RBV, DF reduces the asymmetry of information and widens access to financial resources. Through DF platforms, enterprises can search external resources more efficiently and contact potential investors, market opportunities, and partners, which promotes the generation of EO. At the same time, the use of DF tools can help enterprises reasonably allocate and integrate internal resources, improve the utilization efficiency of capital resources, and optimize investment decisions. Therefore, based on the RBV, we have established a research framework of "DF-BDAC-EO/II-FGP", as shown in Figure 1.

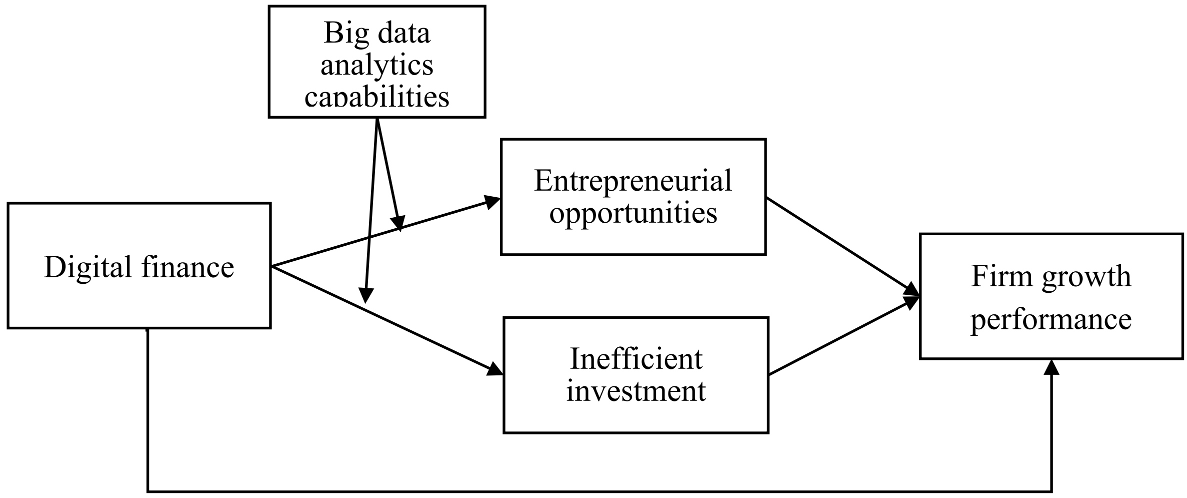

Figure 1. Research framework

2.2 Main Effect of EF and FGP

In recent decades, DF has been developing continuously, and its information processing capabilities have been expanding and improving (Gomber et al., 2017a), attracting the interest of a wide range of researchers. The current study adopts the definition of DF from Tang et al. (2002), where they describe DF as enhancing the value of strategic emerging enterprises through three approaches: replenishing funds, reducing risks, and promoting innovation, to achieve sustainable development. DF can offer financial services through the digital payment system to facilitate quick decision-making (Durai & Stella, 2019). Its development can also boost residents' consumption and consumption upgrading, lower transaction costs, and support high-quality economic growth (Feng & Zhang, 2021; Risman et al., 2021).

Studies by Pelham (1999) and Isobe et al. (2008) have shown that industry environment, strategic decisions, and technological capabilities influence enterprise earnings, thereby impacting overall enhanced performance. This study defines FGP as the improvement of enterprise operational efficiency and operator performance resulting from internal and external factors over a specific period.

From the perspective of RBV, DF uses new DF technology to provide enterprises with more resources, enabling them to have greater development opportunities, improve enterprise efficiency, and enhance innovation capabilities, thereby promoting FGP. This is mainly demonstrated in two aspects:

1) DF can meet the varied needs of users while offering a variety of financial products and services (Ozili, 2023), enabling enterprises to access unique information that supports more informed strategic decisions. Other than that, it can enhance and expand financing opportunities for companies, promote formalization and financial inclusion (Ketterer, 2017), reduce financing

costs, and diversify financing channels through digital platforms (Mu et al., 2023). This enables enterprises to obtain more financial support, which directly encourages FGP.

2) DF can reduce the financing constraints of enterprises through technological innovation, help to upgrade the internal structure of enterprises and the development of the manufacturing industry, enhance the competitiveness of enterprises' products (Feng et al., 2022), and promote the improvement of FGP. Therefore, we propose the following hypothesis:

H1: DF has a positive effect on FGP.

2.3 The Mediating Role of EO

This article conceptualizes EO as an opportunity that is highly appealing and facilitates entrepreneurial efforts (Wu et al., 2020). From the perspective of RBV, the positive effect of DF on EO is mainly reflected in two ways: 1) DF allows enterprises to overcome geographical barriers through various digital technologies. Even amid environmental shifts and capital constraints, they can access more resources and opportunities (Maine et al., 2015), effectively broaden their market reach, and increase their chances of discovering new prospects. 2) The inclusive nature of DF today enables companies to gather substantial amounts of financial data (Mhlanga, 2020). This data offers valuable insights into market demand and helps identify potential opportunities. Based on these points, this study proposes the following hypothesis.

H2a: DF has a positive effect on EO.

