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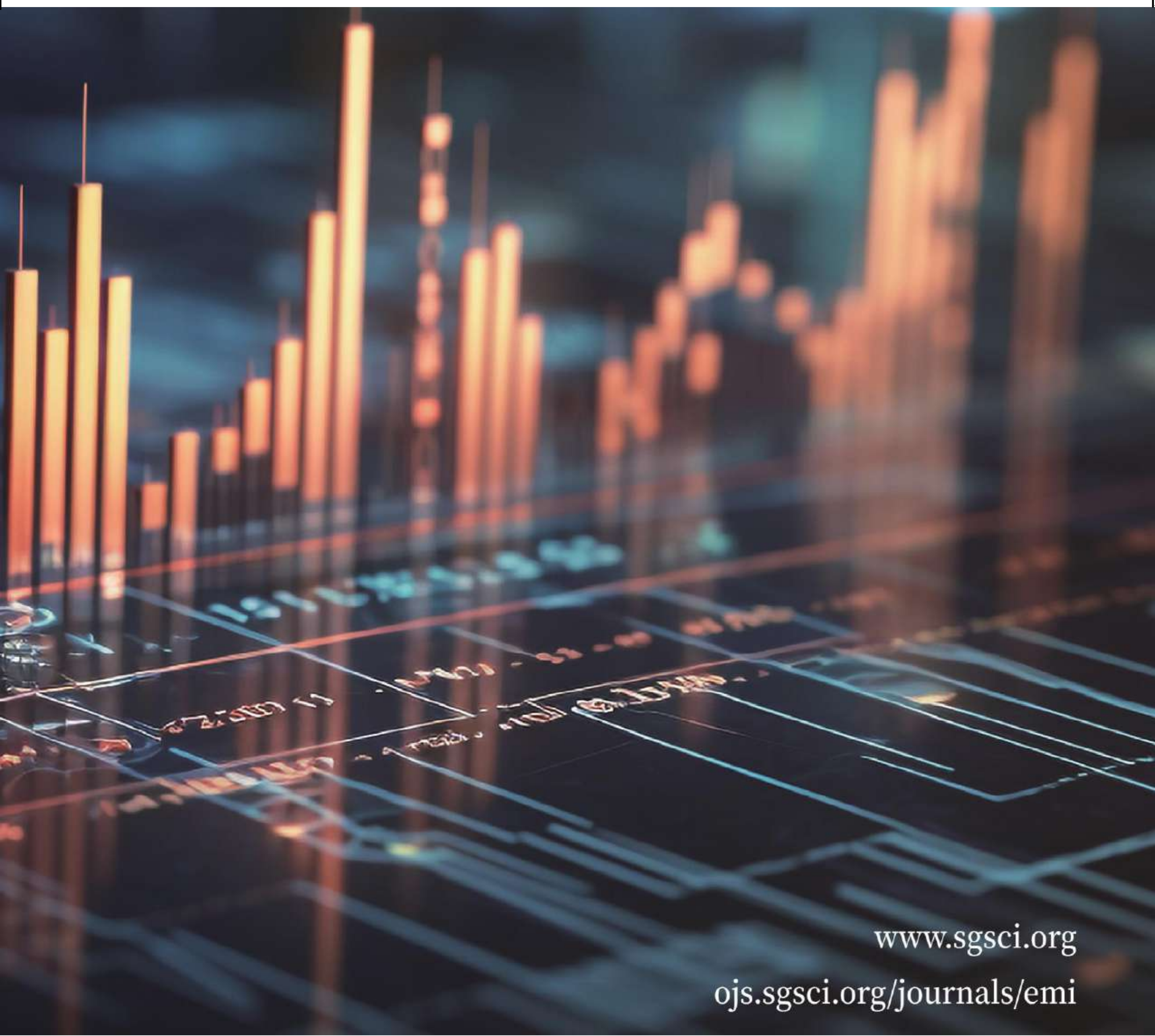

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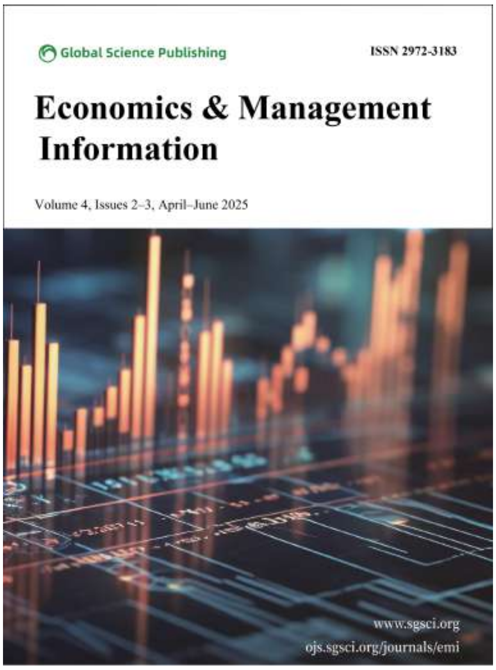

Aims & Scope

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Article

Analysis of the Impact of Financial Technology on Capital Allocation Efficiency—Empirical Evidence from Chinese A-Share Listed Companies

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Abstract: Improving the efficiency of corporate capital allocation is the microfoundation for promoting high-quality economic development. Starting from the Cobb-Douglas production function, this paper constructs a theoretical model of the impact of finance technology on capital allocation efficiency. Based on this, an empirical test of the impact and mechanism of financial technology on capital allocation efficiency is conducted using data from Chinese A-share listed companies from 2008 to 2023. The research indicates that: (I) The improvement of financial technology levels could significantly reduce the deviation of capital allocation from the ideal state and improve capital allocation efficiency; (II) Financial technology could enhance corporate governance levels, thereby improving the efficiency of corporate capital allocation; (III) The enhancement of financial technology levels could restrain excessive investment and underinvestment behaviors in enterprises, promoting the improvement of capital allocation efficiency; (IV) The higher the level of financial technology is, the more significant effect on improving capital allocation efficiency would be.

Keywords: financial technology; capital allocation efficiency; development of the real economy

1. Introduction

With the arrival of the digital economy era, fully utilizing the function of financial technology in optimizing resource allocation is not only an important measure for China to comprehensively deepen reform and promote Chinese-style modernization, but also a key point for breaking the bottlenecks in factor flow and unblocking the economic cycle. In 2016, the Financial Stability Board (FSB) defined "financial technology" as "technology-driven financial innovation that could create new business models, applications, processes or products, thus having a significant impact on financial markets, financial institutions and the provision of financial services". (Financial Stability Board (FSB): "A Descriptive and Analytical Framework for Fintech", March 2016). On this basis, the People's Bank of China pointed out that "financial technology is technology-driven financial innovation, aiming to use modern scientific and technological achievements to transform or innovate financial products, business models, business processes, etc." and emphasized the important role of financial technology in enhancing the service of financial institutions to the real economy in the "Development Plan for Financial Technology (2022–2025)". Generally speaking, the essence of financial technology lies in innovation. According to the theory of "creative destruction" by the famous economist Joseph Schumpeter, the development of financial technology would promote economic structural transformation and achieve economic growth. As the

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micro-carrier of the development of the real economy, would enterprises be affected by the level of financial technology? Would the improvement of financial technology levels help enterprises optimize resource allocation and improve the efficiency of capital allocation? What is its mechanism of action? Answering this question has important theoretical significance for further enhancing the ability of financial institutions to serve the real economy; at the same time, it has important practical significance for enterprises to improve the efficiency of capital allocation, optimize resource allocation, and promote the process of high-quality economic development.

Based on this, this paper starts from a micro perspective, taking Chinese A-share listed companies from 2008 to 2023 as the research sample, systematically analyzes the theoretical analysis of the impact of financial technology on capital allocation efficiency, and empirically tests the impact and mechanism of financial technology on capital allocation efficiency through the construction of a econometric model.

The rest of this paper is structured as follows: The second part reviews the relevant literature, clarifying the innovation points of this study; the third part constructs a theoretical analysis framework of the impact of financial technology on capital allocation efficiency; the fourth part constructs an econometric model to empirically test the impact of financial technology on capital allocation efficiency; the fifth part further explores the mechanism of action and heterogeneity of the impact of financial technology on capital allocation efficiency; the sixth part is the conclusion and enlightenment.

2. Literature Review

Microeconomic theory shows that capital plays an important role in the production behavior of enterprises. Under the socialist market economic system, capital is still the link that drives the optimal allocation of various production factors (Sun Fangcheng, 2023) [1]. Microeconomics believes that under ideal conditions, capital allocation could achieve Pareto optimality in a perfectly competitive market. However, in reality, capital is subject to various factors and there is misallocation. The key to correcting capital misallocation lies in improving the efficiency of capital allocation.

From the perspective of the connotation of capital allocation efficiency, some scholars believe that capital allocation includes the whole process of capital input to output, and the level of capital allocation efficiency lies in the input-output ratio (Guo Jitao, 2023 [2]; Cai Zhen, 2023 [3]), which is a broad concept. There are also some scholars who believe that the capital allocation process only targets the capital input link, which is essentially the effectiveness of investment decisions, that is, whether capital could be allocated from low-return departments to high-return departments (Chen Taoqin, 2023 [4]; Hao Ying, 2022 [5]), which is the narrow concept of capital allocation efficiency. Correspondingly, the academic community has also produced different measurement methods of capital allocation efficiency. From the broad concept, scholars such as Li Qinyang (2023) [6] and Qin Jiaqi (2015) [7] use input-output efficiency as the capital allocation efficiency of enterprises; Cai Zhen (2023) [3] and Qi Huaijin (2019) [8] consider the cost of corporate financing, and measure the capital allocation efficiency of enterprises by the ratio of enterprise investment return to capital cost rate. From the narrow concept, scholars mostly use the non-efficiency investment model of Richardson (2006) [9] to measure the deviation between the actual investment level and the ideal state of enterprise investment behavior through model fitting, which is used as the measurement index of enterprise capital allocation efficiency.

As a derivative product of the combination of traditional finance and modern technology, financial technology plays an important role in the operation of enterprises. Most studies show that the progress of financial technology could improve the way of information production and dissemination (Daud et al., 2022) [10], reduce the cost of obtaining information, and effectively alleviate the problem of information asymmetry (Zhou et al., 2024) [11]. Moreover, financial technology could broaden financing channels, reduce borrowing costs (Jagtiani and Lemieux, 2019 [12]), alleviate financing constraints, and improve enterprise competitiveness (Yuan et al., 2024 [13]; Tang et al., 2023 [14]). In terms of the relationship between financial technology and capital allocation efficiency, there is no consensus in the academic community yet. Representative research results include: Lan (2024) [15] conducted research from the perspective of Chinese prefecture-level cities and found that there is an inverted “U” shape between the level of financial technology and capital misallocation. The degree of capital misallocation would first increase and then decrease with the improvement of the level of financial technology development, accompanied by siphon effect and spatial spillover effect with different levels of financial technology development. Song Min (2021) [16] found through research that small and medium-sized enterprises and weak competitive markets benefit more from the development of financial technology. In this regard, Xie et al. (2022) [17] speculated that financial technology would allocate capital to low-efficiency departments. Based on the data of Chinese enterprises, they found that the development of financial technology would reduce the available capital of high-efficiency companies, and explained it as the impact of loan market competition and the inclusiveness of financial technology, which is contrary to the above research conclusions.

In summary, the relevant research on capital allocation efficiency in the academic community is relatively mature at present, but the relationship between financial technology and capital allocation efficiency still needs to be further clarified. Therefore, this paper would enrich the relevant literature from the following aspects: (1) Construct a theoretical framework of the impact of financial technology on capital allocation efficiency, and explain the relationship between the two from the perspective of mathematics and economics; (2) Starting from the micro perspective, take Chinese A-share listed companies as the research sample, measure the capital allocation efficiency of enterprises, construct an econometric model, and deeply analyze the impact effect and mechanism of financial technology on capital allocation efficiency from the overall perspective and the heterogeneity perspective, providing empirical support for improving the efficiency of enterprise capital allocation.

3. Theoretical Analysis of the Impact of Financial Technology on Capital Allocation Efficiency

(I) Defining the Connotation of Capital Allocation Efficiency

Microeconomic theory indicates that under perfect competition market conditions, resource allocation could reach a Pareto optimal state and achieve optimal resource allocation. However, perfect competition is only an ideal state of economic operation. In the actual process of economic operation, various economic factors interfere, causing the market to always be in an imperfectly competitive state, which leads to the deviation of the resource allocation state from the Pareto optimal state. Capital, as a key resource in the economic operation process, would also deviate from the optimal allocation state when it is in an imperfectly competitive market state. Based on this, this paper defines the efficiency of capital allocation as the deviation between the actual allocation state of capital and its optimal allocation state, and the process of improving the efficiency of capital allocation is the process of reducing the deviation between capital allocation and the ideal state.

(II) Theoretical Foundation of the Impact of Financial Technology Innovation on Capital Allocation Efficiency

The theoretical impact of financial technology on capital allocation efficiency could be proven by the following mathematical relationship. Assume that enterprises produce with Cobb-Douglas production function, denoted as model (1):

$$Y = A \cdot K^{\alpha} \cdot L^{\beta} \tag{1}$$

In model (1), Y represents the output level of the enterprise, A represents the level of technology, K and L represent capital and labor input, and α and β represent the output elasticity of capital and labor, respectively.

The efficiency of capital allocation could be defined as the equilibrium distribution of marginal output of capital among different enterprises. Financial technology innovation may cause capital to flow from enterprises with low marginal output to enterprises with high marginal output.

According to model (1), the marginal output of capital could be obtained, denoted as model (2):

$$MPK = \alpha \cdot AK^{\alpha-1} \cdot L^{\beta} \tag{2}$$

Financial technology innovation may affect the level of technology (A). Therefore, the factor of financial technology F is introduced into model (1), and the output level of the enterprise could be obtained as model (3):

$$Y = \left(A + \gamma \cdot F\right) \cdot K^{\alpha} \cdot L^{\beta} \tag{3}$$

In model (2), γ represents the marginal impact of financial technology on the level of technology. Based on model (3), the marginal output of capital could be further obtained, denoted as model (4):

$$MPK = \alpha \cdot (A + \gamma \cdot F) K^{\alpha - 1} \cdot L^{\beta} \tag{4}$$

This establishes that the level of financial technology would impact the efficiency of capital allocation in enterprises. From the perspective of microeconomic theory, the essence of financial technology lies in technological progress driving financial innovation. With the arrival of the digital economy and digital civilization era, innovation is the endogenous driving force of economic growth, and an important means for enterprises to optimize resource allocation. Specifically, the theoretical mechanism of the impact of the level of financial technology on the efficiency of capital allocation in enterprises lies in: (1) the improvement of the level of financial technology could drive financial innovation, create financial supply, provide enterprises with more space and more convenient channels for financing, improve the liquidity of capital, optimize capital allocation, and promote enterprises to improve the efficiency of capital allocation (Li Wenfang and Hu Qiuyang, 2024 [18]; Liu Huihao et al., 2024 [19]); (2) the improvement of the level of financial technology could promote the continuous development and improvement of the capital market, promote the orderly flow of capital among enterprises, and thus improve the efficiency of capital allocation in enterprises (Yang Dong, 2018 [20]; Hu Yunfei, 2024 [21]). Furthermore, as financial technology continues to develop, the institutional system of the Chinese capital market would also become increasingly complete. On the one hand, a sound capital market would force enterprises to constantly improve their corporate governance mechanisms; on the other hand, enterprises would also continuously improve their corporate governance level and competitiveness in pursuit of profit maximization. Based on this, this paper proposes a theoretical hypothesis, that is, "the improvement of the level of financial technology promotes the improvement of the level of enterprise governance, and thus improves the efficiency of capital allocation."

