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Research on the Influence of Technological Innovation Capability of Enterprises on Financial Performance under Financial Intelligence

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Abstract

Based on the data of A-share listed companies in Shanghai and Shenzhen from 2017 to 2020, this paper empirically examines the impact of corporate technological innovation capability on financial performance under financial intelligence. It is found that technological innovation capability significantly improves financial performance, and performance increases by 7.07% for every 1% increase in R&D expenditure. Preceding financial performance forms a dynamic gain effect by driving innovation, and the intensity of the effect decreases to 2.97% after endogenous correction. Heterogeneity analysis shows that the effect of SOEs is weaker than that of non-SOEs (0.0611 vs 0.119), the effect is stronger in the East and West due to resource adaptation and policy tilt (0.102, 0.135), and the Northeast is not significant due to structural constraints. It is suggested that enterprises should strengthen R&D investment and data integration, optimize business-finance synergy and capital risk control based on intelligent technology, and formulate appropriate strategies based on regional and organizational differences. The conclusion provides theoretical and practical support for the transformation of corporate finance in the era of digital economy.

Keywords: financial intelligence, digital transformation, enterprise technology innovation

1. Introduction

Currently, the digital economy is developing rapidly under the support of government policies, and the digital transformation of enterprises has become a core issue in the industry and academic research. The flourishing of the digital economy has not only reshaped the business ecology, but also formed a significant impact on the traditional business model. In recent years, the application of artificial intelligence in the field of accounting and finance has been discussed in depth in the academic community. According to the “2021 China Enterprise Finance Intelligence Status Survey Report” [1], the development of intelligent finance in Chinese enterprises presents five major features: first, the popularity of the concept of intelligent finance is high, but the progress of construction and the depth of application are uneven. Second, enterprises pay more attention to the actual output effectiveness of accounting technology. Third, organizational synergy is still the core challenge of intelligent financial construction. Fourth, the intelligent transformation of finance urgently needs composite talents with both technical and business capabilities. Fifth, management's strategic support and resource investment is the key to successful transformation.

At present, the enterprise's financial intelligence is concentrated in the basic work and processes of financial personnel, and lacks decision-making, management, forecasting and other deep-level applications and intelligent considerations. Intelligent financial construction still requires management and organizational changes. By optimizing the organizational structure and enhancing the ability to collaborate and other measures to promote the virtuous cycle of intelligent finance [2]. In the past two years, the COVID-19 pandemic has promoted the implementation of the development of online business related to cloud concepts, but it still needs to further cultivate a new type of financial personnel with technical literacy as well as the construction of an effective enterprise intelligence platform [3]. In the future, intelligent finance is still a hot topic and one of the important innovative reform directions for enterprises. The financial intelligence construction of enterprises will be inseparable from their various business hubs. The use of data for modeling, analysis and forecasting, and management decision-making [4] is not only a technological engine for enterprises to break down old barriers, but also an important hand in the digital transformation of enterprises. With the help of digital and intelligent technology forecasting, financial intellectualization provides more basis for enterprise financial decision-making, realizes the transformation of finance from accounting to management [5], improves enterprise technological innovation ability, and helps enterprises to use the value of data and technological advantages to enhance their competitiveness in the industry.

Based on this, this paper firstly establishes a fixed-effects model using A-share listed companies in China's Shanghai and Shenzhen cities from 2017 to 2020 as the research sample to explore the linear relationship between enterprises' technological innovation capability and financial performance under financial intellectualization. Second, the instrumental variable method is used to discuss the endogeneity problem between the two, and then the robustness test is carried out by replacing the explanatory variables and shrinking the tail to ensure that the model can still obtain similar results under different settings and ensure the robustness of the model. Next, the heterogeneity analysis is carried out according to the organizational form of enterprises and the region where they are located. Finally, relevant suggestions are put forward from the perspectives of enhancing the technological innovation ability of enterprises and promoting the development of enterprises by utilizing intelligent technology, which help enterprises to have the ability of refinement in the aspects of operation analysis, budget management, and capital management.