A large number of empirical studies have shown that the company's growth, scale, and differentiation strategy will have a significant impact on the company's performance (Ekadjaja & Wijaya, 2021; Pelham, 1999). Meanwhile, Ma and Yang (2022) stated that discovering and seizing potential new opportunities can help enterprises improve corporate performance by improving entrepreneurial ability. In fact, the positive effect of EO on FGP is reflected in two aspects: 1) EO encourages enterprises to continuously learn and explore, acquire more market and technical knowledge (Siegel & Renko, 2012), promote technological innovation and progress of enterprises (Mrożewski & Kratzer, 2017), provide intellectual support and core competitiveness for enterprises, and improve FGP. 2) When used to discover EO, enterprises can identify potential opportunities in business creation through social media and other channels, establish closer ties with peers, partners, or customers (Park et al., 2017), stabilize the supply chain, and optimize partner relationships, bringing sustained profit growth to enterprises. Therefore, this paper puts forward the following assumptions:

H2b: EO has a positive effect on FGP.

With the rapid development of the digital economy, DF, as a financial innovation that combines Internet information technology with conventional finance, has provided unprecedented momentum for the growth of enterprises (Wang, 2022) and plays a greater role in enhancing their financial performance (Wu & Huang, 2022). From the perspective of accessing external resources, DF can ease enterprises' financing constraints (C. Li et al., 2023; Lin et al., 2022; Luo, 2022), offer more financial support and EO, help enterprises quickly expand their business, and promote improvements in FGP. From the perspective of internal opportunities, DF broadens the range of financial services, lowers the barriers to accessing financial services, supports technological innovation (Tang et al., 2023), enhances their internal innovation capabilities and external competitive advantages, and adopts more flexible management methods to create new EO. This further enhances operational efficiency and innovation capacity, ultimately improving FGP. Based on this, we propose the following hypothesis:

H2c: EO plays a positive mediating role between DF and FGP, where DF can promote FGP by enhancing EO production.

2.4 The Mediating Role of II

In this study, II is defined as the behavior of insufficient or excessive capital investment that directly affects the profitability and operational risks of enterprises and affects the financing and financial policies of enterprises based on Di (2019). According to the RBV, the inhibitory effect of DF on II is mainly reflected in two aspects: 1) In the financial market, II, which is characterized by either insufficient funds or excessive investment, may occur due to enterprises' or managers' information asymmetry (Chen et al., 2021; Gao et al., 2021). High-quality DF can provide enterprises with more information references and prevent II problems caused by information asymmetry by creating a large information network (Ai et al., 2023). 2) DF helps optimize the enterprise structure (Zhong et al., 2022), promote enterprise transformation and upgrading, facilitate resource allocation, significantly enhance investment efficiency, and reduce II. Based on this, we propose the following hypothesis:

H3a: DF has a negative effect on II.

Investment efficiency directly shapes the development trajectory of enterprises, given that efficient investment boosts value creation and enhances the quality of enterprise development (Lou et al., 2023). In fact, the negative effect of II on FGP is mainly reflected in two aspects: 1) The investment efficiency of enterprises is related to corporate social responsibility (Benlemlih & Bitar, 2018). When the investment efficiency of enterprises is low, it will have a negative impact on corporate social responsibility, making enterprises at a disadvantage in terms of financing, investment, and market competition, which is not conducive to the FGP. 2) Overinvestment and inefficient investment behavior caused by II promote the separation of internal ownership and management power of enterprises (Dong-mei & Yan, 2018), resulting in decision-making errors or insufficient management ability. When the internal management efficiency of the enterprise is affected, the overall operation efficiency of the enterprise will decline, and the enterprise’s performance will also decline. Therefore, we propose the hypothesis as follows:

H3b: II has a negative effect on FGP.

A study by Huang et al. (2023) demonstrates that DF can significantly enhance enterprise investment efficiency and resource allocation by reducing financing constraints and stimulating innovation. From the perspective of accessing external resources, DF offers companies more diverse and high-quality information and resource technologies through big data, cloud computing, and other technologies. High-quality information can ease financing constraints and agency conflicts, effectively improve investment efficiency (Qi-Zhi & Tao, 2013), curb II, and ultimately support the growth and improvement of enterprise performance. From an internal opportunity perspective, DF encourages the adoption and application of digital technology within enterprises, improves the ability and willingness to disclose information, and decreases uncertainty and information asymmetry (Peng & Luxin, 2022). Lowering the enterprise's II helps reduce supervision costs during operations, restrains unreasonable decision-making by management, and boosts operational efficiency and growth. Based on this, we propose the following hypothesis.

H3c: II plays a negative mediating role between DF and FGP. Specifically, DF can mitigate the negative impact of II on FGP by suppressing II.

2.5 The Moderating Role of BDAC

Enterprise companies gain a competitive advantage by developing various capabilities, which are created by combining and integrating resources at multiple levels of the organization (Gupta & George, 2016). However, evaluating, deploying, and allocating the resources necessary to enhance enterprise performance remains a key challenge. BDAC may be an effective approach to help enterprises overcome this obstacle.

This paper defines BDAC as the company's unique ability to effectively deploy technology and talents in the big data environment to capture, store, and analyze data to generate insights and identify loyal customers, referring to studies such as Akter et al. (2016) and Mikalef et al. (2020). BDAC enhances organizational decision-making quality through data-driven insights (Awan et al., 2021) and enables data to be classified, analyzed, and transformed into an efficient decision-making process (Ferraris et al., 2019), optimizing resource utilization. Previous studies show that BDAC can promote digital innovation within enterprises (Bhatti et al., 2024). Additionally, BDAC has been linked to organizational performance growth and enterprise innovation behavior (Su et al., 2022), contributing positively to the EO of enterprises. Therefore, when an enterprise's BDAC is low, it is difficult to extract valuable information from the large amount of data provided by DF, which cannot be transformed into business insights, thus hindering the exploration of EO and diminishing DF's impact on EO. Conversely, when an enterprise's BDAC is high, it can use DF effectively to manage various risks during entrepreneurship, offer diversified services through multiple channels, and develop a unique competitive advantage. In this scenario, the impact of DF on EO is strengthened. Based on this, we propose the following hypothesis:

H4: BDAC enhances the positive effects of DF on EO. Specifically, the stronger the BDAC, the more significant the positive effect of DF on EO.