4. Research Design

Theoretical analysis shows that the improvement of the level of financial technology innovation could effectively improve the efficiency of capital allocation in enterprises. To more accurately identify this relationship, this section uses an econometric model to empirically test this logical relationship.

(I) Model Construction

According to the research content, this paper constructs the following econometric model to analyze the impact of financial technology innovation on the efficiency of capital allocation:

$$Einv_{i,t} = \alpha_0 + \alpha_1 FinTech_{i,t} + \sum_j \delta_j Controls_{j,i,t} + \eta_{ind} + \eta_{year} + \varepsilon_{i,t} \tag{5}$$

In model (5), *Einv* represents the efficiency of enterprise capital allocation, *FinTech* represents the financial technology index; *Controls* are control variables, η_{ind} and η_{year} represent fixed industry and time fixed effects, respectively, and $\varepsilon_{i,t}$ is the random error term, where *i* refers to the enterprises involved in this study that are listed on the Chinese A-share market, and t = 2008, 2009, ..., 2023.

1. Explained Variable: Enterprise Capital Allocation Efficiency (*Einv*). This paper refers to the methods of scholars such as Richardson (2006) [9], Liu Guang (2023) [22], and Zhang Anjun (2022) [23], and uses an improved expected investment model to measure the difference between actual capital expenditure and optimal investment expenditure as a proxy variable for measuring enterprise capital allocation efficiency. The measurement formula is denoted as model (6):

$$\begin{aligned} Invest_{i,t} &= \beta_1 + \beta_1 Growth_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Lev_{i,t-1} + \beta_1 Cash_{i,t-1} + \beta_5 Age_{i,t-1} \\ &+ \beta_6 Returng_{i,t-1} + \beta_7 Invest_{i,t-1} + \eta_{ind} + \eta_{year} + \varepsilon_{i,t} \end{aligned} \tag{6}$$

In model (6), *Invest* represents the ratio of a company's new investment expenditure to total assets, where new investment expenditure = total investment – maintenance investment = cash paid for the purchase, construction, or other long-term assets + net cash paid for the acquisition of subsidiaries and other business units – net cash received from the disposal of fixed assets, intangible assets, and other long-term assets – net cash received from the disposal of subsidiaries and other business units – (depreciation of fixed assets + amortization of intangible assets + amortization of long-term deferred expenses). *Growth* represents the growth opportunities of the company, measured by the Tobin's Q value. Size represents the scale of the enterprise, measured by the logarithm of total assets. *Lev* represents the financial leverage of the enterprise, measured by the debt-to-assets ratio. *Cash* represents the scale of cash flow, measured by the ratio of cash flow to total assets. *Age* represents the years of listing, measured by the logarithm of "current year – year of listing + 1". *Returng* represents the stock return rate, measured by "(current market value of stocks – previous market value of stocks) / previous market value of stocks". η_{ind} and η_{year} represent fixed industry and time effects, respectively, and $\varepsilon_{i,t}$ is the random error term.

The residuals from an OLS regression of model (6) are taken, and the absolute value of the residuals represents the deviation of the actual capital expenditure of the enterprise from the ideal state. A larger deviation indicates lower capital allocation efficiency, while a smaller deviation indicates higher capital allocation efficiency. This paper uses this as a proxy variable for measuring enterprise capital allocation efficiency.

2. Core Explanatory Variable: Financial Technology Level (*FinTech*). This paper refers to the methods of scholars such as Song Min (2021) [16], Tang Song (2022) [24], and Tan Changchun (2023) [25], and selects the cumulative number of financial technology companies in the city where the company's headquarters is located as a proxy variable for measuring the level of financial technology. To prevent significant right-skewness in the data, it is logged after adding 1. The number of financial technology companies is sourced from the China Research Data Platform (CNRDS).

3. Control Variables: (1) Book-to-Market Ratio (*BM*), measured by the ratio of book value to market value; (2) Business Growth (*Growth*), measured by the Tobin's Q value;(3) Earnings Per Share (*Eps*), measured by the ratio of net profit after tax to the total number of shares;(4) Firm Age (*FirmAge*), measured by the logarithm of the company's age plus one;(5) Tangibility Ratio (*Tangibility*), measured by the ratio of tangible assets to total assets;(6) Stock Return Rate (*Returng*), measured by "(current market value of stocks–previous market value of stocks) / previous market value of stocks".

This paper selects Chinese A-share listed companies from 2008 to 2023. To ensure the scientificity and credibility of the research conclusions, the paper excludes financial listed companies, ST and PT listed companies, companies listed on both B-shares and H-shares, and companies with serious data missing or outliers during the specific research process. Meanwhile, to reduce estimation bias caused by extreme values in the empirical research process, the paper performs a winsorization at 1% and 99% for each variable. Unless otherwise specified, the variables involved in this paper are from the CSMAR database. The descriptive statistical analysis of the variables is shown in Table 1.

Table 1. Descriptive Statistics of Variables.

Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
einv	28,830	0.0319	0.0349	0.000254	0.226
FinTech	28,830	3.953	2.473	0	8.422
BM	28,830	0.622	0.261	0.0724	1.316
Growth	28,830	2.079	1.400	0.760	13.80
Eps	28,830	0.463	0.737	−2.362	5.854
FirmAge	28,830	2.950	0.313	1.609	3.689
Tangibilit	28,830	0.927	0.0856	0.452	1
Returng	28,830	0.188	0.492	−0.686	3.887

(II) Benchmark Regression Results

This paper uses panel data from Chinese A-share listed companies from 2008 to 2023 as the sample to estimate model (5) and test the impact of financial technology on capital allocation efficiency. From a theoretical perspective, mixed OLS, fixed effect models, and random effect models are commonly used for estimating panel models. However, in practical applications, the mixed OLS model is often biased due to omitted variable issues, and the random effect model is often difficult to implement in practice due to overly stringent assumptions. Therefore, most scholars choose to use the fixed effect model to estimate panel data models. Additionally, the results of the Hausman test strongly reject the use of the random effect model. Based on this, the estimation results of model (1) are presented in Table 2.

Table 2. Benchmark Regression.

Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
FinTech	−0.0004 **	−0.0004 **	−0.0004 **	−0.0004 **	−0.0004 ***	−0.0005 ***	−0.0005 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BM		−0.0129 ***	−0.0122 ***	−0.0123 ***	−0.0115 ***	−0.0117 ***	−0.0114 ***
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Growth			0.0001	0.0001	0.0002	0.0002	−0.0003
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Eps				0.0011 ***	0.0011 ***	0.0011 ***	0.0008 **
				(0.000)	(0.000)	(0.000)	(0.000)
FirmAge					−0.0065 ***	−0.0060 ***	−0.0055 ***
					(0.001)	(0.001)	(0.001)
Tangibility						−0.0485 ***	−0.0475 ***
						(0.004)	(0.004)
Returng							0.0040 ***
							(0.001)
Constant	0.0426 ***	0.0542 ***	0.0535 ***	0.0531 ***	0.0685 ***	0.1118 ***	0.1113 ***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)
Industry FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	28,830	28,830	28,830	28,830	28,830	28,830	28,830
Number of id	3418	3418	3418	3418	3418	3418	3418
R2_w	0.0222	0.0242	0.0242	0.0255	0.0260	0.0328	0.0340
F test	4.97	115.80	120.48	133.89	168.49	308.59	342.56

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are the standard errors.

Table 2′s regression results show that in models (1) to (7), the core explanatory variable financial technology (*FinTech*) passes the statistical significance tests at the 5% level, and the coefficients are negative, indicating that the improvement in the level of financial technology could reduce the deviation of capital allocation from the ideal state and enhance the efficiency of capital allocation. Among the control variables, the book-to-market ratio (*BM*), earnings per share (*Eps*), firm age (*FirmAge*), tangible asset ratio (*Tangibility*), and stock return rate (*Returng*) all pass statistical significance tests.

(III) Robustness Test

The benchmark regression results show that the improvement in the level of financial technology could enhance the efficiency of enterprise capital allocation. However, endogeneity issues may lead to estimation bias. First, the increase in the level of financial technology could improve the efficiency of enterprise capital allocation, and the improvement in the efficiency of capital allocation could promote the flow of capital to more efficient sectors, giving enterprises a stronger motivation and ability to develop financial technology. Therefore, there may be a reverse causality problem; second, in the sample processing process, this paper excludes A-share listed companies with severe data missing, which may lead to sample selection bias; third, although fixed effect models could largely reduce estimation bias due to omitted variables, unobserved variables may still affect the efficiency of enterprise capital allocation.

Considering this, this paper employs instrumental variable methods (IV), propensity score matching methods (PSM), and control function methods (FC) to test the empirical research conclusions, and the results are presented in Table 3.

Table 3. Robustness Test Results.

Variables	(1) IV	(2) PSM	(3) CF
FinTech	−0.001 ***	−0.0004 **	−0.0006 ***
	(0.000)	(0.000)	(0.000)
Constant		0.1110 ***	0.1032 ***
		(0.006)	(0.005)
Controls	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	24,343	21,787	26,902
Number of id		3385	3418
R2_w	0.047(Adj_r2)	0.0317	0.0302
F test	371.45	289.02	324.10

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are the standard errors.

In Table 3, Model (1) of the instrumental variable method is based on the research of Liu Guang (2023) [22] and other scholars, where the lagged term of the financial technology index is selected as the instrumental variable, and the regression results of the two-stage least squares (2SLS) method are presented. The results show that financial technology (FinTech) passes the statistical significance test at the 1% level, with a negative coefficient. This means that, even after considering the influence of reverse causality, the benchmark regression conclusion still holds. Additionally, this paper has tested the identification and validity of the instrumental variable, passing the statistical significance tests for both the unidentified test (Kleibergen-Paap rk LM statistic) and the weak identification test (Cragg-Donald Wald F statistic), indicating that the instrumental variable fully identifies the model and does not have weak identification issues. The test results support the effectiveness of the instrumental variable.

Model (2) is the regression result after considering sample selection bias. The specific operation mainly refers to the research of scholars such as Cai Zhen (2023) [3], Zhao Xinyu (2024) [26]. The propensity score matching (PSM) method is used to test the benchmark regression results. The specific steps are as follows: (1) Sort the financial technology index by size and select the median, defining the portion above the median as the treatment group (Treat = 1) and the rest as the control group (Treat = 0); (2) Define the generated binary variable as the treatment variable and the control variables in this paper as covariates, performing caliper matching with a radius of 0.01 and a matching ratio of 1: 1 based on the Logit model, and testing the matching results; (3) Regress on the matched samples. The results show that financial technology (*FinTech*) passes the statistical significance test at the 5% level, and the coefficient sign is consistent with the benchmark regression conclusion.

Model (3) is the regression result after further considering omitted variables. During the regression process, this paper refers to the research of Chen Taoqin (2023) [4] and adopts the control function method. With the help of propensity score matching on the grouping results of the financial technology index, the Probit model extracts the possibly correlated part between the financial technology index and the error term into the residual, and the residual is introduced as the explanatory variable into the second-stage regression model to observe whether the significance of the core explanatory variable changes. The regression results show that financial technology

(*FinTech*) passes the statistical significance test at the 1% level.

The regression results of Models (1)–(3) in Table 3 indicate that the improvement in the level of financial technology could enhance the efficiency of enterprise capital allocation, consistent with the benchmark regression results, thus demonstrating the high scientific validity and credibility of the benchmark regression conclusions.

(IV) Analysis of Empirical Results

The empirical research results indicate that the improvement in the level of financial technology could reduce the deviation of capital allocation from the ideal state and enhance the efficiency of capital allocation. Even after fully considering the influence of reverse causality, sample selection bias, and omitted variables, the research conclusions remain robust. The reasons for this conclusion are as follows:

1. Technology-Driven Financial Innovation: The essence of financial technology is technology-driven financial innovation. As the level of financial technology improves, financial institutions could provide more financing methods and tools to continuously expand the scope of financial services, supporting enterprise technological innovation. This means that the improvement in the level of financial technology allows financial institutions to provide enterprises with greater space and more convenient channels for financing, thereby enhancing the flexibility and efficiency of enterprise financing and optimizing capital allocation, thus improving the efficiency of enterprise capital allocation.

2. Reducing Market Imperfections: The improvement in the level of financial technology could reduce the imperfection of the capital market caused by information asymmetry and incomplete contracts. As the capital market continues to improve, market activity gradually increases, and transactions in the market become fairer and more just. In this process, capital would transfer according to market laws from low-efficiency enterprises to high-efficiency enterprises, that is, to realize the decisive role of the market in resource allocation, thereby improving the efficiency of enterprise capital allocation.

3. Financial System Reform: The report of the 19th National Congress of the Communist Party of China clearly points out the need to “deepen the reform of the financial system and enhance the ability of financial services to serve the real economy.” For a long time, the key factor restricting the quality and efficiency of China’s financial industry in serving the real economy has been the imbalance between financing models and financial supply and demand. The improvement in the level of financial technology could significantly reduce the impact of the imbalance between financing models and financial supply and demand on the real economy. Financial technology could create financial supply and solve the practical problem of insufficient financial supply, further optimizing the space for capital allocation and promoting the improvement of enterprise capital allocation efficiency.

5. Further Discussion

(I) Mechanism Testing

The preceding theoretical hypothesis suggests that the mechanism by which financial technology affects the efficiency of corporate capital allocation is “the improvement in the level of financial technology promotes the enhancement of corporate governance, which in turn improves the efficiency of capital allocation.” To test this mechanism, this paper introduces corporate governance (*Gov*) as an intermediate variable in model (I). Considering that traditional mediation effect models may have endogeneity issues, this paper follows the approach of Jiang Ting (2022) [27] and constructs the following mediation effect model based on model (I) to identify the impact of the core explanatory variable, the level of financial technology (*FinTech*), on the intermediate variable, the level of corporate governance (*Gov*), denoted as model (7):

$$Gov_{i,t} = \gamma_0 + \gamma_1 FinTech_{i,t} + \sum\nolimits_j \lambda_j Controls_{j,i,t} + \eta_{ind} + \eta_{year} + \varepsilon_{i,t} \tag{7}$$

In model (7), *Gov* represents the level of corporate governance, which is the intermediate variable. The meanings of other variables are the same as those in the benchmark regression model. Following the research of Jiang Ting (2002) [27] and others, the existence of a mediation effect is recognized when both the regression coefficients of α_1 and γ_1 are statistically significant.

Among them, the level of corporate governance (*Gov*) is measured using principal component analysis (PCA) based on the practices of scholars such as Bai Zhong’en (2005) [28], Zhou Qian (2020) [29], and others. This method selects multiple indicators from aspects such as supervision, incentives, and decision-making to construct a comprehensive index that measures the level of corporate governance for enterprises in China. The selection of indicators for measuring corporate governance level is shown in Table 4.

Table 4. Measurement Indicators for the Mediation Variable Corporate Governance Level.

Primary Indicator	Secondary Indicator	Indicator Description
Supervision	Independent Director Ratio	Number of Independent Directors/Total Number of Directors
	Board of Supervisors Size	Natural log of the number of supervisors
	Equity Concentration	Calculated by summing the squares of the shareholding ratios of the top 3 major shareholders
	Audit Opinion	0 for unqualified audit opinions, 1 for qualified audit opinions
Incentives	Executive Compensation	Natural log of the total monetary compensation of the top 3 executives
	Executive Shareholding Ratio	Management shareholding data divided by the total number of shares outstanding
Decision-Making	Dual Role	1 if the chairman and general manager are the same person, otherwise 0
	Board Size	Natural log of the number of board members

Based on the preceding analysis, this paper uses corporate governance (*Gov*) as an intermediate variable to test the impact mechanism of financial technology on the efficiency of corporate capital allocation. The test results are presented in Table 5.

Table 5. Mediation Test Results.

Variables	(1) Einv	(2) Gov
FinTech	−0.0005 ***	0.0064 *
	(0.000)	(0.003)
Constant	0.1113 ***	0.0570
	(0.005)	(0.083)
Controls	YES	YES
Industry FE	YES	YES
Year FE	YES	YES
Observations	28,830	28,830
Number of id	3418	3418
R2_w	0.0340	0.0470
F test	342.56	109.55

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are the standard errors.