2. Literature Review

2.1 Current Status of Research on Financial Intelligence in Enterprises

Currently, financial changes centered on artificial intelligence, big data, RPA and other technologies are accelerating the evolution. Traditional business intelligence (BI) relies on OLAP multi-dimensional presentation model has been difficult to meet the needs of dynamic management decision-making, enterprise financial intelligence gradually to big data-driven, intelligent and self-service direction of transformation, and is in the transition stage of the fusion of business intelligence and algorithmic models. Deanne Larson [6] pointed out that the agile approach and big data characteristics are reshaping the traditional BI project process. The degree of intelligence of enterprise financial information systems has increased significantly, and big data technology has built a more complete supply chain data ecosystem by integrating unstructured information such as network logs, sensor logs, and communication data, complementing traditional transaction data such as ERP and CRM. In this context, finance personnel need to rely on management information systems to realize automated decision-making (Şükrü Ada et al., 2015) [7] and strengthen the accuracy of short-term planning and long-term budgeting. Artificial intelligence and big data not only reconfigure the skills needs and thinking mode of financial personnel (Sun Rui, 2017) [8], but also give rise to a new form of digital workforce - human-machine collaboration needs to redefine the division of roles and responsibility boundaries. At the same time, blockchain technology promotes the "blockchain + finance" model as an important support for financial change by guaranteeing data security, traceability and efficient processing capabilities, helping enterprises output centralized and unified financial information. Zhang Chao (2020) [9] emphasized that financial intellectualization achieves the improvement of strategy execution efficiency and solves the problem of information lag and asymmetry through the financial sharing center. By correlating financial indicators and operational data, enterprises can optimize business innovation and management decisions, ultimately forming a data-driven collaborative ecology.

2.2 Current Status of Research on the Financial Performance of Enterprises' Technological Innovation Capability

Edwin Mansfield (1988) [10], by comparing the innovation practices of Japan and the United States, points out that there is a significant difference between the two countries in the cost of innovation, time and resource allocation methods, emphasizing the key role of external technology integration capabilities on innovation efficiency. Zhu Qingxiang et al. (2021) [11] focus on high-tech enterprises, empirical evidence shows that independent innovation capability significantly improves financial performance through value creation effect (the strength of the effect is higher than the investment risk), and suggests that enterprises strengthen R&D investment, optimize innovation strategy and attract technical talents. Zhu Hao et al. (2020) [12] further proposed that Logistic regression, BP neural network, deep learning and other technologies can deeply support financial analysis and forecasting, while RPA, OCR, NLP and other digital intelligence tools can significantly improve the efficiency of financial processing, and promote the transformation of automation of financial processes. With regard to blockchain technology, Chunliu Zhang (2021) [13] verified the positive correlation between its R&D investment and financial performance, and advocated that enterprises need to increase capital investment and optimize the structure of R&D teams to ensure the sustainability of technological innovation. Yang Huixian et al. (2021) [14] found that for energy enterprises, technological innovation inputs have a stronger effect on financial performance than outputs, and there is a significant threshold effect of enterprise size - smaller enterprises need to focus on improving innovation capabilities, while larger enterprises should optimize production and operation through innovation in order to achieve the benefits of transformation.

3. Theoretical Review and Research Hypotheses

3.1 Technological Innovation Capability of Enterprises and Their Financial Performance Under Financial Rationalization

Enterprise financial intellectualization relies on emerging technologies such as big data, artificial intelligence, mobile Internet, cloud computing, Internet of Things, blockchain, etc. In the context of digital economy reshaping business models, enterprises need to enhance their technological innovation capability through digital transformation and smart technology application to accelerate the process of financial intellectualization (Liu Qin et al., 2019, 2020) [15-17]. Endogenous growth theory suggests that financial intellectualization is driven by the internal development dynamics of enterprises, and scientific and technological innovation, as a core endogenous process, requires enterprises to strengthen their technological accumulation and integration capabilities (Zhao Weiliang and Zhang Hongjie, 2021) [18]. Financial intellectualization realizes efficient and standardized management by reconfiguring financial management concepts and models and embedding intelligent technology into financial processes (Yang Yin and Liu Qin, 2020) [19-20]. Empowered by technology, enterprises can deeply mine financial reports, vouchers and other data to analyze profitability and assess development space, and then optimize financial performance; big data, cloud computing and blockchain technology help optimize business processes and centralize resources, dynamically respond to market supply and demand, and reduce the risk of information asymmetry. Continuously increasing R&D investment and intensity help enterprises develop heterogeneous technologies and products, form core competitiveness and promote innovation output (Tong Ziqiang et al. 2021; Yang Jun et al. 2020; Zhao Xi et al. 2021) [21-23]. Based on this, this paper proposes the following hypotheses:

H1: Other things being equal, the technological innovation capability of firms under financial intellectualization has a positive impact on firms' financial performance.