The moderating effect of BDAC on DF and II is mainly reflected in three aspects: First, in the context of DF, big data analysis can filter and clean large amounts of heterogeneous data to prevent information overload (Wang, 2017). This helps enterprises acquire high-value information. The process makes the data more effective and precise, lowers the information search costs for enterprises, and reduces the information asymmetry (Wang et al., 2024). Therefore, an enterprise's BDAC can help managers make decisions based on reliable, accurate information to some extent and use data-driven insights to optimize investment strategies and achieve the best resource allocation.

Secondly, Hadoop, Spark, Apache Storm, and other big data analysis technologies can identify abnormal fluctuations in data (Habeeb et al., 2019). Enterprises use BDAC to analyze financial data, market data, industry data, customer behavior, and more, often detecting abnormal behaviors, unusual values, and counterintuitive data values(Bose & Mahapatra, 2001). Therefore, the ability to identify abnormal and potential risks in investment activities through big data analysis can enhance an enterprise's early warning capabilities, enabling timely detection of unreasonable investment opportunities and risks that should be avoided (Ahmed et al., 2017).

Finally, previous studies have shown that big data analysis capabilities can help managers overcome some irrational factors and make more informed decisions (Power et al., 2019; Wang et al., 2016). Leaders' emotional bias, risk perception, individualism, masculinity dimensions, and overconfidence (Azouzi & Anis, 2012; Lassoued & Osman, 2021; Malmendier & Tate, 2005) may negatively impact the investment efficiency of enterprises. By relying on big data analysis, managers can shift from decision-making based on intuition and experience to data- and algorithm-driven decisions (Provost & Fawcett, 2013). When making investment decisions, big data analysis ability can effectively reduce deviations caused by experience and habits, minimize irrational choices, and help develop efficient investment plans. Therefore, this study proposes the following hypothesis:

H5: BDAC enhances the inhibitory effect of DF on II, meaning that the stronger the BDAC, the more significant the inhibitory effect of DF on II.

3. Method

3.1 Measurement

3.1.1 DF

Referring to the findings by (Ozili, 2018) and (Guo et al., 2020), this study defines DF as financial services provided using digital technology, such as transactions through digital trading platforms and financial services delivered via mobile devices and other digital tools. Guo et al. (2020) examined DF from three aspects: 1) coverage, 2) depth of use, and 3) level of digitization. The study believes that the breadth of coverage is mainly influenced by the number of electronic accounts, including Internet payment accounts and linked bank accounts. Depth is measured by the actual use of Internet financial services, including payment, credit, insurance, investment, and credit reporting services. Regarding digital service support, convenience and cost are the key factors affecting the level of digitization.

Therefore, this study measured DF from three aspects stated by Guo et al. (2020) by considering the following points: 1) The financial services offered by the enterprises cover many types of business. 2) Customers frequently use digital payment, digital credit, digital insurance, digital investment, digital credit reporting, and other Internet financial services. 3) The DF services provided by the enterprises are efficient in terms of convenience and cost, allowing customers to easily access services through digital channels at relatively low prices.

3.1.2 FGP

There are four key dimensions used to measure FGP: sales growth, improvements to business models, consumer group size, and profit growth over the past three years (Jacobs et al., 2011; Lee, 2018). The following items corresponded to these dimensions: 1) Over the last three years, the enterprises' sales growth has shown a notable acceleration. 2) Over the same period, the enterprises' business model has undergone significant optimization and improvement. 3) During the past three years, the consumer base for the products has expanded considerably. 4) In the last three years, the enterprises have seen a substantial increase in profits.

3.1.3 II

In this study, II includes both overinvestment and underinvestment. Overinvestment refers to managers investing company funds into projects with low profit opportunities or negative net asset value to benefit themselves or others (Xu et al., 2018). Underinvestment occurs when factors such as information asymmetry cause managers to increase financing costs, leading them to deviate from high net present value projects (Tian et al., 2021). To measure II, this study used the following items: 1) Over the past three years, the enterprise has invested funds in projects with small profit opportunities. 2) Over the past three years, the enterprise has invested corporate funds into projects with negative net asset value. 3) Over the past three years, the enterprises have deviated from some high net present value projects due to factors like information asymmetry; 4) Over the past three years, the enterprises have invested less in, and supported fewer, high net present value projects because of factors such as information asymmetry.

3.1.4 EO

Casson (1982) believed that EO is defined as the objective situation that requires the discovery of new methods, such as relationships that generate economic value through the introduction of new goods, services, raw materials, and organizational methods. Companys and McMullen (2007) defined entrepreneurial opportunity as an opportunity that can be grasped and utilized through entrepreneurial action to create value and maintain competitive advantage. According to Casson (1982) and Companys and McMullen (2007), this study suggests that EO refers to the opportunities that can be transformed into real economic value and market advantage through innovation and entrepreneurial behavior. The present study measured entrepreneurial opportunity from three aspects listed byCompanys and McMullen (2007): economy, cultural cognition, and social politics, and designed the following items. 1) The enterprises have explored and seized new market opportunities by integrating existing resources and capability information (such as producer, network, market, and consumer feedback), as well as by using technological innovation or product innovation. 2) The enterprises have utilized knowledge, network structures, and governance mechanisms within cultural communities to identify and seize opportunities arising from cultural cognitive differences or changes. 3) The enterprises were capable of sensitively detecting and responding to changes in the political environment (such as policy adjustments and regulatory changes), shifts in market demand, and evolving consumer preferences, allowing us to explore and capitalize on opportunities created by social and political factors.