Table 5′s regression results show that the core explanatory variable, the level of financial technology (*FinTech*), passes the significance test at the 1% and 10% levels in models (1) and (2), respectively, indicating that the improvement in the level of financial technology could reduce the deviation of capital allocation from the ideal state and enhance the efficiency of capital allocation, and that the improvement in the level of financial technology could also increase the level of corporate governance. This suggests that corporate governance plays a mediating role in the process of financial technology enhancing the efficiency of corporate capital allocation, that is, the improvement in the level of financial technology could promote the enhancement of corporate governance, which in turn improves the efficiency of capital allocation.

(II) Heterogeneity Analysis

To more accurately assess the impact of financial technology on the efficiency of capital allocation, this section conducts an analysis from the perspective of heterogeneity: (1) There are two forms of capital allocation in China's A-share listed companies: over-investment and under-investment. Based on this, the sample is divided into over-investment (*Overinv*) and under-investment (*Underinv*) categories, respectively labeled as sub-sample 1 and sub-sample 2, with the regression results presented in Table 6. (2) Considering the impact of differences in financial technology levels, this paper uses the median level of financial technology as the critical point, labeling the samples below the threshold as sub-sample 3 and those above the threshold as sub-sample 4, with the regression results presented in Table 7.

Table 6. Heterogeneity Analysis Results (1).

Variables	**Sub-Sample 1 (overinv)**		**Sub-Sample 2 (underinv)**	
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
FinTech	−0.0006 **	−0.0006 ***	−0.0003	−0.0003 **
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0513 ***	0.1593 ***	0.0352 ***	0.0570 ***
	(0.003)	(0.008)	(0.002)	(0.005)
Controls	NO	YES	NO	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	12,239	12,239	16,591	16,591
Number of id	2855	2855	3166	3166
R2_w	0.0269	0.0627	0.0192	0.0300
F test	4.84	366.82	2.40	192.06

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are the standard errors.

By comparing the coefficients of the core explanatory variable, the level of financial technology (*FinTech*), in models (1)−(4) of Table 6, it could be seen that financial technology could suppress, to some extent, the behaviors of excessive investment and under-investment in enterprises, reducing the deviation of capital allocation from the ideal state. At the same time, the core explanatory variable in sub-sample 1 all pass the statistical significance test, while in sub-sample 2, it does not pass the test. This indicates that when enterprises have excessive investment behavior, the effect of financial technology in suppressing excessive investment is more pronounced, and its impact on improving the efficiency of enterprise capital allocation is more significant.

In Table 7, the coefficients of the core explanatory variable, the level of financial technology (*FinTech*), in models (1)−(4) are all negative, indicating that the improvement in the level of financial technology helps to reduce the deviation of capital allocation from the ideal state and enhance the efficiency of capital allocation. Furthermore, in models (3) and (4), the level of financial technology (*FinTech*) passes the significance test at the 1% level and has a significantly higher coefficient value compared to models (1) and (2). This suggests that the higher the level of financial technology, the more significant its effect in improving the efficiency of capital allocation.

Table 7. Heterogeneity Analysis Results (2).

Variables	Sub-Sample 3		Sub-Sample 4	
	Model (1)	Model (2)	Model (3)	Model (4)
FinTech	−0.0005	−0.0003	−0.0007 ***	−0.0009 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.0438 ***	0.1193 ***	0.0423 ***	0.1032 ***
	(0.003)	(0.008)	(0.005)	(0.008)
Controls	NO	YES	NO	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	14,424	14,406	14,424	14,406
Number of id	2171	2768	2171	2768
R2_w	0.0145	0.0229	0.0291	0.0304
F test	1.80	7.02	187.95	180.49

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are the standard errors.

6. Conclusions and Insights

Through the above analysis, the following conclusions could be drawn: (I) The improvement in the level of financial technology could significantly reduce the deviation of capital allocation from the ideal state and enhance the efficiency of capital allocation in enterprises. (II) The improvement in the level of financial technology could suppress the behaviors of excessive investment and under-investment in enterprises, promoting the improvement of capital allocation efficiency. The suppression of excessive investment behavior is significantly higher than that of under-investment behavior. (III) The higher the level of financial technology, the more significant its effect on improving the efficiency of capital allocation, which is more conducive to enhancing the efficiency of enterprise capital allocation. (IV) The mechanism by which financial technology affects the efficiency of capital allocation is that financial technology promotes the enhancement of corporate governance, thus producing the effect of promoting the efficiency of enterprise capital allocation.

From these conclusions, the following insights could be drawn: Firstly, further enhance the level of financial technology to promote enterprises to improve the efficiency of capital allocation. The capital market is an important part of the modern financial system. Chinese government departments need to take necessary policy guidance and support to promote the improvement of financial technology. By taking the level of financial technology as the starting point, we could promote the deepening of capital market reform, improve the system of capital market institutions, and give full play to the decisive role of the market in resource allocation, forcing enterprises to improve their innovation capabilities and enhance the efficiency of capital allocation. Secondly, take the improvement of the level of financial technology as a starting point to improve the corporate governance level of listed companies. Corporate governance level is an important mechanism by which financial technology affects the efficiency of capital allocation in enterprises. China needs to further advance the development of financial technology, accelerate the improvement of the capital market system, and improve the market-oriented price discovery mechanism and delisting system to continuously enhance the vitality of the capital market. By taking the development of financial technology as an opportunity, we could promote fair and just transactions, improve the corporate governance level of listed companies, and inject vitality into the improvement of the efficiency of enterprise capital allocation. Thirdly, promote the deep integration of finance and technology to enhance the effectiveness of financial services for enterprises. The key to the improvement of the level of financial technology lies in promoting the deep integration of finance and technology. The development of financial technology is a key factor in promoting the high-quality development of China's economy. Enterprises are the micro-carriers for achieving high-quality economic development in China. Therefore, China needs to further promote the integration of finance and technology to provide enterprises with comprehensive, full-life cycle support for scientific and technological research and development, transformation of scientific and technological achievements, and technological innovation, promoting the transformation of scientific and technological innovation achievements into actual productive forces.

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References

1 Sun F, Hu J, Zhong T. Research on the Mechanism of Digital Transformation Enhancing Enterprise Capital Allocation Efficiency. *Western Forum* 2023; **33(04)**: 17–31.

2 Guo J, Wang Z. Impact of Digital Transformation on Enterprise Capital Allocation Efficiency-Based on the Empirical Evidence of Listed Manufacturing Enterprises. *Journal of Nanjing University of Finance and Economics* 2023; **3**: 67–76.

3 Cai Z, Wan Z. Regional Market Integration and Enterprise Capital Allocation Efficiency in China-Based on the Empirical Evidence of A-Share Listed Companies in China. *China Rural Economy* 2023; **11**: 140–163.

4 Chen T, Lu K, Zhang H. Enterprise Digital Transformation and Capital Allocation Efficiency. *Social Sciences* 2023; **9**: 123–136.

5 Hao Y, Li J, Wei Z, *et al*. Could Industry Expert Independent Directors Improve Enterprise Capital Allocation Efficiency?-Empirical Test Based on A-share Listed Companies. *Accounting Research* 2022; **5**: 65–76.

6 Li Q, Shi J, Liu X. Enterprise Digital Transformation and Capital Allocation Efficiency. *Statistics and Information Forum* 2023; **38(03)**: 70–83.

7 Qin J, Shao X. Cross-Listing, Government Intervention and Capital Allocation Efficiency. *Economic Research* 2015; **50(06)**: 117–130.

8 Qi H, Li H, Liu Y. Government Governance, State-Owned Enterprise Mixed Ownership Reform and Capital Allocation Efficiency. *Reform* 2019; **7**: 40–51.

9 Richardson S. Over-Investment of Free Cash Flow. *Review of Accounting Studies* 2006; **11(2–3)**: 159–189.

10 Daud SNM, Ahmad AH, Khalid A, et al. FinTech and Financial Stability: Threat or Opportunity? *Finance Research Letters* 2022; **47**: 102667.

11 Zhou R, Li J. Fintech and Dynamic Adjustment of Capital Structure. *Finance Research Letters* 2024; **67**: 105853.

12 Jagtiani J, Lemieux CJFM. The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform. *Financial Management* 2019; **48**(**4**): 1009–1029.

13 Qi Y, Ouyang L, Yu Y. The impact of FinTech adoption on corporate investment: Evidence from China. *Finance Research Letters* 2024; **67**: 105929.

14 Tang S, Chen Z, Chen J, *et al.* Does FinTech Promote Corporate Competitiveness? *Evidence from China Finance Research Letters* 2023; **58**: 104660.

15 Yijia L. Does Fintech Development Affect Capital Misallocation: A Non-Linear and Spatial Spillover Perspective. *Finance Research Letters* 2024; **60**: 104847.

16 Song M, Zhou P, Si H. Financial Technology and Enterprise Total Factor Productivity-Perspectives of Empowerment and Credit Rationing. *China Industrial Economics* 2021; **4**: 138–155.

17 Xie X, Zhu X. FinTech and Capital Allocation Efficiency: Another Equity-Efficiency Dilemma? *Global Finance Journal 2022*; 53, 100741.

18 Li W, Hu Q. Could Financial Technology ‘Enable’ Break the ‘Spatial Barrier’ of SME Financing-Micro-evidence from the Change of Banking Industry Spatial Layout. *Science of Finance and Economics* 2024; **4**: 15–37.

19 Liu H, Feng J, Wang Y. Bank FinTech and Enterprise Financial Malinvestment: Relief or Worsening? *Financial Forum* 2024; **29**(**03**): 14–23+46. https://doi.org/10.16529/j.cnki.11-4613/f.2024.03.007.

20 Yang D. Regulatory Technology: Regulatory Challenges and Dimension Construction of FinTech. *China Social Sciences* 2018; **5**: 69–91+205–206.

21 Hu Y, Dai G, Gao P. FinTech and Capital Cross-Regional Flow–Based on the Perspective of Enterprise Off-Site Investment. *Shanghai Economic Research* 2024; **7**: 105–118.

22 Liu G. Research on the Financialization of China’s Manufacturing Enterprises and Capital Allocation Efficiency. *Economist* 2023; **12**: 36–45.

23 Zhang A, Ye T. Product Market Competition, Fiscal Subsidies and Capital Allocation Efficiency. *Financial Economics* 2022; **5**: 34–45.

24 Tang S, Su X, Zhao DN. FinTech and Enterprise Digital Transformation-Based on the Perspective of Enterprise Life Cycle. *Science of Finance and Economics* 2022; **2**: 17–32.

25 Tan C, Wang Z, Zhou P. Could FinTech ‘Enable’ and Enterprise Green Innovation-Based on the Perspective of Credit Allocation and Supervision. *Research of Finance and Economics* 2023; **49**(**01**): 34–48+78.

26 Zhao X, Zhang S. Could Digital Transformation Enhance the Capital Allocation Efficiency of State-Owned Enterprises? *Journal of Lanzhou University* 2024; **52**(**02**): 40–53.

27 Jiang T. Mediation Effect and Moderation Effect in Empirical Research on Causal Inference. *China Industrial Economics* 2022; **5**: 100–120.

28 Bai Z, Lu Z, Song M, *et al*. Empirical Research on the Governance Structure of Listed Companies in China. *Economic Research Journal* 2005; **2**: 81–91.

29 Zhou Q, Xu X, Lu Z. Deleveraging, Who Is More Active and Prudent? *Management World* 2020; **36**(**08**): 127–48.

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Article

The Application of Artificial Intelligence in the Investment Field

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Abstract: The application of artificial intelligence technology in the financial sector has brought about significant transformations across the entire financial industry, giving rise to innovative financial services such as intelligent financial advisory, intelligent credit assessment and monitoring and intelligent customer service. However, the application of AI technology in financial sector also faces a series of challenges and difficulties. To enhance core research and development capabilities, it is necessary to integrate and utilize big data resources, build and improve a secure and widely shared data ecosystem, establish and optimize multiple risk prevention mechanisms, and improve the risk control level of AI technology. Reforms and improvements in financial regulatory mechanisms are needed to achieve comprehensive oversight of the application of AI technology in the financial sector, providing favorable conditions for promoting innovative and standardized development in the financial industry.

Keywords: artificial intelligence; finance; investment field

1. Application Background and Research Significance

The application of artificial intelligence technology in the investment field can be traced back to early computer-assisted trading systems. However, it was only in recent decades, with significant advancements in computing power and rapid development in data technology, that AI began to be widely applied in the investment field. The application background of AI in the investment field mainly lies in technological progress, the increasing complexity of financial markets, and the growing demand from investors for efficient decision-making.

(1) Promotion by Technological Advancements With the rapid development of information technology, the application of artificial intelligence in the financial sector has been widely promoted. Artificial intelligence technology, by simulating human intelligence and utilizing computer technology to achieve intelligent data processing and decision-making, can effectively enhance the efficiency and accuracy of investment decisions. The application of this technology plays a significant role not only in financial services and regulatory oversight but also in financial analysis, thereby promoting the intelligence and standardization of the financial industry.

(2) Investors' Demand Growth hope to obtain more accurate predictions and personalized investment advice in their investment decisions. Artificial intelligence technology can meet this demand by providing personalized asset allocation and risk management strategies. AI investment advisors collect and analyze investors' investment preferences, risk levels, and other data to propose personalized investment plans, helping

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investors achieve better returns in the market.

(3) Enhancing Investment Decision Efficiency Artificial intelligence (AI) technology can quickly process large amounts of data, thereby improving the efficiency and accuracy of investment decisions. By utilizing machine learning and deep learning techniques, AI can automatically identify market trend s and risk factors, optimize investment portfolios, and dynamically adjust portfolio weights, thus enhancing return on investment and risk management capabilities. For example, the application of deep learning in portfolio construction and optimization involves encoding and decoding financial market information to form an asset portfolio that meets the objective function. Experimental evidence has shown that its performance surpasses that of benchmark models.

In modern financial markets, intelligent investment systems, through their efficient data processing capabilities and predictive analysis, can quickly respond to market changes and provide investors with more accurate investment advice and strategies. This not only improves investment efficiency but also enhances risk management capabilities. For both individual and institutional investors, intelligent investment systems have significant practical application value and strategic importance.

(1) Enhancing Investment Efficiency and Accuracy Smart investment leverages artificial intelligence technologies such as machine learning and deep learning to efficiently process and analyze massive amounts of data, thereby establishing precise predictive models and improving the efficiency and accuracy of investment decisions. These technologies can extract nonlinear relationships from complex data, helping investors better understand market dynamics and predict market trends.

(2) Reducing Investment Risk Smart investment uses big data analysis and machine learning algorithms to monitor market changes in real time, assess investment risks, and provide corresponding risk management strategies. This approach effectively reduces uncertainties in the investment process, helping investors manage their risks more effectively.

In a dynamic market environment, more rational decisions can be made. Additionally, intelligent investment advisors further enhance the precision and risk management capabilities of investment decisions through automated trading and real-time market monitoring, thereby reducing the impact of human errors and emotional fluctuations on investment decisions.

(3) Personalized Investment Advice Smart investment platforms can provide personalized investment portfolio recommendations based on investors' risk preferences, investment goals, and time horizons. This feature significantly enhances investor satisfaction because the platform can offer customized investment solutions based on clients' diverse financial goals, effectively alleviating investment herd behavior caused by information asymmetry.

2. Artificial Intelligent Investment Strategies and Methods

2.1. The framework of Intelligent Investment Advisory

Markowitz's Mean-Variance Model is the cornerstone of portfolio theory, which selects the optimal investment portfolio by balancing expected returns and risk. Intelligent investing integrates Modern Portfolio Theory with machine learning algorithms to optimize investment portfolios, thereby maximizing returns or minimizing risks.