3.2 Firms' Technological Innovation Capabilities and Their Size and Capacity Under Financial Rationalization

The development of enterprise financial intelligence relies on professional talents and capital investment, and its scale and foundation determine the direction of resource allocation. R&D investment needs to take into account two aspects: one is the training of talents, whose scientific research ability directly affects the transformation value of the results, and the human-computer synergy mode puts forward higher requirements on the compound knowledge and technology application ability of accounting personnel, and the lack of support will weaken the management's decision-making efficacy (Liu Qin, 2020) [24]; the second is the R&D or the introduction of technology, and technology-leading enterprises tend to be self-innovation, while follower-type enterprises focus on the introduction of technology (John R. Graham, 2005; Luo Kaming, 2006) [25-26]. John R. Graham, 2005; Luo Kamming, 2006) [25-26], but both need to gradually integrate with the industrial structure and face time cost and risk of failure. Technology upgrading needs to be matched with the stability of the firm's financial chain (e.g., operating and solvency), which is ultimately mapped to financial performance. In addition, the technological path, application scenarios, and resource requirements of financial intellectualization are differentiated due to the differences in corporate environments and objectives (Robert J. Shiller et al., 2003-2020) [27-33]. Based on this, this paper proposes the following hypotheses:

H2: The impact of firms' technological innovation capabilities on firms' financial performance under financial intelligence can vary depending on firm size and capabilities.

3.3 Technological Innovation Capability of Enterprises and Their Organizational Forms under Financial Intelligence

The process of enterprise financial intelligence is influenced by both governance strategies and organizational forms. Different enterprises face differentiated macroeconomic conditions, investment subject characteristics and development goals due to differences in competitive markets, technological mutations and regulatory environments. There is a significant difference between SOEs and non-SOEs in terms of technological innovation and R&D investment management mode (Zhao Tianyu et al., 2020)[34]: SOEs are controlled by a single state-owned shareholder, which is relatively less innovative and has greater resistance to expanding into the international market, but the advantage of its resource endowment can alleviate the restriction of financing constraints on the investment in innovation (Di Lingyu and Bu Danlu, 2021)[35]. Based on this, this paper proposes the following hypotheses:

H3: The impact of firms' technological innovation capabilities on firms' financial performance under financial intellectualization can be heterogeneous depending on the organizational form of the firm.

3.4 Technological Innovation Capacity of Firms and Their Locations under Financial Intelligence

The benefits of enterprise financial intellectualization are significantly affected by the external environment, and differences in regional technological environments, industry competition, and economic levels lead to utility differentiation of the same R&D investment. Regions with developed economy and high-quality educational resources are more likely to meet the demand for high-quality talents for enterprise financial intellectualization, thus enhancing the match between the technological environment and strategy (Yao Lu et al., 2019; Lu Tingting, 2021) [36-37]. Inter-regional human resource differences directly affect the efficiency of the enterprise's technological innovation ability, which ultimately plays a role in the degree of improvement of financial performance.

H4: The impact of firms' technological innovation capability on firms' financial performance under financial intelligence can be heterogeneous depending on the location of the firm.

4. Research Design

4.1 Data Sources and Variable Definitions

Deloitte and Kira Systems launched “Xiao Qinren” in 2017, marking China's entry into the stage of accounting intelligence. Nowadays, the concept of enterprise smart finance has been widely popularized but the construction progress and application degree are uneven, therefore, this paper selects A-share listed companies in China's Shanghai and Shenzhen cities from 2017 to 2020 as a research sample to establish a fixed effect model to explore the impact of enterprise technology innovation ability on enterprise financial performance under financial intelligence.