3.1.5 BDAC

(Gupta & George, 2016; Wang et al., 2018) define BDAC as the ability to manage a large volume of heterogeneous data, classify it, and perform analysis to enable rapid data response, which this study adopts. Based on this definition, the current study measured BDAC across seven aspects: data, technology, basic resources, technical skills, management skills, data-driven culture, and organizational learning intensity. The items were as followed: 1) Analyze large amounts of data by accessing and combining external and internal data to promote high-value analysis of the business environment. 2) Utilize parallel computing, visualization tools, cloud services, and open-source software to process data, conduct analysis, and store data in a database. 3) Allocate sufficient funds and time for the big data analysis project to achieve its objectives. 4) The big data analysts are well-trained, and committed to providing ongoing training for the employees. 5) The big data analytics managers are not only experts in data analytics but also understand the business context and coordinate big data-related activities to support other functional managers and suppliers. 6) Continuously evaluate and improve business rules based on insights extracted from data, treating data as a tangible asset. (7) Consistently strive to utilize existing capabilities and acquire new knowledge.

3.1.6 Controlled Variables

The characteristics of enterprise samples influence FGP. Referring to Yao et al. (2023), they introduced several controlled variables, including size, revenue, age, ownership, FS, RD, and NP. The specific measurements for these variables are as follows: 1) The number of employees measures size. 2) State ownership is indicated by 1, while private ownership is indicated by 0. 3) RD is measured as a ratio of R&D investment to sales revenue.

3.2 Data Collection

Before the data collection, the application scope and privacy protection measures of the data have been explained to the respondents, and the permission of the respondents has been obtained. The data acquisition process for this study was as follows:

First, sample selection. Scientific and technological enterprises occupy an important position in China's economic growth and are at the forefront of digital transformation. Therefore, the focus of this study's data collection was on Chinese science and technology enterprises.

Secondly, expert argumentation. During the variable measurement, several scholars and business leaders collaborated and discussed, leading to many revisions of the questionnaire. Ultimately, this process resulted in the development of the measurement indicators and questionnaire items used in this study.

Thirdly, questionnaire distribution. The data collection for this study took place from August to October 2024. A total of 407 questionnaires were distributed to targeted enterprises via MBA, EMBA, and DBA platforms; 315 were recovered. After removing 13 unqualified questionnaires, 302 valid questionnaires remained, resulting in an overall effective rate of 74.2%.

3.3 Reliability and Validity

In order to eliminate the influence of common method variance (CMV), this study used Harman's single-factor test to conduct factor analysis on all variables. The total variance interpretation table showed that the explanatory variance of the first factor, with an eigenvalue greater than 1 before rotation, was 25.538%, which is less than 30%. Therefore, it is considered that there is no serious common method bias in the data used in the present study.

Then, principal component analysis was performed to examine the potential variables. The results showed that the dimension division after factor rotation matched the questionnaire setup in this study. This indicates that the potential variable combinations corresponding to each variable in this research accurately reflect the sample distribution characteristics.

Later, SPSS was performed to calculate key indicators related to the reliability and validity of each variable. As shown in Table 1, Cronbach's alpha values for all variables were above 0.7, indicating that the questionnaire results in this study have good reliability. The KMO values for all variables exceeded 0.7, and the factor loadings were all greater than 0.7, confirming that the questionnaire results have strong validity and were appropriate for factor analysis. Additionally, the CR values for all variables were above 0.7, and the AVE values all exceeded 0.5. Based on these results, the reliability and validity measures of the questionnaire in this study met high standards.

Table 1. Reliability and Validity

Variable	Cronbach's alpha	KMO	Factor Loading	CR	AVE
DF	0.900	0.753	0.910 0.911 0.917	0.9373	0.833
EO	0.912	0.756	0.931 0.921 0.914	0.9445	0.8501
II	0.922	0.810	0.876 0.899 0.942 0.884	0.9449	0.8111
BDAC	0.970	0.947	0.910 0.919 0.903 0.931	0.9752	0.8491

			0.924 0.934 0.929		
FGP	0.902	0.851	0.869 0.879 0.878 0.890	0.9315	0.7727

Furthermore, we conducted confirmatory factor analysis using AMOS. As shown in Table 2. that the χ2/df value is 1.711, which is less than 3. The RMSEA is 0.049, which is below the recommended threshold of 0.08. The SRMR is 0.0294, which is less than 0.05. Additionally, the CFI, GFI, TLI, IFI, and NFI are 0.978, 0.913, 0.974, 0.978, and 0.949, respectively, all exceeding the recommended value of 0.9, further demonstrating the good structural validity of this questionnaire.