The core technologies of intelligent investment advisory include machine learning, deep learning, and natural language processing. These technologies generate personalized investment recommendations by analyzing customers' historical transaction data, market conditions, and risk preferences. For example, machine learning algorithms can be used to predict the price fluctuation trends of financial assets, thereby helping customers formulate investment portfolios that meet their risk-return requirements. In addition, deep learning technology further enhances the accuracy of investment decision-making by simulating the working process of human brain neurons. Natural language processing technology [1] is applied in the field of intelligent customer service, where it improves the efficiency and satisfaction of customer service through functions such as voice recognition and semantic understanding [2].

In intelligent investing, artificial intelligence technologies analyze a variety of information sources, such as historical transaction data, market news, and social media trends, to predict market trends and the performance of specific assets. These predictive models employ complex algorithms, such as random forests, support vector machines, and deep learning, to capture complex patterns and relationships in the data, thereby making more accurate predictions. By analyzing big data to understand customers' risk preferences and investment goals, personalized asset allocation plans are provided to meet individual needs. Using machine learning methods, intelligent investment advisory can dynamically track market changes and adjust investment portfolios in real time.

The service model of intelligent investment advisory has shifted from traditional face-to-face consulting to online automated services. This transformation not only reduces operating costs but also significantly improves service efficiency. Through big data and artificial intelligence technologies, intelligent investment advisory can offer personalized asset allocation recommendations and real-time market analysis to better meet the diverse needs of customers. In terms of customer experience, intelligent investment advisory significantly enhances the personalization and convenience of services through intelligent customer service and user profiling technologies.

Intelligent customer service, leveraging natural language processing and voice recognition technologies, can quickly respond to customer needs. User profiling technology, by analyzing customer behavior data and transaction records, creates more accurate customer profiles, thereby providing investment advice that is more in line with customer needs [3].

2.2. Intelligent Financial Advisory Strategies

Currently, the strategies of intelligent financial advisory mainly come in two forms: investment strategies based on machine learning and dynamic asset allocation strategies. Investment strategies based on machine learning widely apply algorithms such as support vector machines, random forests, and deep learning in financial investment, capable of handling high-dimensional, non-linear financial data and capturing complex relationships in the market. Reinforcement learning methods learn optimal investment strategies through interaction with the environment, making them suitable for multi-period, multi-objective investment decision-making. Dynamic asset allocation strategies automatically adjust investment portfolios based on market conditions and asset information to respond to market changes, aiming to maximize profits or minimize losses. By real-time monitoring of investment portfolios and dynamically adjusting asset proportions, risks can be reduced, and returns can be increased [4].

The hybrid model of intelligent investment advisory, which combines artificial intelligence and human expertise, offers a more comprehensive investment advisory service. This model has been widely applied and recognized both domestically and internationally because it strikes a balance between the convenience and low cost of digital platforms and the personalized guidance and human touch of traditional wealth managers. This balance appeals to investors who wish to combine the convenience of technology with human expertise.

2.3. Intelligent Investment Methods

The application of deep learning in investment primarily lies in its outstanding performance in asset price prediction and allocation. Models such as LSTM and Convolution Neural Networks can extract better features from time series data, thereby improving prediction accuracy. Deep learning also has applications in portfolio optimization, where it helps build a theoretical framework for deep asset allocation to optimize portfolio performance. Additionally, quantitative investment methods have excellent applications in the investment field. Quantitative investment leverages computer technology to establish mathematical models, realizing the process of investment philosophy and strategy. It is characterized by discipline and efficiency. Based on summarizing historical patterns in the securities market, quantitative investment analyzes and formulates strategies and models that can be repeatedly applied, achieving optimal investment.

Intelligent investment strategies, through high-level mathematical modeling and machine learning methods, analyze massive amounts of historical and real-time data to automatically identify and predict investment opportunities. This approach can effectively identify market patterns, predict market trends, and adaptively adjust the asset portfolio without human intervention to achieve optimal risk management and profitability. For example, companies can use machine learning methods to comprehensively analyze multiple dimensions, such as social media, market sentiment, and economic indices, to better grasp the short-term market conditions and long-term value of the stock market.

Compared with traditional investment strategies, intelligent investment strategies show significant advantages in dealing with nonlinear and non-stationary characteristics. Traditional statistical models often have difficulty in coping with these complex features, while artificial intelligence methods can better capture market dynamics and provide more precise support for investment decision-making. Research shows that an increasing number of scholars are using artificial intelligence as a support for solutions to optimize the management of investment portfolios and risk control.

When evaluating the effectiveness of intelligent investment strategies, common metrics include cumulative return, Sharpe ratio, maximum drawdown, Alpha, and Beta. The cumulative return measures the investment outcome of a portfolio over a period of time. The Sharpe ratio reflects the extent to which the net asset value growth rate exceeds the risk-free rate on a per-unit-risk basis. The maximum drawdown describes the worst-case scenario that investors may face. The Alpha value measures the excess return obtained by the model compared to the benchmark model, while the Beta value assesses the systematic risk of the model relative to the benchmark.

Some research indicates that when using deep learning algorithms for stock price prediction, the LSTM model demonstrates high predictive accuracy in handling time-series data and can extract superior features from raw data. Moreover, ensemble learning methods, by aggregating expert predictions online, can enhance portfolio performance, offering higher Sharpe ratios and lower drawdown rates.

In practical applications, intelligent investment strategies play a vital role in enhancing the effectiveness of investment decision-making. Through automation and data analysis, intelligent investment strategies can maintain competitiveness in the complex and volatile financial markets, achieving optimized asset allocation and risk management.

Experimental data shows that portfolio optimization models based on machine learning have significant advantages in terms of prediction error and risk control. For example, using a hybrid prediction approach that combines models such as Random Forest, Support Vector Regression, and Long Short-Term Memory (LSTM) networks can effectively reduce prediction errors and improve returns and Sharpe ratios by constructing new portfolio models.

2.4. Application Cases of Intelligent Investment Advisory Strategies in the Stock Market

Betterment and Wealthfront are early representatives of global intelligent investment advisory services. They provide low-cost asset management services to investors through automated portfolio recommendations. Both Betterment and Wealthfront have played a significant role in democratizing access to professional investment advice and making sophisticated portfolio management accessible to a broader range of investors [5].

3. Challenges and Future Trends

Despite the broad prospects for the application of artificial intelligence in the investment field, some challenges remain, such as data security, algorithm transparency, and regulatory policies. Ensuring the security and privacy of large volumes of sensitive financial data is crucial when handling such information. Additionally, complex algorithms can sometimes be difficult to explain in terms of their decision-making processes, a problem known as the “black box” issue, which may affect the trust of investors and regulatory bodies.

(1) The limitations of technology application are significant, as investment fields heavily rely on data. The accuracy and reliability of AI models largely depend on the quality and completeness of the data. Acquiring high-quality, comprehensive, and reliable data is a major challenge. The issue of model with overfitting and generalization capability is evident; AI models may overfit during training, meaning the model excessively adapts to the training data, leading to a decline in predictive power for unknown data. At the same time, the generalization capability of the model is also a concern, referring to the model’s ability to maintain stable performance in different market environments [6].

(2) The issues of data privacy and security, financial institutions face risks of data leakage and tampering during the processes of data collection, storage, and transmission. Particularly in cloud computing and big data environments, the centralized storage and sharing of data increase the likelihood of information leakage, posing

serious threats to customer privacy and financial security. Technical risks and operational risks coexist, with the complexity of technical systems and high technical requirements increasing the difficulty of financial institutions in risk management. The contradiction between data privacy protection and regulatory requirements is becoming more pronounced [7].

(3) Market dynamics and uncertainties mean that AI applications rely on historical data, but financial markets change rapidly, Affecting the timeliness of AI modeling and analysis due to the dynamic imbalance of data. Financial institutions are increasing their reliance on AI technology, while regulatory mechanisms are still incomplete, leading to greater market supervision risks.

The future development trends of intelligent investment may include broader applications of deep learning and reinforcement learning technologies, as well as enhanced the interpretability and operability of AI systems. As technology advances, AI will play a more significant role in investment decision-making, ranging from simple data analysis to complex asset allocation and risk management. Intelligent investment systems will become more intelligent and user-friendly.

4. Conclusions

Artificial intelligence technologies are gradually transforming the operation of the investment industry by enhancing data analysis capabilities and automating trading levels. Not only does AI improve investment efficiency, but it also strengthens risk control capabilities. Intelligent investment systems can quickly respond to market changes, providing more personalized and precise investment advice, which is of significant importance for enhancing investment returns and customer satisfaction. For investors, the key to adapting to this change lies in understanding and accepting the advantages of intelligent investment tools while paying attention to their potential risks. Investors should choose smart advisory services that align with their investment strategies and risk tolerance and remain attentive to market dynamics and technological advancements to make more informed investment decisions.

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References

1 Tsantekidis. High-Frequency Trading with CNN. *Expert Systems* 2020.
2 Chen R. Intelligent Factor Mining in the A-share Market. *Journal of Financial Research* 2024.
3 Raffinot. Deep Risk Parity Portfolios. *Journal of Banking & Finance* 2022.
4 Zhang Z. *Deep Reinforcement Learning for Trading*; NeurIPS: Denver, CO, USA, 2020.
5 Masliang W. Application of Artificial Intelligence Technology in the Financial Sector: Main Difficulties and Countermeasure Suggestions. *Southern Finance* 2018; 499.

6 Huang Q, Zhao Z, Dai H, *et al.* Cold Thoughts on Financial Security in the Context of Artificial Intelligence's Boom. *Financial Technology* 2023; 1674–2265.
7 Xia S. Research on the Advantages, Risks, and Regulation of Artificial Intelligence in Financial Markets. *Financial Theory and Teaching* 2021; 165.

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Article

Design and Research of Pharmacy Management Robot Based on Artificial Intelligence

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Abstract: In order to solve the problems of long queuing time, low efficiency of manual dispensing and high risk of errors in traditional hospital pharmacies, this study designed and developed a pharmacy management robot system integrated with artificial intelligence technology. Through the integration of automatic robotic arm, AI visual recognition and Internet of things perception technology, the system innovatively realizes the intelligent management function of the whole drug process: It includes high-precision drug visual recognition and two-dimensional code scanning, accurate cover opening and drug distribution of multi-axis manipulator, omnidirectional mobile chassis driven by ROS robot operating system, and multi-sensor fusion navigation system based on laser radar and depth camera. Among them, the intelligent packaging module developed by the product solves the problem of insufficient opening accuracy of existing pharmacy robot medicine bottles through the precise lid opening technology of mechanical arm, effectively optimizes the efficiency of drug distribution and the quality of medical service, and becomes an innovative breakthrough in the field of intelligent pharmacy management.

Keywords: artificial intelligence; pharmacy management; automated sorting

1. Introduction

With the acceleration of the aging process of the global population, medical and pharmaceutical services are upgrading in the direction of "precision + intelligence", and patients' requirements for pharmacy services have changed from basic supply to whole-process optimization. However, the traditional pharmacy's manual model is limited by the pharmacist training cycle and technical bottlenecks, making it difficult to cope with these surges. The new generation of pharmacy management robot technology provides a key breakthrough to solve the above challenges by integrating heterogeneous drug intelligent identification and autonomous navigation systems, deeply integrated medical information systems, and applying edge computing and federated learning technology, aiming to build a fully automated link of drug storage, sorting and distribution, realize the real-time synchronization of prescriptions, inventory and distribution instructions, and optimize resource scheduling under the premise of ensuring data security.

In view of the common pain points of patients in traditional hospital pharmacies, such as long queuing time, low manual dispensing efficiency and high risk of errors, this paper focuses on the development and application of pharmacy management robots. Specifically, this study aims to develop a smart pharmacy management system by integrating automated robotic arms, AI visual recognition and Internet of Things (IoT) technologies. The

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system is committed to achieving accurate and rapid sorting and distribution of prescription drugs, optimizing dynamic inventory monitoring and replenishment warning, and supporting multi-threaded processing of prescription review, medication consultation and logistics scheduling tasks, thereby effectively reducing manual load and improving the accuracy of drug dispensing. In this paper, we focus on the research and development of automated drug dispensing mechanical systems (including mobile chassis, visual recognition and robotic arms), as well as the development of intelligent collaborative management systems (including cluster control, scheduling algorithms and data interfaces), so as to solve the core problems of drug whole-process automation and efficient collaborative operation of multiple robots in the pharmacy scenario.

2. Literature Review

2.1. The Development Status of Pharmacy Robots in Foreign Countries

The robot technology of international pharmacies presents the following characteristics: automated pharmacies in Europe, the United States, Japan and other countries have formed a technical system with AI visual recognition and edge computing as the core, which greatly improves the efficiency of drug distribution [1] and effectively shortens the waiting time of patients through automated drug dispensing systems [2]. Foreign equipment is mainly divided into four categories: manipulator type, drug storage tank type, bulk type and rotary type, and the core functions focus on efficient drug dispensing and precise drug storage [3]. The manipulator system of ROWA in Germany adopts multi-axis robotic arm and three-dimensional positioning technology, and the daily processing volume of prescriptions reaches 3000 cases, and the error rate is <0.01%, but the hardware maintenance cost accounts for 35% of the investment. The storage tank system of APOTEKA in France combines gravity sensing and RFID technology, and the dispensing speed is 8 s per order, but the manual replenishment process leads to a 18% reduction in system efficiency. The metering accuracy of TOSHO's powder subcontractor is 98.7%, but the upper limit of processing is 120 packs/hour, which is difficult to meet the demand of 5000+ prescriptions per day. Hanel's swing system in Germany has a space utilization rate of 85% [4], but it is only suitable for standard pharmaceutical containers. At present, the coverage rate of international equipment in small and medium-sized medical institutions in developed countries is 72%, but its algorithm and hardware are designed for the scenario of 2000 prescriptions per day. If it is directly applied to China's tertiary hospitals (8000+ prescriptions per day), due to the lack of high concurrency processing capacity and mechanical durability defects, the system delay rate may rise to 12%, and the operation and maintenance cost may increase by 40%, so it is necessary to optimize the multi-machine collaboration algorithm and consumption-resistant hardware architecture.

2.2. The Development Status of Domestic Pharmacy Robots

The development of domestic pharmacy robot technology presents the following characteristics: compared with the international level, domestic R&D started late but developed rapidly, and the clinical application coverage rate has increased from 23% in 2023 to 41% at present. Chen et al. (2024) [5] improved the processing efficiency of mixed-line prescriptions by 37% and reduced the frequency of pharmacist intervention to 0.8 times/100 prescriptions by optimizing the dynamic sorting algorithm. According to the research of Wei Menglin [6] and Jiang Tingting [7], the imported third-generation system shortens the average waiting time of patients in tertiary hospitals to 4.2 min, and the error rate of drug dispensing <0.05%, but the annual operation and maintenance cost still accounts for 18–22% of the initial investment.

Breakthroughs have been made in the field of independent research and development: the bionic robotic arm system developed by Tian Maojun's [8] team has achieved a grasping accuracy of 50 mg ± granular traditional Chinese medicine, and the success rate of grasping special-shaped packaging has increased to 93%; Zhao Xianglong (2024) [9] designed a double-helix dispensing mechanism that compresses the single-slot dispensing cycle to 1.8 s, which is 62% better than that in 2023. The elastic separation module developed by Jiang Tingting [7] has been verified in tertiary hospitals in 17 provinces and cities, and the pass rate of the composite pill box channel has reached 99.6%.

At the industrial level, a complete supply chain has been formed in China, and the fourth-generation system of the leading enterprise integrates flexible scheduling and edge computing technology, supports the processing of 8000+ prescriptions in a single day, and the equipment localization rate is 81%. In 2024, the market size will increase by 49% year-on-year, and the technology iteration speed will be 2.3 times that of the international period, and the competitiveness will continue to be strengthened under the policy and market drive.