This paper takes the financial performance of enterprises as the dependent Variable to explore the impact of technological innovation capability under financial intellectualization. Earnings per share (EPS) is selected as the main variable, reflecting the enterprise's operating results and profitability, and the problem of heteroskedasticity is mitigated by taking the logarithm (lnEPS); the robustness test adopts the rate of return on assets (ROA), and the same logarithm is taken to ensure the reliability of the results (lnROA).

Technological innovation capability is the core independent Variable, and research and development expenditure (RD) is used as a proxy. Referring to the studies of Jaffe et al. (1995) [38-39] and Dongmin Zhang et al. (2021) [40], this paper adopts firms' R&D expenditures to characterize innovation capability, and takes the logarithm (lnRD) to mitigate heteroskedasticity and analyze its driving effect on financial performance.

In order to control other potential influencing factors, this paper selects control variables based on enterprise cost and scale dimensions, see Table 1. including enterprise size (log of total assets), gearing ratio, operating cash flow, etc., in order to strip external interference and ensure the net effect of the relationship between technological innovation capability and financial performance.

Table 1. List of variables

Variable type	Variable name	Variable description
Dependent Variable	EPS	Earnings per share, which is used to represent the financial performance of the firm, taken in logarithms
	ROA	Return on assets, which is used as a proxy for EPS for robustness tests, is taken to be logarithmic
Independent Variable	RD	R&D expenditures, to represent the firm's technological innovation capacity, taken in logarithms
Control variable	overhead	Overheads, to represent the expenditure on corporate overheads, taken in logarithms
	salary	Compensation per employee, which represents the cost of labor for the firm, logarithmic.
	cost	Total operating costs, to represent the operating costs of the business, taken in logarithms
	size	Total assets, to represent the size of the enterprise, taken in logarithms
	growth	The year-on-year growth rate of gross operating income, which represents the growth capacity of the enterprise

Z	Z-value to represent the magnitude of the financial risk of the enterprise
LEV	Gearing ratio, which represents the capital structure of a company
CR	Current ratio, which represents the solvency of the enterprise
TAT	Total asset turnover, which represents the operating capacity of the enterprise
form	Form of organization, dummy variable assignment, state-owned enterprises = 1, non-state-owned enterprises = 0
year	Time dummy variable indicating period t
province	Region, dummy variable assignment, East = 1, Center = 2, West = 3, Northeast = 4

4.2 Model Construction

In order to study the influence of enterprise's technological innovation ability on enterprise's financial performance under financial intellectualization, this paper sets the fixed effect model as follows:

$$lnEPS_{it}=\alpha_0+\alpha lnRD_{it}+\sum_{m=1}^{m=n}\beta^m Z_{it}^m+\gamma^t I_i+\gamma^t T_i+\varepsilon_{it} \ (1)$$

Where i denotes each firm in the sample, $lnEPS_{it}$ denotes the financial performance of firm i in period t, $lnRD_{it}$ denotes the technological innovation capability of firm i in period t, Z_{it}^m denotes the total of all control variables, I_i is the regional dummy variable, T_i is the temporal dummy variable, ε_{it} is the stochastic perturbation term, and α、β、γ^t are the coefficients of the corresponding explanatory variables. coefficients of the variables, and α_0 is the constant term. This paper focuses on the coefficient α of the core explanatory variable, enterprise technological innovation capability $lnRD_{it}$.

4.3 Descriptive Statistics

The sample of this paper is set as the financial report data of China's A-share listed companies in Shanghai and Shenzhen from 2017 to 2020, and the descriptive statistics of the main variables are shown in Table 2.