Table 2. Confirmatory factor analysis

Indicators	X^2/df	RMESA	SRMR	CFI	GFI	TLI	IFI	NFI
Recommended	<3	<0.08	<0.05	>0.9	>0.9	>0.9	>0.9	>0.9
Actual value	1.711	0.049	0.0294	0.978	0.913	0.974	0.978	0.949

Furthermore, we conducted principal component analysis on all variables except for the control variables, and the results are shown in Table 3. The variables corresponding to each set of questions are highly consistent with the variable settings of this study, providing strong support for the discriminant validity of the research.

Table 3. Principal component analysis

Item			Component		
Q1	0.019	-0.095	0.244	0.203	0.849
Q2	-0.005	-0.143	0.23	0.261	0.829
Q3	-0.039	-0.149	0.194	0.175	0.868
Q4	0.004	-0.153	0.188	0.883	0.178
Q5	0.041	-0.083	0.128	0.888	0.197
Q6	0.01	-0.054	0.165	0.871	0.214
Q7	0.027	0.869	-0.088	-0.086	-0.12
Q8	-0.026	0.877	-0.151	-0.072	-0.13
Q9	0.019	0.911	-0.213	-0.071	-0.073
Q10	-0.003	0.829	-0.299	-0.084	-0.067
Q11	0.911	-0.019	0.043	-0.002	0.007
Q12	0.918	-0.009	-0.043	0.037	-0.033
Q13	0.903	0.029	0.013	0.018	-0.011

Q14	0.932	-0.014	0.001	-0.025	-0.021
Q15	0.923	0.08	-0.031	0.015	-0.025
Q16	0.933	-0.017	-0.051	0.003	-0.012
Q17	0.929	-0.022	-0.05	0.021	0.061
Q18	-0.028	-0.179	0.831	0.128	0.132
Q19	-0.044	-0.161	0.827	0.153	0.202
Q20	-0.016	-0.181	0.829	0.131	0.178
Q21	-0.01	-0.218	0.835	0.118	0.175

3.4 Descriptive Statistics and Correlation

Table 4 presents the mean, standard deviation, and correlation of each variable in this study. The data indicates a causal relationship between FGP, EO, II and DF, which is consistent with the research hypothesis and predictions. The highest correlation coefficient between variables in Table 4 is 0.478 (DF & FGP), which is less than 0.7. Furthermore, the maximum VIF in all models is less than 10, ruling out collinear interference.

3.5 Empirical Results

We conducted regression analysis using SPSS, Process and Amos to test the hypotheses proposed in this study.

3.5.1 Main Effect and Mediating Effect Tests

As shown in Table 5, we examined the main effect model and the mediation effect model. The dependent variable in models M1-M4 is FGP, in models M5-M6 is EO, and in models M7-M8 is II.

M1, M5, and M7 are all control variables for FGP. The regression models of EO and II show that size and age significantly impact EO and II, while ownership significantly impacts EO. Financial subsidies have a significant effect on both FGP and II. R&D intensity significantly influences FGP, EO and II.

M2 represents the regression model of the independent variable on FGP. The results showed that DF has a positive effect on FGP ($\beta=0.321$, $p<0.001$), thus supporting H1.

M6 represents the regression model of the independent variable on EO. The results show that DF has a positive effect on EO ($\beta=0.346$, $p<0.001$), supporting H2a.

M8 represents the regression model of the independent variable on II. The results show that DF has a negative impact on II ($\beta=-0.206$, $p<0.01$), supporting H3a.

M3 represents the regression model of EO on FGP. The results show that EO has a positive effect on FGP ($\beta=0.118$, $p<0.5$), supporting H2b. M4 represents the regression model of II on FGP. The results show that II has a negative effect on FGP ($\beta=-0.273$, $p<0.001$), supporting H3b. Based on the results of M1-M6, we argue that EO and II play a partial mediating role in the relationship between DF and FGP.

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Size	1											
2. Revenue	0.356***	1										
3. Age	0.240***	0.073	1									
4. Ownership	0.070	0.052	0.121*	1								
5. Financial subsidy	0.156**	0.092	0.186**	0.146*	1							
6. R&D intensity	0.139*	0.156**	-0.076	0.076	0.226***	1						
7. Net profit	0.239***	0.027	-0.028	0.209***	0.109	0.215***	1					
8. DF	0.284***	0.123*	-0.066	0.198***	0.146*	0.381***	0.325***	1				
9. EO	0.261***	0.053	-0.041	0.231***	0.187**	0.239***	0.330***	0.478***	1			
10. II	-0.170**	-0.022	0.099	0.037	-0.207**	-0.256***	-0.195***	-0.309***	-0.244***	1		
11. BDAC	-0.013	0.059	0.012	-0.045	-0.007	-0.012	0.067	-0.017	0.025	0.012	1	
12. FGP	0.190***	0.073	-0.055	0.176**	0.241***	0.384***	0.299***	0.476***	0.371***	-0.434***	-0.045	1
Mean	2.407	2.546	2.639	0.374	2.854	2.755	2.715	3.990	3.969	3.938	4.151	3.906
Standard deviation	1.363	1.340	1.346	0.485	1.435	1.419	1.480	1.899	1.818	1.779	1.779	1.718

Table 4. Descriptive analysis and collinearity test

Note: *p < 0.05; **p < 0.01, ***p < 0.001; Two-tailed, N=302.