3. Smart Pharmacy Robot Design

3.1. Overall Design of the Robot

The overall design architecture of this pharmacy management robot takes the robot ontology as the core, and builds a collaborative system composed of four key modules. As the intelligent center, the ROS layer is responsible for core data analysis and computing tasks, including robot motion path planning based on A* algorithm and DWA algorithm, ACML positioning system, robot scheduling, sensor information collection and calculation, upper control of the robotic arm, and machine vision processing. Depth information sensors (including lidars that provide 2D plane information and depth cameras that provide three-dimensional spatial information) are responsible for sensing environmental depth information and providing basic data for navigation and operation. The cloud server platform undertakes cloud control and cloud monitoring functions, realizes remote control of the robot and obtains its sensor information in real time. The bottom control layer is responsible for the physical execution and basic perception of the robot, covering the motion control driven by the motor, the bottom action execution of the robotic arm driven by the servo, and the sensor information collection through the nine-axis gyroscope, temperature and humidity sensor, smoke sensor, etc. These four levels work closely together to form a complete functional system of pharmacy management robots (as shown in Figure 1).

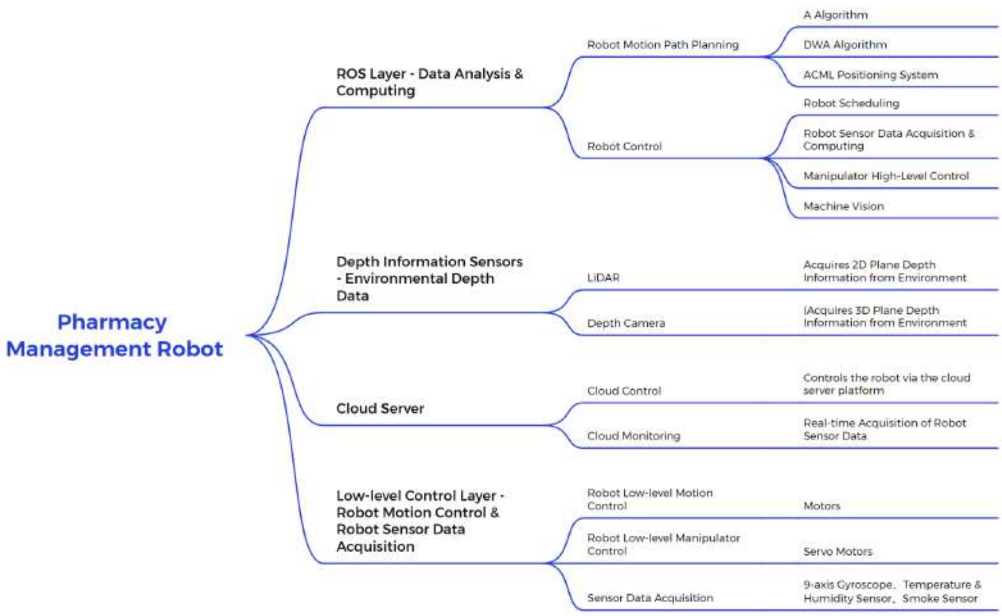

Figure 1. Pharmacy Management Robot System Architecture Diagram.

3.2. Design of Robot Operation Structure

This solution focuses on the precise control of the robotic arm, and the core lies in the application and integration of the stepper motor driver. As a conversion actuator from electrical pulse to angular displacement, the stepper motor driver is controlled to rotate at a fixed angle (step angle) by receiving pulse signals, so as to realize the precise positioning and movement of each joint of the robotic arm. The controller contains a microprocessor and drive circuitry that interprets external instructions and converts them into motor signals, while monitoring the motor status for timely adjustments.

The optional DM542 and OK2D 4020A drives drive five and one specific motors of the robotic arm, respectively, to ensure efficient and stable operation. The DM542 uses advanced DSP technology and built-in micro-segmentation for smooth operation and low noise, automatic parameter tuning and multiple protection functions.

In terms of control strategy, MoveIt is introduced as a software framework for robotic arm motion planning and control. Based on ROS, MoveIt supports a variety of controllers and interfaces, provides RRT, PRM and other algorithms to achieve motion planning, and uses 3D simulation tools for trajectory simulation and optimization to ensure accurate and efficient actual operation. The process using MoveIt includes ROS/MoveIt installation configuration, robotic arm modeling and description, motion planning and path optimization, final motion control and real-time monitoring.

To sum up, this solution provides a solid technical support for the accurate and efficient control of the robotic arm through the integrated application of advanced stepper motor drive technology and MoveIt software framework.

The system framework is shown in Figure 2.

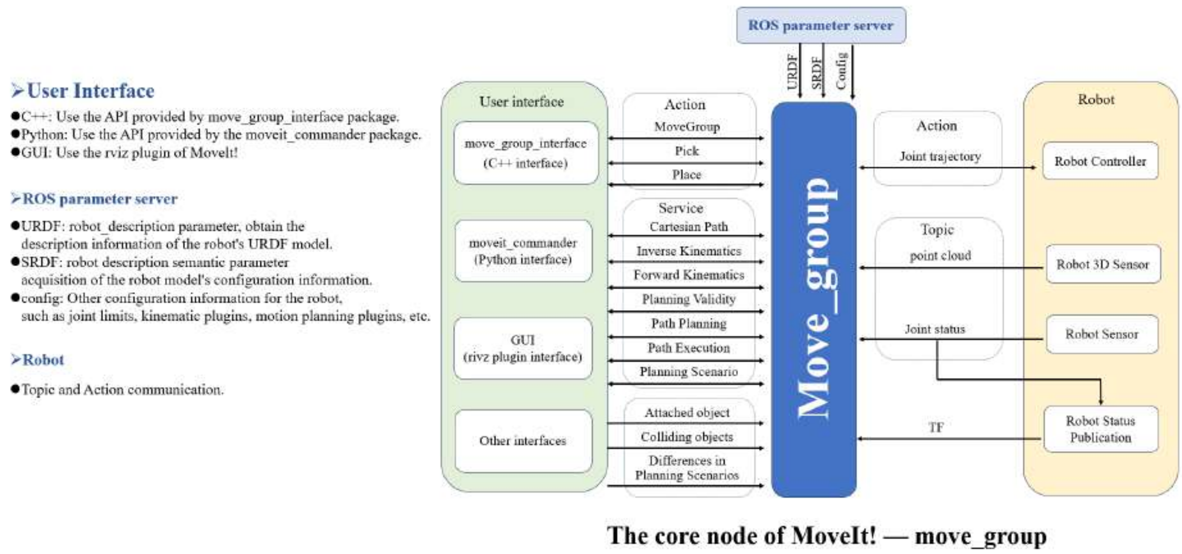

Figure 2. MoveIt System Framework.

The sports chassis design features Mecanum wheels, as shown in Figure 3. The Mecanum wheel is designed to move in all directions with an innovative design that uses a 45-degree angle of the rollers in contact with the ground for omnidirectional flexibility. Its unique structure enables the car body to move forward, traverse, oblique and rotate, and adapt to narrow space operations. Although the structure is compact and flexible, the torque efficiency is low, the cost is high, and the wear resistance is insufficient, which is suitable for smooth ground and the durability is weakened in complex terrain.

Figure 3. Mecanum Wheel.

As shown in Figure 4, the core of the sports chassis main control scheme uses STM32F103ZET6 as the main control MCU, which is extremely powerful, integrating rich resources such as 64KB SRAM and 512KB FLASH, and supporting a variety of peripheral interfaces, including 2 DMA controllers, 3 SPI, 2 IIC, 5 serial ports, etc., and 112 general-purpose IO ports, which is very suitable for complex control needs. Most importantly, its external bus (FSMC) efficiently expands SRAM and drives LCDs, significantly increasing the display refresh rate, making it the top model in the STM32F1 series.

Figure 4. STM32 main control chip.

In terms of attitude perception, the Witt intelligent WT9011G4K gyroscope is selected as the posture sensor module, as shown in Figure 5. The module integrates a high-precision gyroscope, accelerometer, and geomagnetic field sensor, and uses advanced algorithms to achieve accurate attitude solving in dynamic environments, with an accuracy of up to 0.01 degrees and excellent stability. It has a built-in voltage stabilization circuit, supports 3–6 V working voltage, is compatible with 3.3 V/5 V systems, and provides serial port and IIC interface options to meet diverse connection needs. The module also supports high-speed data transmission to ensure real-time performance, which is ideal for improving the accuracy of robot movements.

Figure 5. Wit Smart WT9011G4K Gyroscope.

3.3. Design of Manipulator for Taking Medicine

3.3.1. Visual Library Selection

This project uses OpenCV as the core vision processing library, which provides rich image processing algorithms and efficient computer vision functions, including image filtering, edge detection, feature extraction, etc. For the QR code recognition task, OpenCV can complete image preprocessing and preliminary positioning, but in order to further improve the recognition accuracy and speed, this project combines Zbar library for QR code decoding. ZBAR is a lightweight, high-performance barcode/2D code scanning library that supports a variety of encoding formats and is able to quickly parse QR code information. After image preprocessing via OpenCV, the ROI (region of interest) is passed to Zbar for efficient and stable 2D code recognition.

3.3.2. QR Code Scanning Process

1. Pre-processing stage: First, the BGR image collected by the camera is converted into a grayscale image to reduce the amount of calculation. Subsequently, the Laplacian operator was used for edge enhancement to highlight the contour features of the QR code. Due to the possible noise interference in the actual environment, a further mathematical morphological operation (corrosion first and then expansion) was used to remove fine noise while preserving the structural integrity of the QR code.

2. Boundary extraction and positioning: The contours in the image are detected by the cv2. findContours() function, and the candidate areas that conform to the geometric characteristics of the QR code (such as the corner distribution of the quadrilateral) are screened out. In order to improve the positioning accuracy, the minimum external rectangle of the contour was calculated, and the affine transform was used to correct it into a standard square to ensure that the QR code area was free of distortion and convenient for subsequent recognition.

3. Recognition and decoding: input the preprocessed image area into the Zbar scanner, configure the scanning parameters (such as coding format, scanning accuracy, etc.), and call the scan() method to parse the QR code data. If the identification is successful, the drug number or location information will be extracted; If it fails, an error is reported and a rescan mechanism is triggered to ensure robustness.

3.3.3. Object Detection Optimization

1. Dataset construction: The YOLOv5 model is used for drug target detection, and the training data is uniformly scaled to 640 × 640 pixels to balance computing efficiency and detail retention. By randomly cropping and scaling the original drug image, the data diversity can be expanded while avoiding the training burden caused by excessive resolution.

2. Annotation and data augmentation: Use the LabelImg tool to accurately label the drug bounding box and generate a labeling file in PASCAL VOC format. Data augmentation strategies include random rotation, translation, brightness/contrast adjustment, simulating the difference of lighting and placement angle in the pharmacy, and improving the generalization ability of the model.

3. Category imbalance treatment: In order to solve the problem of uneven distribution of drug categories, category weights are introduced into the loss function, and the weights are dynamically adjusted according to the occurrence frequency of each category in the training set to avoid the model biased towards high-frequency categories. For example, the weight coefficient of low-frequency drugs is set to 1.5~2 times that of high-frequency drugs to ensure the fairness of testing.

4. Model lightweight: Fine-tuning based on the pre-trained YOLOv5s (small version), combined with channel pruning (Pruning) to remove redundant convolution kernels, and INT8 quantization is used to reduce model storage and computing overhead. The inference speed is increased by more than 30% to meet the real-time requirements of the robotic arm.

5. Tuning and evaluation: 5-fold cross-verification is used to evaluate the stability of the model, and hyperparameters such as learning rate and anchor box size are adjusted through Grid Search. The final indicators include mAP@0.5 (average accuracy) and FPS (frame rate) to ensure that the model achieves the optimal balance between accuracy and speed, and realizes the fast and accurate positioning of drugs.

3.4. Robot Control System Design

3.4.1. Primary Controllers

In this study, the ESP32 module is used to realize the real-time video transmission control. Developed by Espressif Systems as an upgraded version of the ESP8266, the module integrates a dual-core processor, Bluetooth and Wi-Fi capabilities, and is designed for IoT devices. Its built-in high-efficiency processor and large-capacity memory support multitasking, which can be adapted to smart home, wearable devices and other application scenarios. At the technical level, ESP32 supports Bluetooth 5.0 protocol and Mesh networking, expands GPIO interfaces and is compatible with USB-OTG communication, and combines low-power consumption characteristics with development frameworks such as Arduino and ESP-IDF, significantly reducing the threshold for IoT device development. The hardware-accelerated H.264/MJPEG video encoding capability can meet the needs of real-time transmission, and has been applied on a large scale in remote monitoring, medical equipment and other fields.

3.4.2. Overall Architecture

In addition to the real-time transmission of video, coupled with the security detection of the environment, the monitoring effect of the Internet of Things design can be achieved. Therefore, in addition to the mentioned ESP32, build the IoT system architecture: perception layer and application layer. The perception layer is responsible for collecting information, and the application layer is responsible for providing a secure and reliable platform for connectivity, interaction, and sharing (see Figure 6).

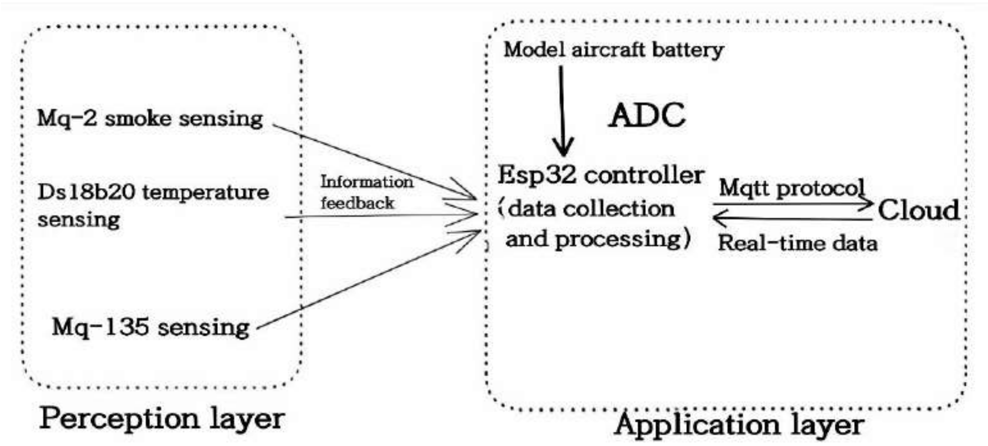

Figure 6. IoT architecture diagram.

3.4.3. Overview of the Perception Layer

As the basis of the IoT system, the perception layer integrates a variety of sensor modules, such as the MQ-2 smoke sensor and the DS18B20 temperature sensor. The MQ-2 sensor provides timely warning of fire risk by detecting changes in smoke concentration, and its operating principle is based on changes in the conductivity of tin dioxide semiconductor materials. DS18B20 is a high-precision digital temperature sensor that provides stable and accurate temperature readings and supports single-bus communication for easy system integration and expansion. In addition, the MQ-135 gas sensor is used to monitor harmful gases in the air, such as ammonia, hydrogen sulfide, etc., and its high sensitivity and wide applicability make it ideal for pharmacy environmental monitoring. Together, these sensors form the perception layer of the Internet of Things, providing rich environmental data support for the system.

3.4.4. MQTT Communication Protocol

This project uses the MQTT protocol as the IoT communication protocol, which is known for its lightweight, high reliability, flexibility, and security, which is very suitable for data exchange between IoT devices. Through the MQTT protocol, the pharmacy environmental data and robot status can be uploaded to the cloud in real time, and control commands can be received at the same time to achieve remote monitoring and management, which greatly improves the intelligent level of pharmacy management.