Table 2. Descriptive statistics

Variables	Sample size	Mean value	Standard deviation	Maximum	Minimum
lnEPS	16833	-1.008	1.203	-6.502	3.707
lnRD	16517	3.979	1.493	-6.096	10.288
lnsalary	18840	2.604	0.495	0.077	5.33
lnoverhead	18876	0.156	1.408	-3.738	7.596
lncost	18876	2.771	1.575	-4.519	10.271
lnsize	18877	3.556	1.638	-2.008	12.717
growth	18892	24.448	325.432	-130.916	26375.477
Z	18892	5.688	12.252	-522.737	467.547
LEV	18892	43.895	134.005	0	17834.547
CR	18892	2.505	2.909	0	80.664
TAT	18892	0.695	0.563	-0.048	11.975
lnROA	16974	1.596	1.064	-5.045	6.107
form	18892	0.263	0.44	0	1
year	18892	2.5	1.118	1	4
province	18892	1.477	0.838	1	4

5. Empirical Analysis and Testing

5.1 Regression to the Base Line

Table 3. Regression results

	Mixed regression	Within-group estimates	Fixed effect	Intergroup estimates	Stochastic effect
lnRD	0.150***	0.0707***	0.0707***	0.142***	0.142***
	(10.16)	(3.17)	(4.59)	(9.98)	(13.92)
lnoverhead	-0.0784**	0.215***	0.215***	0.00294	0.00294
	(-2.90)	(7.07)	(9.97)	(0.14)	(0.17)
lnsalary	0.281***	0.0651	0.0651*	0.266***	0.266***
	(7.59)	(1.18)	(1.67)	(7.78)	(9.77)
lncost	0.342***	0.194*	0.194***	0.437***	0.437***
	(3.47)	(1.96)	(4.62)	(4.65)	(13.95)
lnsize	0.301***	0.557***	0.557***	0.446***	0.446***
	(3.18)	(5.72)	(15.20)	(4.71)	(15.16)
growth	0.00000291	0.000362*	0.000362***	0.000159	0.000159***
	(0.02)	(1.78)	(5.43)	(0.94)	(3.37)
Z	0.00350	0.00404***	0.00404***	0.00534***	0.00534***
	(1.56)	(3.50)	(4.81)	(3.50)	(6.69)
CR	0.000158	0.0122	0.0122**	0.00814	0.00814**
	(0.02)	(1.46)	(2.73)	(0.91)	(1.97)
LEV	0.00682***	0.00768**	0.00768***	0.00811***	0.00811***
	(4.79)	(2.16)	(11.60)	(2.73)	(14.20)
TAT	0.890***	1.036***	1.036***	1.082***	1.082***
	(5.78)	(5.96)	(24.22)	(6.62)	(31.11)
_cons	2.798***	3.297***	3.297***	3.111***	3.111***
	(14.72)	(14.53)	(29.96)	(15.96)	(35.01)
N	14774	14774	14774	14774	14774

Note：*** p<0.01, ** p<0.05, * p<0.1, same as below

The regression results are shown in Table 3, with the first row of data for the variables showing the corresponding coefficients and the size of the t-value below. The results show that lnRD is always significant at the 1% significance level, and the coefficients are 0.150, 0.0707, 0.0707, 0.142, 0.142, respectively, which is a stable result. In the fixed effect model, the coefficient of lnRD is 0.0707, which indicates that under other conditions unchanged, the technological innovation capacity of enterprises under financial intelligence has a positive impact on the financial performance of enterprises, and every 1% increase in the technological innovation capacity of enterprises can improve the financial performance of enterprises by 7.07%, which is consistent with the research hypothesis.

5.2 Endogeneity Test

In order to mitigate the endogeneity problem caused by the inverse effect of antecedent financial performance on technological innovation, this paper introduces the lagged one-period financial performance as an instrumental variable, which is estimated using the two-stage least squares (2SLS) method and supplemented with LIML and GMM methods to enhance the robustness. The results show that after controlling for endogeneity, the lnRD coefficient is reduced from the initial overestimation to 0.0297 (see Table 4), indicating that for every 1% increase in the firm's technological innovation capability, the financial performance grows by 2.97%, and the results converge to be reasonable. In the instrumental variable validity test, the F-statistic (2832.210>10) excludes the risk of weak instrumental variables; the DWH test (p<0.05) confirms that L.lnEPS is endogenous and the model setting is reliable.