Table 5. Main effect and mediating effect test

Variables	DV: FGP M1-M4				DV: EO M5-M6		DV: II M7-M8	
	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
1. Size	0.111(0.073)	0.041(0.071)	0.025(0.072)	0.012(0.069)	0.214(0.079)***	0.139(0.076)*	-0.151(0.08)*	-0.107(0.081)
2. Revenue	-0.028(0.071)	-0.026(0.067)	-0.019(0.067)	-0.009(0.064)	-0.059(0.076)	-0.057(0.072)	0.064(0.077)	0.063(0.076)
3. Age	-0.092(0.069)	-0.056(0.066)	-0.047(0.066)	-0.026(0.064)	-0.112(0.074)*	-0.073(0.071)	0.135(0.076)*	0.112(0.075)
4. Ownership	0.102(0.187)	0.059(0.18)	0.045(0.181)	0.092(0.173)	0.164(0.202)**	0.118(0.192)*	0.091(0.205)	0.119(0.204)*
5. Financial subsidy	0.144(0.065)**	0.135(0.061)**	0.124(0.061)*	0.089(0.06)	0.104(0.069)	0.094(0.066)	-0.175(0.071)**	-0.169(0.07)**
6. R&D intensity	0.289(0.066)***	0.196(0.066)***	0.193(0.065)***	0.164(0.063)**	0.13(0.071)*	0.031(0.07)	-0.176(0.072)**	-0.117(0.074)
7. Net profit	0.172(0.064)**	0.115(0.062)*	0.098(0.062)	0.093(0.059)	0.204(0.069)***	0.143(0.066)**	-0.119(0.07)*	-0.083(0.07)
8. DF		0.321(0.051)***	0.28(0.054)***	0.264(0.05)***		0.346(0.055)***		-0.206(0.058)**
9. EO			0.118(0.054)*					
10. II				-0.273(0.049)***				
R^2	0.221	0.296	0.303	0.356	0.194	0.282	0.125	0.154
F	13.193***	16.799***	15.560***	19.524***	11.373***	15.754***	7.161***	7.871***
Max VIFs	1.307	1.371	1.533	1.414	1.307	1.371	1.307	1.371

Note: N=302, *p < 0.05, **p < 0.01, ***p < 0.001.

To further test the robustness of the mediation effect in the model, we conducted a Bootstrap analysis using PROCESS software with 5000 samples and a 95% confidence interval. Table 6. shows that the total effect of EO on FGP is 0.2901, with a direct effect of 0.2533, accounting for 87.31%, and an indirect effect of 0.0368, accounting for 12.69%. Since all 95%

confidence intervals do not contain 0, we conclude that the direct and indirect effect of EO on FGP are statistically significant. Similarly, the total effect of II on FGP is 0.2901, with the direct effect of 0.2391, accounting for 82.42%, and an indirect effect of 0.0510, accounting for 17.58%. Therefore, we argue that the mediating effect results of this study have a certain degree of robustness, supporting hypotheses H2c and H3c.

Table 6. Bootstrap analysis

Mediator	Item	Coeff.	5000 times, CI=95%		Rate
			LLCI	ULCI	
EO	Total	0.2901	0.1895	0.3906	100%
	Direct	0.2533	0.1472	0.3593	87.31%
	Indirect	0.0368	0.0021	0.0774	12.69%
II	Total	0.2901	0.1895	0.3906	100%
	Direct	0.2391	0.1412	0.3371	82.42%
	Indirect	0.0510	0.0196	0.0908	17.58%

3.5.2 Moderating Effect Test

To prevent collinearity interference, we decentralized the independent variables and moderating terms and then multiplied them to create the interaction term. The regression analysis results are shown in Table 7. The regression results of M9 indicate that the interaction term between DF and BDAC has a positive impact on EO ($\beta=0.186$, $p<0.001$). This indicates that BDAC positively moderates the relationship between DF and EO, supporting hypothesis H4. Conversely, the regression results of M12 show that the interaction term between DF and BDAC has a negative impact on II ($\beta=-0.153$, $p<0.001$). This indicates that BDAC negatively moderates the relationship between DF and II, supporting hypothesis H5.

Table 7. Moderating effect test

Variables	DV: EO		DV: II	
	M9	M10	M11	M12
1. Size	0.141(0.077)*	0.104(0.076)	-0.106(0.081)	-0.076(0.082)
2. Revenue	-0.06(0.072)	-0.056(0.07)	0.062(0.077)	0.059(0.076)
3. Age	-0.074(0.071)	-0.062(0.069)	0.112(0.075)	0.102(0.075)
4. Ownership	0.121(0.193)*	0.111(0.189)*	0.119(0.205)*	0.128(0.203)*
5. Financial subsidy	0.094(0.066)	0.095(0.064)	-0.169(0.07)**	-0.169(0.069)**
6. R&D intensity	0.032(0.070)	0.009(0.069)	-0.117(0.074)	-0.098(0.074)
7. Net profit	0.139(0.066)*	0.126(0.065)*	-0.084(0.07)	-0.073(0.07)
8. DF	0.346(0.055)***	0.356(0.054)***	-0.206(0.058)**	-0.214(0.057)**

9. BDAC	0.034(0.050)	0.026(0.049)	0.01(0.054)	0.016(0.053)
10. DF*BDAC		0.186(0.027)***		-0.153(0.028)**
R^2	0.295	0.301	0..152	0.171
F	14.030***	14.596***	6.978***	7.227***
Max VIFs	1.375	1.417	1.375	1.417

Additionally, we used Origin software to illustrate the moderating effect. Figure 2 shows that the positive effect of DF on EO enhances (slope increases) as the level of BDAC increases. This suggests that BDAC positively moderates the relationship between DF and EO. Figure 4, on the other hand, shows that the positive effect of DF on II decreases (slope decreases) as the level of BDAC increases. This indicates that BDAC negatively moderates the relationship between DF and II.