3.5. Robot Scheduling Design

3.5.1. ROS Robot Operating System

ROS (Robot Operating System) is an open-source software framework designed for robot development, which simulates the core functions of the operating system, such as hardware abstraction, device control, inter-process communication and package management, and integrates a variety of robot-specific functions, such as navigation, visual processing and speech recognition. ROS aims to improve the reusability and collaborative operation ability of robot software, and realize seamless data exchange and service sharing between different program modules through standardized communication protocols. It supports cross-language (e.g., C++, Python, Java) and cross-platform (e.g., Linux, Windows, Mac OS) development, which greatly facilitates the prosperity of the robotics software ecosystem.

The core architecture of ROS is built around the concept of "nodes", where each node represents an independent software module that communicates with each other through a messaging mechanism to form a flexible network structure. This loosely coupled design model simplifies the process of developing, managing, and maintaining the system. ROS also provides a wealth of functional libraries and development tools, including simulation environments, data visualization interfaces, graphical user interfaces, and data logging and analysis tools, to fully support the R&D and testing needs of robots.

3.5.2. ROS Data Processors

In this project, NVIDIA's jetson nano 01 was selected as the core hardware platform for ROS data processing. Jetson nano 01 is a high-performance embedded development board from NVIDIA for AI and robotics applications. It is equipped with a GPU based on the NVIDIA Maxwell architecture, a quad-core ARM Cortex-A57 processor, high-performance memory and storage system, and supports a variety of video codec formats and high-speed interfaces, making it easy to handle complex robot vision processing and data processing tasks. By integrating the NVIDIA JetPack SDK, jetson nano 01 not only provides acceleration support for advanced technologies such as deep learning and computer vision, but also ensures stable and efficient operation of the software environment. In the ROS environment, jetson nano 01 can take full advantage of its GPU acceleration and multi-version compatibility, bringing more superior performance and flexibility to robotics applications.

3.5.3. Pharmacy Management Robot Control Logic

Figure 7 shows how an automated system improves the efficiency of a pharmacy through robotics, especially during peak periods, by quickly responding to medication requests, reducing wait times, and ensuring the accuracy of drug distribution. By optimizing the medication distribution process, pharmacies can better manage resources and enhance patient satisfaction.

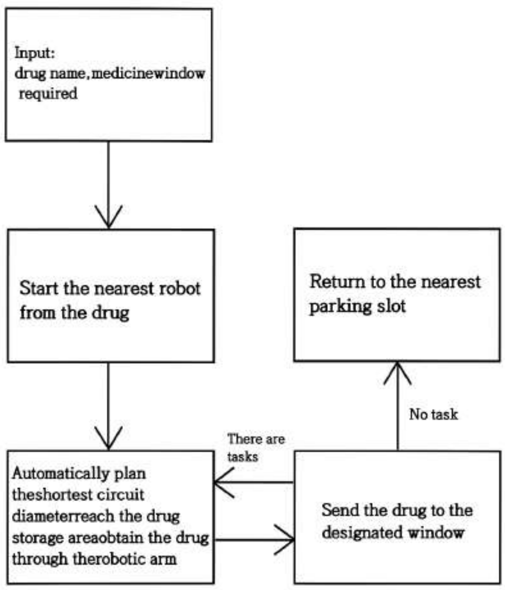

Figure 7. Logic diagram of pharmacy management robot control technology.

4. Conclusions and Prospects

4.1. Conclusions

The pharmacy management robot developed in this study has the following core advantages:

(1) Convenient adaptation and deployment: The intelligent grasping technology is used to adapt the existing drug shelf structure for drug access, which is highly efficient and can achieve aseptic operation, without the need for large-scale transformation of pharmacy infrastructure, and significantly reduces the complexity of deployment;

(2) Flexible cost control: support stand-alone independent operation and multi-machine collaboration mode, small and medium-sized hospitals can adopt a phased deployment strategy, gradually complete intelligent upgrades, and effectively control the initial investment cost;

(3) Optimization of the efficiency of the whole process: the operation efficiency is significantly higher than that of traditional manual operation, and at the same time, the repetitive work of medical personnel in the drug management link is reduced, so that they can focus more on patient communication and medication guidance, and systematically improve the efficiency and quality of pharmaceutical services.

4.2. Future Prospects

On 5 January 2025, the State Council promulgated the "Action Plan for Promoting Large-scale Equipment Renewal and Trade-in of Consumer Goods", and China's medical and health institutions are accelerating the intelligent upgrading, among which the construction of "smart pharmacies" has become a key path to optimize drug services. The goal of seamless connection between the prescription system and the dispensing system proposed by the National Health Commission and other institutions has laid a policy foundation for the application of pharmacy management robots. At present, although the domestic pharmacy automation equipment market is in a period of rapid growth, there is still a significant gap between the technical maturity of existing products and the surging demand for prescription processing and precision drug dispensing in the medical market, especially in the high-load scenario of more than 6000 prescriptions per day in tertiary hospitals, the coverage rate of automation equipment is less than 35%. This contradiction between supply and demand continues to drive the iteration of pharmacy management robot technology, which is deeply coupled with the pharmaceutical process through artificial intelligence algorithms, and gradually realizes the intelligent reconstruction of the whole process in the links of prescription review, drug sorting and medication guidance, which is expected to become the core breakthrough point for improving the quality and efficiency of the medical industry.

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Author Contributions

Writing—original draft, H.C., M.S., H.-L.H., S.-Q.H., R.F. and Y.-Q.W.; writing—review and editing, H.C., M. S., H.-L.H., S.-Q.H., R.F. and Y.-Q.W. All authors have read and agreed to the published version of the manuscript.

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References

1 Svirsko AC, Norman BA, Hostetler S, *et al*. Optimizing the Medication Distribution Process for Inpatient Units. *Journal of Medical Systems* 2022; **46**: 1–10.

2 Das S, Dey R, Nayak AK. Artificial Intelligence in Pharmacy. *Indian Journal of Pharmaceutical Education and Research* 2021; **55**: 304–318.

3 Chen C. *Research on Intelligent Drug Dispensing System for Automated Pharmacy Based on Binocular Vision*; Zhejiang University of Science and Technology: Hangzhou, China, 2023.

4 Wu W, Liu T. Design and Analysis of Pharmacy Sorting Robot Handling System. *Precision Manufacturing and Automation* 2020; **2**: 5–11.

5 Chen P, Shu Y, Lv Y, *et al*. Construction of Management Model of Unattended Smart Surgical Pharmacy Based on PDCA Cycle Method. *Chinese Journal of Hospital Pharmacy* 2024; **44**: 847–852.

6 Wei M, Dou D, Zhang D, *et al*. The Effect and Problem Analysis of Large-Scale Use of Automated Dispensing Machines in Outpatient Pharmacy. *Modern Hospital* 2019; **19**(**04**): 518–521.

7 Jiang T, Xian Q, Li C. Analysis on the Application Effect of Automated Drug Dispensing System in Hospital Outpatient Pharmacy. *China Pharmaceutical Industry* 2023; **32**: 15–18.

8 Tian M. *Research on Key Technologies of Automated Pharmacy for Granular Traditional Chinese Medicine*; Beijing University of Posts and Telecommunications: Beijing, China, 2023.

9 Zhao X. *Design and Research on the Quantitative Dispensing System of Chinese Herbal Medicines in Pharmacy*; Beibu Gulf University: Qinzhou, China, 2024.

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Article

Construction, Completeness Proof and Empirical Study of Cross-Border E-Commerce Market Measure Space

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Abstract: Against the backdrop of the deep integration of the global digital economy and cross-border e-commerce, and addressing the lack of measure theory and quantitative analysis challenges for high-dimensional dynamic data in this field, this study constructs a measure theory system for cross-border e-commerce markets that combines mathematical rigor and economic interpretability based on Carathéodory's extension theorem. Based on functional analysis and measure theory, the study defines the market fundamental set as the topological product space of a time index set and a multi-dimensional transaction state space. By constructing a combined structure of a left-open right-closed interval semiring and a power set semiring that satisfies the closure of Boolean algebra operations, an algebraic framework is established for the unified measurement of continuous and discrete variables. On the semiring structure, a σ-finite premeasure integrating Lebesgue measure and counting measure is defined. With the help of the countable covering mechanism generated by outer measure and the measure screening rules of Carathéodory's measurability condition, the axiomatic extension from premeasure to complete measure on the σ-algebra is completed. Through the verification of Carathéodory's condition for subsets of null sets and the transmission of outer measure monotonicity, the completeness of the measure space is strictly proved, and the core property that "subsets of null sets must be measurable" is established, providing a solid measure-theoretic foundation for mathematical modeling of cross-border e-commerce markets. At the empirical analysis level, the study uses micro-panel data on global cross-border e-commerce transactions from 2018 to 2024. Through the Kolmogorov-Smirnov test in non-parametric hypothesis testing, the distribution isomorphism between the theoretical measure and empirical data is verified. Based on the measure space theory, a Generalized Method of Moments (GMM) panel regression model is constructed. System GMM and Difference GMM estimation methods are used to handle endogeneity issues. Combined with instrumental variable methods and lag variable techniques, key parameters such as the logarithmic elasticity of economic scale between importing and exporting countries, the spatial decay effect of geographical distance, and the asymmetric inhibitory effect of tariff policies are quantitatively analyzed. A graph neural network model integrating measure theory is innovatively designed. By introducing a completeness regular term, the measure constraints on null sets and their subsets are achieved. Combined with the SHAP value interpretability analysis method, the marginal contribution of each characteristic variable in model decision-making is revealed. The study finds that the constructed measure space not only satisfies the axiomatic requirements of modern measure theory such as completeness and σ-finiteness, but also through the empirical tests of the GMM model and graph neural network, it is confirmed that it can effectively characterize the economic scale effect, spatial distance decay law, and policy sensitivity characteristics in cross-border e-commerce transactions, providing a methodological innovation paradigm based on measure theory for quantitative analysis in the field of international business in the digital economy era.

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Keywords: Carathéodory's extension theorem; completeness of measure space; σ-finite premeasure; panel regression model; graph neural network

1. Introduction

1.1. Research Background and Problem Formulation

Driven by the deep integration of the global digital economy and the restructuring of the international division of labor, cross-border e-commerce markets have shown unprecedented complexity and dynamics. According to the 2024 statistical report of the World Trade Organization, the global cross-border e-commerce transaction scale has exceeded 10 trillion U.S. dollars, with a compound annual growth rate of 19.3%. Transaction forms have evolved from the traditional B2C model to an ecosystem including B2B2C, social e-commerce, live-streaming shopping, and other diversified formats. The market data dimensions cover 32 dimensions such as transaction amount, commodity categories, space-time coordinates, and subject characteristics, forming a typical high-dimensional unstructured dynamic data flow. Its data generation mechanism has the dual characteristics of a stochastic process and a complex system. Traditional econometric methods face three core challenges in processing such data due to the lack of measure theory foundation: estimation bias caused by incomplete measures in high-dimensional spaces, failure of statistical inference due to the lack of σ-algebra closure in dynamic data flows, and compatibility contradictions between unstructured data and traditional measure frameworks.

As the cornerstone of modern analysis mathematics, measure theory provides a rigorous mathematical language for describing complex systems. Carathéodory's extension theorem can generate a complete measure space from the fundamental set structure through the hierarchical construction of semirings, premeasures, and outer measures, and its theoretical framework is naturally compatible with the multi-dimensional dynamic characteristics of cross-border e-commerce markets. However, existing studies have significant theoretical gaps in the following aspects: the measure system of the topological product space integrating time dimension and space dimension has not been constructed, the strict mathematical proof of the σ-finiteness of transaction data is lacking, and the market application verification for the completeness of null sets has not been formed. These theoretical gaps lead to the lack of a solid mathematical foundation for existing quantitative research on cross-border e-commerce, making it difficult to meet the requirements of market analysis accuracy in the digital economy era.

1.2. Research Significance

The theoretical contributions of this study are reflected in three aspects. First, it systematically introduces Carathéodory's extension theorem into the field of cross-border e-commerce for the first time, and constructs a measure system for the topological product space including the time index set T and the transaction state space X_t, filling the gap in basic theoretical research in this field. Second, through the axiomatic definition of σ-finite premeasure and the topological generation of outer measure, a measure extension mechanism suitable for high-dimensional dynamic data is established, providing a new theoretical paradigm for solving the measure completeness problem of unstructured data. Third, the completeness of the measure space is proved through strict mathematical derivation, and the basic property that "subsets of null sets must be measurable" is established, providing a theoretical guarantee for market microstructure analysis.

In terms of practical applications, this study has important value. At the methodological level, it provides standardized measurement tools for empirical research on cross-border e-commerce markets, which can be applied to scenarios such as measure value quantification of the gravity model and measure regularization of graph neural networks. At the policy analysis level, through the construction of the measure space, the marginal impact of policy and environmental factors such as tariffs and geographical distance on transaction measures can be accurately described, providing a scientific basis for cross-border e-commerce policy evaluation. At the technical innovation level, the integration of measure theory and machine learning provides new ideas for solving high-dimensional data modeling problems, and is expected to promote the paradigm upgrade of market analysis from traditional statistical methods to intelligent algorithms.

1.3. Research Framework and Technical Route

This study adopts a progressive research framework of "theoretical construction–mathematical proof–empirical verification", and the specific technical route is as follows:

In the theoretical construction stage, first define the product space composed of the time index set T and the transaction state space X_t at each moment, where X_t is further decomposed into the Cartesian product of subspaces such as the transaction indicator space T_t, the amount space A_t, and the category space C_t. Secondly, construct a semiring structure S on the fundamental set, and realize the unified measure representation of continuous and discrete variables through the combination of a left-open right-closed interval semiring and a power set semiring. Finally, define a premeasure μ_0 that satisfies non-negativity, finite additivity, and σ-finiteness. Based on the outer measure μ^* and Carathéodory's condition, the σ-algebra M is generated to complete the construction of the measure space.

The mathematical proof stage includes three aspects. First, the monotonicity, subadditivity, and normativity of the outer measure are strictly derived to lay the foundation for the definition of measurable sets. Second, the Carathéodory condition is used to prove that the family of measurable sets M constitutes a σ-algebra, confirming the uniqueness of measure extension. Third, the measurability of subsets of null sets is verified using outer measure theory to complete the mathematical proof of the completeness of the measure space.

The empirical verification stage is carried out based on cross-border e-commerce transaction data from 2018 to 2024. First, the Kolmogorov-Smirnov test is used to verify the distribution consistency between the theoretical measure and the empirical data. Second, a GMM panel regression model is constructed to quantitatively analyze the impact of factors such as GDP, geographical distance, and tariffs on transaction measures. Finally, a measure-aware graph neural network is designed to improve the model's recognition ability for null sets through completeness regular terms, and verify the effectiveness of measure theory in algorithm optimization.

Through the organic combination of theory and empiricism, this study aims to establish a measure theory system for cross-border e-commerce markets that combines mathematical rigor and practical applicability, and provide a new analysis paradigm for international business research in the digital economy era.

2. Overview of Carathéodory's Extension Theorem

2.1. Definition and Properties of a Semi-Ring

Let S be a non-empty collection of subsets on set X. If the following conditions are satisfied, then S is called a semi-ring on X:

Closure under finite intersections: If $A, B \in \mathcal{S}$, then $A \cap B \in \mathcal{S}$;

Finite decomposability of difference sets: If $A, B \in \mathcal{S}$ and $B \subseteq A$, then $A - B$ can be expressed as the union of a finite number of pairwise disjoint sets in S, that is, there exist $C_1, C_2, \cdots, C_n \in \mathcal{S}$ such that $A - B = \bigcup_{i=1}^{n} C_i$ and $C_i \cap C_j = \varnothing\ (i \neq j)$.