Table 4. Endogeneity test

	2SLS	LIML	GMM
L.lnEPS	0.847***	0.847***	0.853***
	(53.03)	(52.93)	(53.90)
lnRD	0.0297***	0.0297***	0.0261***
	(2.95)	(2.95)	(2.59)
lnoverhead	0.0494**	0.0494**	0.0440**
	(2.31)	(2.31)	(2.07)
lnsalary	0.0543**	0.0543**	0.0548**
	(1.99)	(1.99)	(1.98)
lncost	-0.0903**	-0.0902**	-0.0685
	(-2.05)	(-2.05)	(-1.59)
lnsize	0.0326	0.0326	0.0204
	(0.84)	(0.84)	(0.53)
growth	0.00673***	0.00673***	0.00719***
	(8.76)	(8.76)	(8.68)
Z	0.00114**	0.00114**	0.00102*
	(2.07)	(2.07)	(1.82)
CR	-0.00540	-0.00541	-0.00481
	(-1.30)	(-1.30)	(-1.16)
LEV	0.0000778	0.0000784	-0.000293
	(0.09)	(0.09)	(-0.32)
TAT	0.236***	0.236***	0.212***
	(3.68)	(3.68)	(3.38)
_cons	-0.457***	-0.456***	-0.432***
	(-3.98)	(-3.98)	(-3.79)

5.3 Robustness Check

In order to verify the reliability of the findings, this paper tests them in two ways: one, by replacing the explanatory variable with return on assets (lnROA), denoted as “FE_ROA”; and two, by shrinking the extreme values by 1%, denoted as “FE_winsor “. As shown in Table 5, the coefficients of lnRD under both methods are significant at the 1% level, and the direction is consistent with the main regression, indicating that the promotion effect of technological innovation capability on financial performance is parameter insensitive and the results are robust.

Table 5. Robustness check

	FE_ROA	FE_winsor
lnRD	0.0513***	0.0923***
	(3.52)	(5.82)
lnoverhead	0.139***	0.168***
	(6.87)	(8.08)
lnsalary	0.363***	0.0551
	(10.09)	(1.44)

lncost	-0.242***	-0.385***
	(-6.04)	(-9.16)
lnsize	0.0284	0.715***
	(0.82)	(19.10)
growth	0.000360***	0.00297***
	(5.74)	(14.57)
Z	0.00390***	0.00602***
	(4.70)	(4.34)
CR	-0.0205***	-0.0243***
	(-4.76)	(-3.72)
LEV	-0.00753***	-0.0149***
	(-12.15)	(-16.43)
TAT	1.103***	1.290***
	(27.55)	(25.11)
_cons	0.581***	-3.297***
	(5.61)	(-29.71)
N	14884	14774

5.4 Heterogeneity Analysis

5.4.1 Heterogeneity Due to Differences in Organizational Forms

In order to test the moderating effect of the form of enterprise organization on the relationship between technological innovation and financial performance, the regression results of this paper's grouping show (see Table 6): the lnRD coefficients of SOEs and non-SOEs are 0.0611 and 0.119, respectively, which both pass the 1% significance test, but the effect of non-SOEs is more intense. The difference is attributed to two points: first, SOEs are constrained by international market access resistance and multiple social goal constraints, which limit the efficiency of innovation transformation; second, non-SOEs are more focused on innovation-driven profit growth by virtue of their market-based flexibility, which releases the technological dividend more fully. The results suggest that the positive effect of technological innovation on financial performance is universal, despite the differentiation in the intensity of the effect due to organizational form.

5.4.2 Heterogeneity Due to Regional Differences

The group regression results show (Table 7) that there are significant regional differences in the promotion effect of enterprise technological innovation capability on financial performance: the coefficients of the eastern, central and western enterprises are 0.102, 0.057 and 0.135 respectively, which have passed the significance test (the northeast region is not significant), and the western effect is the strongest. The causes can be categorized as follows: the east relies on high-quality human resources and smart technology suitability, and the technology dividend is fully released; the west benefits from the heterogeneous environment policy tilt, and the innovation transformation efficiency is improved; the northeast is limited by the resource structure or institutional bottlenecks, and the technology-driven path is hindered. The conclusion suggests that regional endowment and policy environment are the key moderating variables in the differentiation of technological innovation effectiveness.