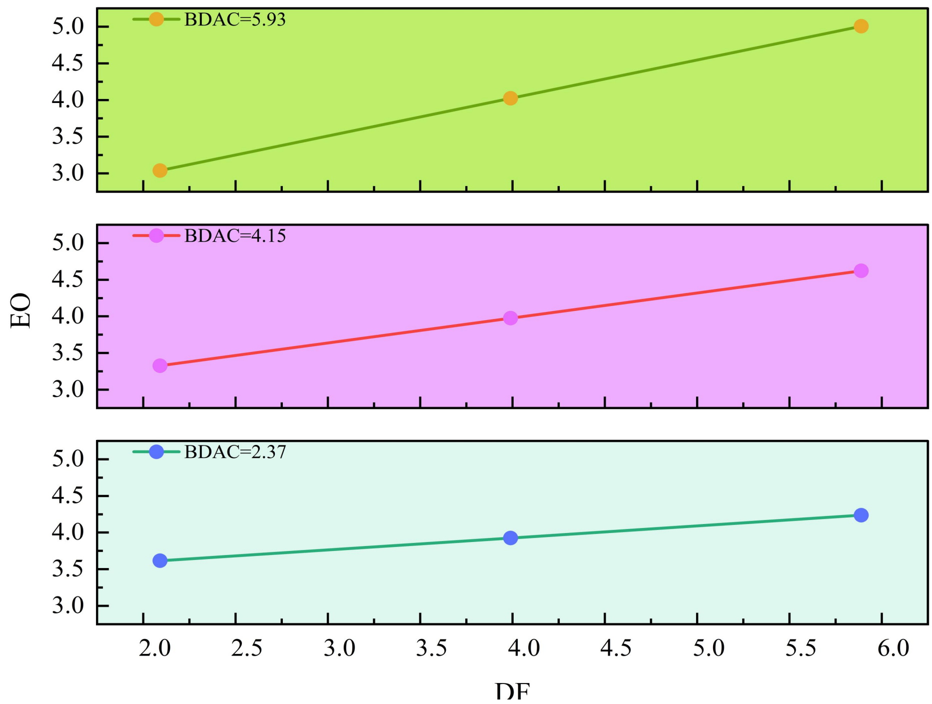

Figure 2. The moderating effect of EO

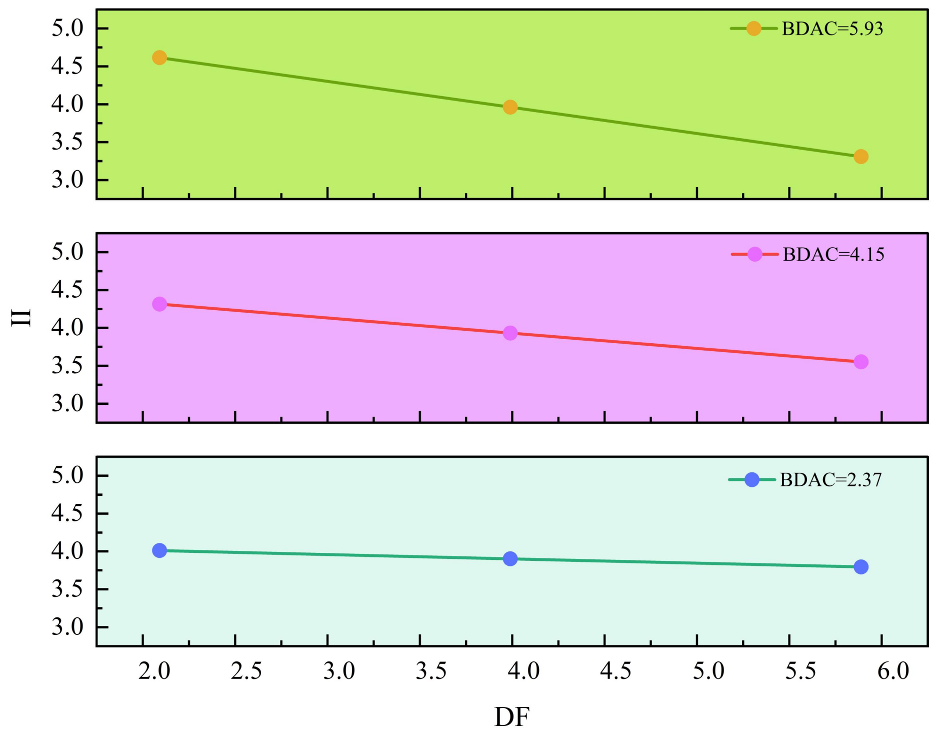

Figure 3. The moderating effect of II

4. Conclusions and Implications

4.1 Conclusions

In the context of the digital economy, the inclusive qualities of DF have improved the financial environment for enterprise growth, enhanced the resource search and integration capabilities of enterprises, and significantly influenced FGP. This study developed a theoretical framework of "DF-BDAC-EO/II-FGP" using 302 enterprises as research samples, examining the mediating roles of EO & II and the moderating effect of BDAC. The findings reveal that: 1) DF positively affects FGP. 2) EO mediates the relationship between DF and FGP positively. 3) II mediates the relationship between DF and FGP negatively. 4) BDAC positively moderates the relationship between DF and EO. 5) BDAC negatively moderates the connection between DF and II. This research broadens the understanding of the theories surrounding DF, BDAC, EO, II, and FGP, offering practical insights for enterprises on leveraging DF to enhance FGP.