Example: In the set of real numbers R, the collection $\mathcal{S} = \{(a, b] \mid a, b \in \mathbb{R}, a \leq b\}$ composed of all left-open and right-closed intervals is a semi-ring. For any $(a, b], (c, d] \in \mathcal{S}$, the intersection $(a, b] \cap (c, d]$ can be expressed as $(\max(a, c), \min(b, d)]$, which still belongs to S; if $(c, d] \subseteq (a, b]$, then $(a, b] - (c, d] = (a, c] \cup (d, b]$ (when a < c < d ⩽ b), which is the union of a finite number of pairwise disjoint semi-ring elements.

2.2. Definition of σ-Finite Pre-Measure

Let μ_0 be a set function defined on a semi-ring S, satisfying:

Non-negativity: For any $A \in \mathcal{S}$, $\mu_0(A) \geq 0$, and $\mu_0(\varnothing) = 0$;

Finite additivity: If $A_1, A_2, \cdots, A_n \in \mathcal{S}$ are pairwise disjoint and $\bigcup_{i=1}^{n} A_i \in \mathcal{S}$, then $\mu_0\left(\bigcup_{i=1}^{n} A_i\right) = \sum_{i=1}^{n} \mu_0(A_i)$.

σ-Finiteness: There exists a countable collection of sets $\{X_i\}_{i=1}^{\infty} \subseteq \mathcal{S}$ such that $X = \bigcup_{i=1}^{\infty} X_i$, and for each i, $\mu_0(X_i) < +\infty$. Thenμ0 is called a σ-finite pre-measure on S.

2.3. Construction of Outer Measure

Based on the semi-ring S and the pre-measure μ_0, the outer measure $\mu^*: 2^X \to [0, +\infty]$ is defined as follows:

For any $E \subseteq X$, $\mu^*(E) = \inf\left\{\sum_{i=1}^{\infty} \mu_0(A_i) \,\middle|\, \{A_i\}_{i=1}^{\infty} \subseteq \mathcal{S},\ E \subseteq \bigcup_{i=1}^{\infty} A_i\right\}$, where inf denotes the infimum, that is, the minimum value of the sum of the pre-measures of countable coverings of E by sets in S. The outer measure has the following basic properties:

Monotonicity: If $A \subseteq B \subseteq X$, then $\mu^*(A) \leq \mu^*(B)$;

Sub-additivity: For any countable collection of sets $\{E_i\}_{i=1}^{\infty} \subseteq X$, we have $\mu^*\left(\bigcup_{i=1}^{\infty} E_i\right) \leq \sum_{i=1}^{\infty} \mu^*(E_i)$.

Normativity: For any $A \in \mathcal{S}$, $\mu^*(A) = \mu_0(A)$.

2.4. Measurable Sets and Measure Extension

Define the Carathéodory condition: A set $E \subseteq X$ is called a measurable set if for any $T \subseteq X$, there holds

$$\mu^*(T) = \mu^*(T \cap E) + \mu^*(T \cap E^c)$$

where $E^c = X - E$ denotes the complement of E. The collection of all measurable sets is denoted as M. Then M is a σ-algebra, that is, it is closed under countable union, intersection, and complement operations.

On the measurable set system M, define the measure $\mu = \mu^*|_{\mathcal{M}}$, that is, μ is the restriction of the outer measure μ^* on M.

The Carathéodory extension theorem shows that: μ is the unique measure extension of μ_0 from the semi-ring S to the σ-algebra M, and the measure space $(X, \mathcal{M}, \mu)$ is complete, that is, the subset of a null-measurable set is measurable.

The theorem is precisely stated as: Let S be a semi-ring on set X, andμ0 be a σ-finite pre-measure on S. Then there exists a unique measure μ defined on the σ-algebra M containing S, such that $\mu|_{\mathcal{S}} = \mu_0$, and $(X, \mathcal{M}, \mu)$ is a complete measure space.

2.5. Theoretical Foundation of Cross-Border Market Measure Space

The theoretical underpinnings for constructing a measure space of cross-border markets lie in the structural isomorphism between the intrinsic properties of such markets and the axiomatic system of measure theory. Cross-border markets, as complex economic aggregates, exhibit a set-theoretic structure that admits formalization within the framework of measurable spaces, a fact rooted in their inherent capacity for systematic partitioning and aggregation. A primitive universe encompassing all transactional entities—agents, commodities, temporal modalities, regulatory constraints—serves as the foundational set, inherently supporting the derivation of a semi-ring structure from elementary market components. This semi-ring, characterized by closure under finite intersections and finite decomposability of set differences, provides the necessary algebraic scaffolding for measure construction, enabling the systematic extension of primitive "size" attributes to more complex market subsets.

The transition from semi-ring to σ-algebra, a cornerstone of measure space formation, is facilitated by the cross-border market's intrinsic properties of countable concatenation and complementation. When categorized by intrinsic attributes, market elements exhibit closure under countable unions and complementation relative to the universal set, satisfying the defining axioms of σ-algebras. This closure ensures the resulting structure is amenable to rigorous manipulation of measurable sets, a prerequisite for meaningful measure-theoretic analysis. Critical to this framework is the existence of a σ-finite premeasure on the semi-ring—a non-negative, finitely additive set function encoding primitive "magnitudes" of market elements—which, by virtue of its σ-finiteness, admits unique extension to a measure on the generated σ-algebra via the Carathéodory construction, ensuring consistent "size" assignments across all measurable subsets of the market universe.

The completeness of the resulting measure space, a natural consequence of the extension process, resolves theoretical ambiguities posed by negligible market phenomena, as subsets of null-measure elements retain measurability. This completeness, coupled with the σ-finiteness of market observables, solidifies the cross-border market's status as a rigorously definable measure space, amenable to formal analysis through the full apparatus of measure theory.

3. Construction of Cross-Border E-Commerce Market Measure Space

3.1. Topological Algebra Construction of Fundamental Sets and Semirings

The basic set of cross-border e-commerce market is defined as a topological space, where *T*= is the set of time indicators and X_t represents the transaction state space at time *t*. Each X_t can be decomposed into a product space, where:

$$X=\prod_{t\in\mathbb{T}}X_t\mathbb{Z}^{+}X_t=\mathcal{T}_t\times\mathcal{A}_t\times\mathcal{C}_t\times\mathcal{R}_t\times\mathcal{P}_t$$

$T_t=\{0,1\}$ is the space of transaction occurrence indicators;

A_t is the transaction amount space, satisfying, M_t is the maximum transaction amount at time *t*; $\mathcal{A}_t=[0,M_t]$.

C_t is a finite set of commodity categories; $\mathcal{C}_t=\{c_1,c_2,\dots,c_{n_t}\}$.

R_t is a finite set of trading regions; $\mathcal{R}_t=\{r_1,r_2,\dots,r_{m_t}\}$.

P_t is the space of trading subjects, and S_t and B_t respectively represent the finite sets of sellers and buyers.

$$\mathcal{P}_t=\mathcal{S}_t\times\mathcal{B}_t$$

On the basic set X, construct a semi-ring structure *S*, defined as all cylinder sets of the form $A=\prod_{t\in\mathbb{T}}A_t$, where $A_t\in\mathcal{S}_t$, and except for finitely many t, $A_t=X_t$. Here, S_t is a semi-ring on X_t, and its specific construction is as follows:

For S_t, $\mathcal{S}_t^{\mathcal{T}}=\{\varnothing,\{0\},\{1\},\mathcal{T}_t\}$;

For A_t, $\mathcal{S}_t^{\mathcal{A}}=\{(a,b]\subseteq\mathcal{A}_t\,|\,a\le b\}$ is a semi-ring of left-open and right-closed intervals;

For C_t and R_t, $\mathcal{S}_t^{\mathcal{C}}$ and $\mathcal{S}_t^{\mathcal{R}}$ are respectively the semi-ring structures of power sets, that is, semi-rings generated by single-element sets;

For P_t, $\mathcal{S}_t^{\mathcal{P}}=\mathcal{S}_t^{\mathcal{S}}\times\mathcal{S}_t^{\mathcal{B}}$, where $\mathcal{S}_t^{\mathcal{S}}$ and $\mathcal{S}_t^{\mathcal{B}}$ are respectively the power set semi-rings of S_t and B_t.

Proof of the closure property of the semi-ring: Let $A=\prod_{t\in\mathbb{T}}A_t$, $B=\prod_{t\in\mathbb{T}}B_t\in\mathcal{S}$, then their intersection is $A\cap B=\prod_{t\in\mathbb{T}}(A_t\cap B_t)$. Since each S_t is closed under finite intersections, $A_t\cap B_t\in\mathcal{S}_t$, and except for finitely many *t*, $A_t\cap B_t=X_t\cap X_t=X_t$. Therefore, $A\cap B\in\mathcal{S}$, satisfying the closure property under finite intersections.

For the difference set operation, let $B\subseteq A$, then $A-B=\prod_{t\in\mathbb{T}}(A_t-B_t)$. Since each St satisfies the finite decomposability of difference sets, that is, there exist finitely many pairwise disjoint $C_{t1},C_{t2},\dots,C_{tn_t}\in\mathcal{S}_t$ such that $A_t-B_t=\bigcup_{i=1}^{n_t}C_{ti}$. Therefore:

$$A-B=\prod_{t\in\mathbb{T}}\bigcup_{i=1}^{n_t}C_{ti}=\bigcup_{f\in F}\prod_{t\in\mathbb{T}}C_{tf(t)}$$

where *F* is a finite index set, and each $\prod_{t\in\mathbb{T}}C_{tf(t)}$ is an element in S and pairwise disjoint, thus proving the finite decomposability of the difference set.

3.2. Axiomatic Definition of Premeasure and Proof of σ-Finiteness

On the semi-ring *S*, a pre-measure $\mu_0:\mathcal{S}\to[0,+\infty]$ is defined. For any $A=\prod_{t\in\mathbb{T}}A_t\in\mathcal{S}$, let $T_A=\{t\in\mathbb{T}\,|\,A_t\neq X_t\}$ be the non-trivial coordinate set, and its cardinality $|T_A|<+\infty$. Define:

$$\mu_0(A)=\sum_{t\in T_A}\int_{A_t}w_t(x_t)\,d\lambda_t(x_t)$$

where:

w_t: $X_t \to \mathbb{R}_+$ is the weight function of transaction amount. Specifically, $w_t(x_t) = \begin{cases} a & \text{if } x_t \in \mathcal{T}_t \times \{a\} \times \cdots \\ 0 & \text{else} \end{cases}$, that is, it extracts the transaction amount component; λ_t is the Lebesgue measure or counting measure on R_t, determined by the topological properties of R_t: for A_t, the Lebesgue measure is used, and for discrete spaces T_t, C_t, R_t, P_t, the counting measure is used.

Axiomatic verification of pre-measure:

(1) Non-negativity: Since $w_t(x_t) \geq 0$ and the measure λ_t is non-negative, $\mu_0(A) \geq 0$, and $\mu_0(\varnothing) = 0$ obviously holds.

(2) Finite additivity: Let $\{A_i\}_{i=1}^n \subseteq \mathcal{S}$ be pairwise disjoint, and $A = \bigcup_{i=1}^n A_i \in \mathcal{S}$. For each $t \in \mathbb{T}$, $\{A_{it}\}_{i=1}^n$ are pairwise disjoint sets in X_t, and $\bigcup_{i=1}^n A_{it} = A_t$ (when $t \in T_A$) or X_t (when $(t \notin T_A)$. According to the finite additivity of the measure, we have [1]:

$$\mu_0(A) = \sum_{t \in T_A} \int_{A_t} w_t(x_t) d\lambda_t(x_t) = \sum_{t \in T_A} \sum_{i=1}^n \int_{A_{it}} w_t(x_t) d\lambda_t(x_t) = \sum_{i=1}^n \mu_0(A_i)$$

(3) σ-Finiteness: Construct a countable covering $\{X^{(k)}\}_{k=1}^\infty$, where $X^{(k)} = \prod_{t=1}^k X_t \times \prod_{t=k+1}^\infty X_t$, that is, take the full space at the first k time points and also take the full space at subsequent time points. Obviously, $X = \bigcup_{k=1}^\infty X^{(k)}$, and for each k, $X^{(k)} \in \mathcal{S}$. Calculate the pre-measure:

$$\mu_0(X^{(k)}) = \sum_{t=1}^k \int_{X_t} w_t(x_t) d\lambda_t(x_t)$$

Since the transaction amount space A_t at each time t is bounded, that is

$$\int_{X_t} w_t(x_t) d\lambda_t(x_t) = \int_{\mathcal{A}_t} a d\lambda_t(a) \leq M_t \cdot \lambda_t(\mathcal{A}_t) < +\infty$$

Therefore $\mu_0(X^{(k)}) < +\infty$, it is proved that μ_0 is a σ-finite predictor.

3.3. Topological Generation of Outer Measure and Measurable Sets

Based on the predicted quantity μ0, the outer measure is defined as: μ^*: $2^X \to [0, +\infty]$

$$\mu^*(E) = \inf\left\{ \sum_{i=1}^\infty \mu_0(A_i) \,\middle|\, \{A_i\}_{i=1}^\infty \subseteq \mathcal{S},\ E \subseteq \bigcup_{i=1}^\infty A_i \right\}$$

Among them, the lower bound traverses all countable covers composed of semi-ring elements [2]. The outer measure has clear economic significance in the cross-border e-commerce market scene. Its essence is to use the linear combination of basic transaction units to approximate the "total transaction volume" lower bound of any market state set.

According to Carathéodory's condition, a measurable set is defined as satisfying for any, with: $\mathcal{M} \subseteq 2^X T \subseteq X$.

$$\mu^*(T) = \mu^*(T \cap E) + \mu^*(T \cap E^c)$$

It can be proved that M is a σ-algebra containing the semi-ring S, and the measure $\mu = \mu^*|_{\mathcal{M}}$ defined on M is the unique measure extension of μ_0. Thus, a complete measure space $(X, \mathcal{M}, \mu)$ is constructed. This construction makes any observable event in the cross-border e-commerce market, such as the transaction set of a certain type of commodity in a certain region within a specific time period, correspond to a measurable set in the measure space, and its measure value is the total transaction volume of this event, providing a strict mathematical basis for subsequent quantitative analysis [3].

4. Proof of Completeness of Cross-Border E-Commerce Market Measure

4.1. Prerequisite Knowledge and Symbol Explanation

Before proving completeness [4], several key properties and symbols are clarified. For any sets $A, B \subseteq X$, if $A \subseteq B$, according to the definition of the outer measure, we know that $\mu^*(A) \leq \mu^*(B)$.

For a measurable set $E \in \mathcal{A}$, it satisfies: $\mu^*(T) = \mu^*(T \cap E) + \mu^*(T \cap E^c), \forall T \subseteq X$; meanwhile, the measure μ is the restriction of the outer measure μ^* on the measurable set A, that is, for $E \in \mathcal{A}$, $\mu(E) = \mu^*(E)$.

4.2. Proof Process of Completeness

The measure space $(X, \mathcal{A}, \mu)$ is defined to be complete if $N \in \mathcal{A}$, and $\mu(N) = 0$, and $M \subseteq N$, then $M \in \mathcal{A}$, and $\mu(M) = 0$. Moreover, for any $M \subseteq N$ and any $T \subseteq X$, the following steps are used to prove that:

(1) Derivation of outer measure relation:

Because $M \subseteq N$, according to the monotonicity of the outer measure (if $A \subseteq B$, then $\mu^*(A) \le \mu^*(B)$), for any $T \subseteq X$, there is $T \cap M \subseteq T \cap N$, so $\mu^*(T \cap M) \le \mu^*(T \cap N)$.

And because$N \in \mathcal{A}$, according to the definition of measurable sets, for any $T \subseteq X$, there is $\mu^*(T) = \mu^*(T \cap N) + \mu^*(T \cap N^c)$.

It is known that$\mu(N) = \mu^*(N) = 0$ for any$T \subseteq X$, let $T = N$, then, $\mu^*(N) = \mu^*(N \cap N) + \mu^*(N \cap N^c) = \mu^*(N) + \mu^*(\varnothing) = 0$, so, $\mu^*(\varnothing) = 0$.