Table 6. Heterogeneity analysis

	Nationalized business	Non-state enterprise	East	Central	West	North East
lnRD	0.0611***	0.119***	0.119***	0.089*	0.123***	0.093
	(2.62)	(5.42)	(5.81)	(1.89)	(3.23)	(1.36)
lnoverhead	0.187***	0.162***	0.127***	0.068	0.138**	0.597***
	(4.06)	(6.91)	(5.70)	(1.26)	(2.04)	(4.61)

lnsalary	0.180**	0.0391	0.076*	-0.061	0.19	-0.476**
	(2.15)	(0.90)	(1.82)	(-0.56)	(1.59)	(-2.24)
lncost	-0.298***	-0.418***	-0.36***	-0.162	-0.393***	-0.823***
	(-3.24)	(-8.77)	(-8.19)	(-1.43)	(-3.83)	(-3.66)
lnsize	0.549***	0.755***	0.625***	0.587***	0.585***	0.685***
	(6.09)	(18.11)	(15.93)	(6.19)	(5.69)	(3.88)
growth	0.00384***	0.00270***	0.004***	0.004***	0.004***	0.005***
	(7.48)	(11.99)	(12.87)	(5.73)	(5.04)	(3.44)
Z	0.0136**	0.00554***	0.013***	0.005	0.013*	0.018
	(2.44)	(3.85)	(5.70)	(0.78)	(1.95)	(1.33)
CR	-0.0214	-0.0245***	-0.019*	0.037	0.024	-0.014
	(-0.98)	(-3.56)	(-1.93)	(1.44)	(0.84)	(-0.27)
LEV	-0.0108***	-0.0154***	-0.014***	-0.011***	-0.002	0.001
	(-4.49)	(-15.70)	(-13.41)	(-4.05)	(-0.58)	(0.09)
TAT	0.923***	1.407***	1.393***	1.52***	1.468***	1.772***
	(8.30)	(24.06)	(23.06)	(9.69)	(8.74)	(4.77)
_cons	-3.803***	-3.245***	-3.259***	-3.637***	-4.245***	-2.156***
	(-14.29)	(-25.58)	(-25.74)	(-12.24)	(-11.79)	(-3.49)
N	3396	11378	10786	1943	1570	463

6. Conclusions and Responses

6.1 Conclusions

Based on the data of A-share listed companies in Shanghai and Shenzhen from 2017 to 2020, this paper adopts the fixed effect model to test the impact of enterprises' technological innovation ability on financial performance under financial intellectualization. It is found that (1) the enhancement of technological innovation capability significantly improves financial performance. (2) Preceding financial performance generates dynamic circular effects by driving technological innovation. (3) Organizational and regional differences lead to heterogeneity: the effect of SOEs is weaker than that of non-SOEs (coefficients 0.0611 vs. 0.119), and the effect of SOEs is significantly stronger in the east and west (coefficients 0.102, 0.135) than in the center and northeast. Therefore, enterprises need to break through the bottleneck of financial and intellectual transformation through technological innovation, organizational adaptation, regional synergy and talent reserves, and reshape their competitiveness with data and intelligence as the core.

6.2 Countermeasures and Recommendations

6.2.1 Enhancement of Technological Innovation Capacity of Enterprises

Driven by both policy and market, enterprises need to realize financial transformation through technological innovation and smart technology application. At the policy level, enterprises should actively utilize government subsidies and regional resource tilting, adapt to the requirements of a heterogeneous environment, respond to the ethical and structural challenges triggered by smart technologies through business model innovation, and deeply integrate internal and external data resources to enhance R&D efficiency. At the market level, it is necessary to reconstruct the business model based on customer value, develop differentiated products and services, and balance the market thrust and resistance with the characteristics of the organizational form to build a sustainable competitive advantage.