4.2 Theory Contributions

DF has gradually expanded new financial services to non-financial enterprises, reducing the cost of financial services for enterprises (Demertzis et al., 2018). It has promoted more efficient resource allocation (Feng et al., 2022) and accelerated entrepreneurial activities (Sun & Xie, 2024). Against the backdrop of digital technology, the complex business environment has brought challenges to the growth of enterprises. The impact mechanism of DF on FGP has attracted more attention from all walks of life. In view of the existing research gap, this study examined the proposed hypotheses, and the main theoretical contributions are as follows:

First, this study constructs measurement indicators for two variables, DF and EO, for the first time, which can serve as a reference for future related research. Referring to the measurement of Guo et al. (2020), this study defines DF and assesses it across three aspects: coverage, depth of use, and degree of digitization. Meanwhile, this study defines EO and evaluates it from three perspectives by referring to(Companys & McMullen, 2007): economy, cultural cognition, and social politics. The concepts and corresponding measurement indicators developed in this study are comprehensive, considering both theory and practice, and they have passed reliability and validity tests. This provides a valuable reference for subsequent research.

Second, this study explains the internal influence mechanism of DF on FGP from the RBV perspective. To achieve enterprise growth, previous studies have explored factors such as entrepreneurial orientation (Wahyuni & Sara, 2020), leadership traits (Koryak et al., 2015), company size (Yeboah, 2021), research and development innovation (Coad et al., 2016), and organizational resilience (Liang & Li, 2024). Most of these studies focus on the internal aspects of the enterprise and pay little attention to how the development and application of DF in the external environment affect FGP. Considering the low-cost, inclusive, intelligent, and other features of DF, it is likely to have a positive impact on enterprises and promote their growth. Therefore, from the RBV perspective, this study constructs a theoretical model of "DF-BDAC-EO/II-FGP," reveals the internal influence mechanisms between these elements with empirical data, and makes a significant contribution to related research on DF and FGP.

Thirdly, this study proposed and verified the moderating effect of BDAC based on RBV, and identified the effective boundary conditions for the influence of DF on FGP. This study believes that BDAC can not only offer enterprises a new and more flexible perspective (Gupta & George, 2016; Mikalef et al., 2018) to discover value creation opportunities (Chen et al., 2012), but also enhance enterprises' investment decisions through data mining and mobile services (Wang et al., 2024), helping them identify EO and II. Despite these benefits, existing studies have not fully explored the relationship between BDAC, DF, and FGP. To address this gap, this study examined the regulatory role of BDAC within the framework of "DF-BDAC-EO/II-FGP" and further expanded the understanding and application of BDAC in the fields of DF and FGP.

4.3 Management Implications

There are four aspects of enlightenment that enterprises focus on in the study. First, the results showed that DF positively influences FGP. This suggests that enterprises should actively incorporate DF into their operations and management activities by emphasizing innovation in financial products and services and effectively utilizing and allocating the financial resources provided by DF. Doing so can help expand financing channels for enterprises, optimize investment decisions, and seek new EO to increase sales, improve business models, grow consumer groups, and boost profits and other key performance indicators.

Second, DF has introduced more market space and EO to enterprises. Enterprises should encourage internal entrepreneurship, explore potential opportunities through data analysis and other methods, innovate products and services based on market demand, and actively pursue new business areas.

Third, enterprises can utilize DF tools to optimize resource allocation and direct limited resources into projects with high growth potential. Simultaneously, they can use DF tools to enhance the evaluation, monitoring, and risk management of investment projects.

Fourth, the moderation of BDAC has shown that enterprises should focus on building BDAC. Enterprises can increase investment in big data analysis technology and develop or hire data analysis experts. By using big data analysis technology to process the large amounts of data from inside and outside the enterprise, the company can better identify EO and reduce II, thereby strengthening the positive effect of DF on FGP.

4.4 Limitations and Future Research

Although this study explores the impact mechanism, there are still some limitations:

First, consider the limitations of the data samples. The samples in this study mainly collected from Chinese science and technology enterprises. There is a lack of samples from other industries and countries. Whether the results are applicable to other industries or countries needs further testing. Future research could include enterprises from different industries or regions to develop more comprehensive and broader conclusions.

Second, the limitations of variable design. The variables in this study, such as DF and EO, are measured for the first time. Although this study fully considered the results of enterprise research, referred to previous relevant studies, and conducted reliability and validity tests during the variable design process, there are still some subjective limitations. Future research can further test and refine the scale to obtain more accurate and objective results.

Third, the limitations of theoretical exploration. DF may influence FGP in various ways. This paper discusses the mediating role of EO and II based on RBV. Future research can explore other perspectives for more in-depth discussion.

AUTHOR CONTRIBUTIONS

Pingping Lu: Conceptualization; research design; methodology; supervision; project administration. Bing Xia: Data collection; investigation; questionnaire administration/interview coordination. Wanting Deng: Formal analysis; data curation; statistical analysis; visualization; validation. Lucille Aba Abruquah: Literature review; theoretical framework development.

ACKNOWLEDGEMENTS

The authors would like to thank the participants and interviewees for their valuable contributions to this study. The authors also appreciate the constructive comments provided by anonymous reviewers and the editorial team.

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no commercial or financial relationships that could be construed as a potential conflict of interest.

DATA AVAILABILITY STATEMENT

The data generated and analyzed in this study are available from the corresponding author upon reasonable request. All data will be provided without undue restriction.

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