6.2.2 Leveraging Smart Technology for Business Development

The application of intelligent technology needs to focus on the reconstruction of business scenarios: build an integrated platform for business and finance through IoT, RPA and other technologies, unify data standards and processes, and realize the synergistic control and management of capital flow and business flow; build a multi-dimensional budget management system, embed strategic objectives into the dynamic monitoring and resource allocation model, and strengthen the mathematical modeling ability to support accurate decision-making; build an intelligent fund management system, and realize visual traceability and centralized scheduling and risk early warning closed loop of fund flow. The establishment of an intelligent capital management system realizes the visualization of capital flow traceability, centralized scheduling and closed loop risk warning. The essence of technological empowerment is to promote the in-depth integration of business, finance and management processes, form a data-driven operation ecology, and ultimately realize the systematic upgrading of the enterprise value chain through the adaptive deployment of the “Big Intelligence, Mobile, Cloud, and Material Area” technological architecture.

Combined with the application value of enterprise financial intelligence, the intelligent application architecture of the enterprise under financial intelligence is constructed. As shown in Figure 1, the four major segments of business system, financial system, budget management, and fund management are combined in series to form the application architecture.

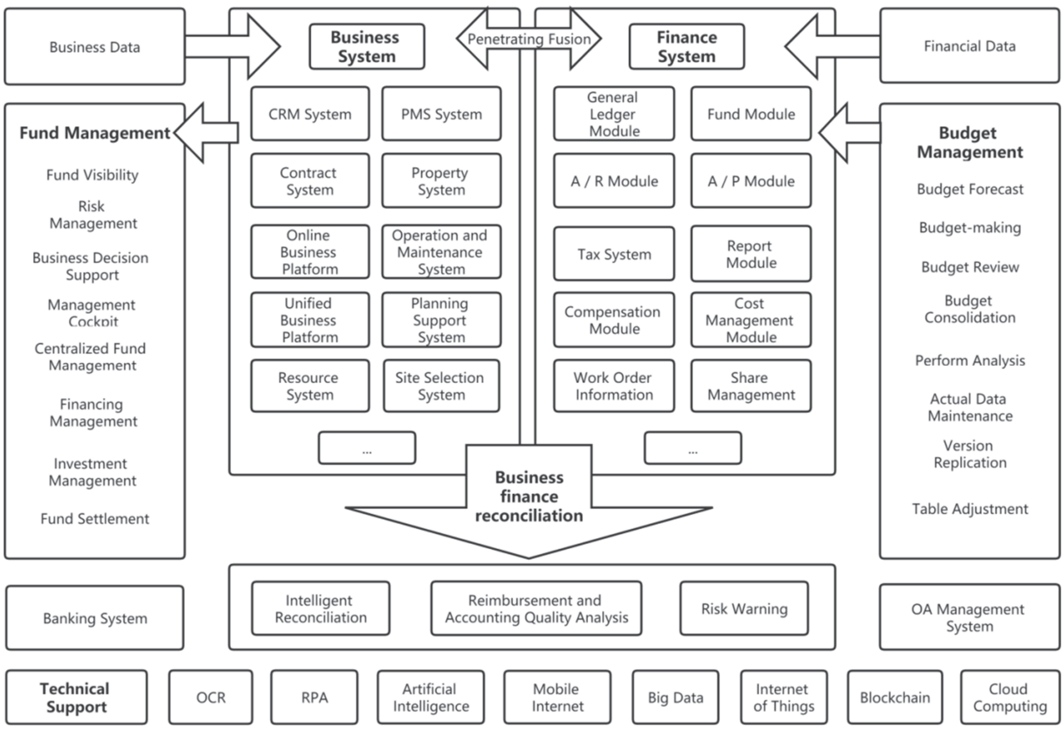

Figure 1. Enterprise Intelligent Application Architecture under the Financial Intelligence

Enterprises realize two-way communication between business and financial data through intelligent technology. The business details are synchronized and mapped to financial accounts, and reconciliation and quality analysis are completed within a unified platform to ensure that the data are homogenous and rules are embedded. Based on big data technology, the system automatically extracts budget data, builds dynamic quantitative models, simulates operating trends with business characteristics and market variables, and supports forward-looking decision-making. At the level of fund management, relying on direct linkage between banks and enterprises and RPA robots, the system realizes centralized monitoring of accounts, real-time feedback of positions and automated processing of transactions; it also builds a digital financing platform, integrates credit management and internal and external financing processes, and forms a closed loop of fund scheduling and risk early warning, thus enhancing the efficiency and transparency of treasury operations.

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