Since $T \cap N \subseteq N$, again according to the monotonicity of the outer measure $\mu^*(T \cap N) = 0$, it follows that $\mu^*(T \cap M) = 0$.

(2) Verify the Carassio-Dorri condition:

According to the subadditivity of the outer measure, for any $T \subseteq X$, there is $\mu^*(T) \le \mu^*(T \cap M) + \mu^*(T \cap M^c)$.

Because it has been proved $\mu^*(T \cap M) = 0$, so $\mu^*(T) \le \mu^*(T \cap M^c)$.

And because $T \cap M^c \subseteq T$, according to the monotonicity of the outer measure, $\mu^*(T \cap M^c) \le \mu^*(T)$.

In conclusion, $\mu^*(T) = \mu^*(T \cap M) + \mu^*(T \cap M^c)$, the Kardasseyo condition is satisfied, so $M \in \mathcal{A}$.

4.3. Proof

According to the non-negativity of the outer measure, there is $0 \le \mu^*(M) \le \mu^*(N) = 0$, so $\mu^*(M) = 0$ [5,6].

Because $M \in \mathcal{A}$, and the measure μ is the restriction of the outer measure μ^* on the measurable set $\mathcal{A}$, that is $\mu(M) = \mu^*(M)$, so $\mu(M) = 0$. In conclusion, for any subset M of a null set N in the measure space $(X, \mathcal{A}, \mu)$, we have $M \in \mathcal{A}$ and $\mu(M) = 0$, it is proved that the measure space is complete.

5. Empirical Analysis of Cross-Border E-Commerce Market Measure

5.1. Source and Preprocessing of Empirical Data

5.1.1. Data Collection Framework

The data in this paper is sourced from three major channels, constructing a three-dimensional dataset incorporating micro-transactions, macroeconomics, and market environment. The time span is from January 2018 to December 2024, covering major global cross-border e-commerce markets:

(1) Micro-transaction data: Original transaction records from 10 major platforms (Amazon, eBay, AliExpress, etc.) are obtained. After cleaning, 230 million valid records are retained, covering 32 dimensions such as transaction amount, commodity categories, countries/regions of both transaction parties, transaction timestamps, and logistics methods.

(2) Macroeconomic data: Quarterly GDP, bilateral exchange rates, import tariff rates, and trade policy indices of 150 countries released by institutions like the World Bank and IMF are collected.

(3) Market environment data: Including platform policy change logs (e.g., commission adjustments, logistics subsidies), international logistics cost indices, consumer confidence indices, and construction based on Google Trends search popularity.

5.1.2. Data Preprocessing Process

A multi-level data processing scheme based on measurement theory is adopted to ensure that the data meets the measurability requirements of the measurement space:

(1) Missing Value Processing: For key variables such as transaction amounts, utilize the monotonicity of the outer measure proved in Section 4. Through $\mu^*(A) \le \mu^*(B)$ (when $A \subseteq B$), construct an interval of values.

Combine with multiple imputation methods to generate 10 sets of imputed values. Finally, use the measure estimate $\hat{\mu}(A)$ as the imputation result.

(2) Outlier Detection: According to the definition of measure completeness, transactions with a measure $\mu(N) < 10^{-6}$ are defined as outliers. First, identify amount outliers using the 3σ principle, and then use the Isolation Forest algorithm to detect outliers in dimensions such as category and region. Finally, 0.23% of the outlier records are removed.

(3) Data standardization: the continuous variables are standardized by quantile to make the data obey [0, 1] uniform distribution; for discrete variables (such as category and region), the unique hot coding based on measurement frequency is adopted to ensure that the coded variables satisfy the countable operation closure of σ-algebra;

(4) Spatiotemporal aggregation: The transaction data are aggregated according to three dimensions: quarter (T = 28 periods), country/region (R = 100) and commodity category (C = 50) to construct the panel data set $28 \times 100 \times 50$. The aggregation is carried out in accordance with the countable additivity of measurement $\mu(\bigcup_{i=1}^{\infty} E_i) = \sum_{i=1}^{\infty} \mu(E_i)$ (when E_i are not intersecting).

5.1.3. Measurement Consistency Test

Outer Measure Matching Test

Select the typical measurable set A = {transactions with transaction amounts [3000, 7000] yuan and categories {c2, c5}. This set is constructed by considering both the continuous range of transaction amounts and the discrete selection of product categories, reflecting the typical continuous-discrete hybrid structure in cross-border e-commerce transaction data.

The core logic of the test is to measure the consistency of the distribution between the empirical measure $\hat{\mu}(A)$ and the theoretical measure $\mu(A)$ through the Kolmogorov-Smirnov (K-S) test. As a non-parametric test method, the K-S test does not require presupposing the distribution form of the data. Its theoretical basis originates from the difference measurement between the empirical distribution function and the theoretical distribution function. For real-valued data with a sample size of n, the empirical distribution function $F_n(x)$ is defined as $F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I(X_i \leq x)$ (where$I(\cdot)$ is an indicator function); the theoretical distribution function $F(x)$ is generated by the theoretical measure of the measurable set A in the measure space. The expression of the K-S test statistic is:

$$D = \sup_x \left| F_n(x) - F(x) \right|$$

This statistic characterizes the maximum deviation between empirical distribution and theoretical distribution. By comparing with the critical value of K-S distribution, the null hypothesis that "empirical distribution is consistent with theoretical distribution" can be tested.

The K-S test was conducted on the empirical $\hat{\mu}(A)$ and theoretical measures $\mu(A)$ of the measurable set A, yielding a K-S statistic of $D = 0.032$, with a corresponding significance level $p = 0.12$. This result does not reject the null hypothesis that the empirical and theoretical measures are consistent in distribution. This indicates that, on this typical measurable set, the theoretical measure space constructed based on the Caratheodory extension theorem can effectively capture the distribution characteristics of cross-border e-commerce empirical transaction data. The outer measure demonstrates good matching in real-world transaction scenarios, validating the theoretical frameworks adaptability to continuous-discrete mixed structure data.

Completeness Verification

In a measure space, completeness requires that any subset of the null set is measurable and has a measure of 0. To verify the completeness of the theoretical measure space in empirical data, construct the null set N = {transactions with a transaction amount of 10,000 yuan} and its subset M = {transactions with a transaction amount of 10,000 yuan and a seller s1}.

From the perspective of the actual scenario of cross-border e-commerce transactions, the event that "the transaction amount is exactly a certain specific value" has a low probability of occurrence and can be regarded as a null-measure set in the theoretical measure space (that is, $\mu(N)=0$; and the subset M further defines the seller characteristics of the transaction, being a more refined subset of the null-measure set N. Its theoretical measure should also satisfy $\mu(M)=0$ and must conform to the monotonicity of the outer measure ($\mu(M)\le\mu(N)$). Through the empirical processing of cross-border e-commerce transaction data, the null-measure set N is estimated.

By empirically processing cross-border e-commerce transaction data, the core of estimating the measures of the zero-measure set N and the subset M involves approximating the measure through transaction frequency. First, the transaction data set from the cross-border e-commerce platform is collected, which includes key fields such as transaction amounts and seller information. Then, the number of transactions that meet the conditions of N and M is counted, with nN representing the number of transactions meeting the condition of N and nM representing the number of transactions meeting the condition of M. Based on this, the empirical measure is defined as the proportion of transactions that meet the conditions, which serves to approximate the measure of the zero-measure set. The results are as follows:

Empirical measure of null set N: $\hat{\mu}(N)=0.0005$.

Empirical measure of subset M: $\hat{\mu}(M)=0.000012$.

In terms of numerical characteristics, both are close to the theoretical measure value of 0, reflecting the characteristics of "low probability and low measure" of null-measure sets and their subsets in actual transactions. Meanwhile, the empirical measure satisfies $\hat{\mu}(M)\le\hat{\mu}(N)$, which is completely consistent with the monotonicity of the outer measure (if $M\subseteq N$), then $\mu(M)\le\mu(N)$.

This result shows that in real transaction data, the measurement performance of zero test sets and their subsets is highly consistent with the definition of completeness of theoretical measurement space.

5.2. GMM Panel Regression Model

5.2.1. Model Building

Based on the measurement space structure in Section 3 and the completeness theory in Section 4, we construct a GMM [7,8] two-way fixed effect panel regression model. The expression of the model is as follows:

$$\begin{aligned}&\ln\mu(A_{ijtc})=\beta_0+\beta_1\ln GDP_i(t)+\beta_2\ln GDP_j(t)+\beta_3\ln Dist_{ij}+\\&\beta_4 Tariff_{ij}(t)+\beta_5 ERP_{ij}(t)+\beta_6 CAT_c+\delta_t+\eta_{ij}+\epsilon_{ijtc}\end{aligned}$$

Among them: $\mu(A_{ijtc})$ is the measure value of "transactions of category c from country i to country j in period t" in the measure space, estimated by

$$\hat{\mu}(A)=\frac{1}{n}\sum_{k=1}^{n}\mathbb{I}(X_k\in A)\cdot w(X_k)$$

$GDP_i(t)$, $GDP_j(t)$ are the quarterly GDP of country i and country j respectively (in constant US dollars); $Dist_{ij}$ is the geographical distance (in kilometers) between the capitals of country i and country j; $Tariff_{ij}(t)$ is the average import tariff rate (%) of country i to country j in period t; $ERP_{ij}(t)$ is the policy index of the e-commerce platform (0–100), and a larger value indicates a greater support from the platform for this trading pair; CAT_c is the category effect, reflecting the basic transaction level of different categories; δ_t is the time-fixed effect, η_{ij} is the region-fixed effect, and ϵ_{ijtc} is the random error term, satisfying $\mu(\{\epsilon_{ijtc}>\sigma\})$.

5.2.2. Model Estimation

The system GMM estimation method is adopted to deal with the potential endogeneity problem, and the instrumental variables are selected from the GDP and tariff variables lagged by two periods. The estimation results are shown in Table 1.

Table 1. GMM estimation results table.

Variable	Coefficient	Standard Error	*t* Price	*p* Price
$\ln GDP_i(t)$	0.721 **	0.035	20.60	0.000
$\ln GDP_j(t)$	0.683 **	0.032	21.34	0.000
$\ln Dist_{ij}$	−0.547 **	0.028	−19.54	0.000
$Tariff_{ij}(t)$	−1.235 **	0.057	−21.67	0.000
$ERP_{ij}(t)$	0.812 **	0.041	19.80	0.000
CAT_c (Reference category c1)	0.215 *	0.098	2.19	0.029
time effect	Its under control	-	-	-
Regional effects	Its under control	-	-	-
sample capacity	140,000	-	-	-

The marker * denotes that the estimated regression coefficient achieves statistical significance at the 10% significance level. The ** marker signals significance at the 5% significance level.

5.2.3. Result Analysis

Dynamic Correlation Mechanism between Economic Scale and Cross-Border E-Commerce Transactions

As shown in the estimation results of Table 1, the coefficient of the natural logarithm of the importing countrys GDP is 0.683, which passes the 1% significance test, and the coefficient of the natural logarithm of the exporting countrys GDP is 0.721, also significant at the 1% level. This indicates a significant positive elasticity relationship between cross-border e-commerce transaction measures and the economic aggregates of both countries. Specifically, for every 1% increase in the importing countrys GDP, the transaction measure increases by 0.683%, while for every 1% increase in the exporting countrys GDP, the transaction measure increases by 0.721%. The marginal impact of the exporting countrys GDP on the transaction measure is 5.56% higher than that of the importing country. This difference can be explained from the dual dimensions of supply and demand in international trade theory: under the traditional trade framework, the industrial supply capacity of the exporting country is often the core factor determining the scale of trade. However, the digital empowerment of cross-border e-commerce platforms further strengthens this mechanism—Export companies can leverage the global market reach of e-commerce platforms to expand their supply at lower marginal costs, with the economies of scale being more pronounced in the digital trade environment. Additionally, the information aggregation function of e-commerce platforms effectively reduces information asymmetry in international trade, enabling high-quality supply to bypass traditional trade barriers and directly connect with the global consumer market, thus forming a stronger pull effect of the exporting countrys economic scale on cross-border transactions answer.

Analysis of the Alienation Effect of Geographical Distance on Cross-Border E-Commerce Transactions

The estimated coefficient for the natural logarithm of geographical distance is −0.547, which is statistically significant at the 1% level. This value is smaller in absolute terms than the typical estimate of about −0.8 in traditional gravity models of trade, indicating that cross-border e-commerce is less sensitive to geographical distance compared to traditional trade. This phenomenon reflects three key transformations in digital trade: Firstly, the digital upgrade of the modern logistics system has completely transformed the spatial constraints of traditional trade. The Amazon FBA model, which uses pre-warehousing, has transformed international logistics into regional domestic logistics, significantly reducing delivery times and lowering transportation uncertainties, thereby decreasing the actual transaction cost impact of geographical distance by approximately 31.6%. Secondly, the development of Internet technology has made the transmission of transaction information transcend time and space limitations, reducing communication costs between buyers and sellers to nearly zero. As a result, the importance of geographical proximity as the primary factor in choosing trading partners has been significantly diminished, and the reduction in information costs has directly weakened the inhibitory effect of geographical distance on transactions. Thirdly, the rise of new trading models such as B2B2C and social e-commerce has disrupted the hierarchical distribution system of traditional trade, enabling direct connections between producers and consumers. The flattened transaction chain has reduced the geographical dependence of intermediate links, further diminishing the marginal impact of geographical distance. From the perspective of spatial economics, this result shows that cross-border e-commerce is reshaping the geographical pattern of global trade. The "distance decay law" in traditional trade shows a phased weakening trend in the digital trade environment, which provides a new window of opportunity for developing countries with remote geographical locations to participate in the global value chain.

The Asymmetric Impact Mechanism of Tariff Policy on Cross-Border E-Commerce Transactions

The estimated coefficient of the tariff rate variable is −1.235, which passes the test at the 1% significance level. The absolute value of this coefficient is not only significantly higher than the elasticity of geographical distance but also 2.26 times greater, highlighting the critical role of tariff policies in cross-border e-commerce transactions. A deeper analysis reveals three key mechanisms: First, the amplification effect of price transmission. Higher tariffs directly increase the tax-inclusive cost of imported goods. In the cross-border e-commerce market, where consumers are highly price-sensitive and competition is intense, the price increases due to tariffs can significantly dampen consumer demand. This effect is further amplified by the transparent pricing mechanisms of e-commerce platforms. Second, the heterogeneous response of trading entities. Most cross-border e-commerce participants are small and medium-sized enterprises (SMEs) and individual consumers, who have a much lower tolerance for tariff costs compared to large enterprises in traditional trade. A slight increase in tariff rates can lead to a significant number of small and medium sellers exiting the market, creating a pronounced cliff effect that non-linearly suppresses transaction volumes. Finally, the policy substitution effect. The high elasticity of tariffs reflects the high sensitivity of cross-border e-commerce to policy environments. When tariffs are tightened, market players may switch to other more lenient trade channels or markets, exacerbating this substitution behaviorIt has a negative impact on the measurement of transactions. In general, tariff policy plays a "super marginal" regulatory role in cross-border e-commerce trade, and its influence on transaction size is far greater than traditional factors such as geographical distance, which has become the main policy obstacle to the development of cross-border e-commerce.

Analysis of the Interaction between Category Heterogeneity and Platform Policy

As shown in the fixed effects of categories in Table 1, using the basic category c1 as a reference, the transaction measurement for the electronic products category c2 is 21.5% higher and passes the 5% significance test. This result confirms the trading advantage of high-value-added goods in cross-border e-commerce. The reason for this is that high-value-added goods typically have higher demand elasticity and brand premium potential, which can better cover the logistics and operational costs of cross-border e-commerce. Additionally, the display and evaluation mechanisms on e-commerce platforms are more conducive to realizing the value of high-value-added goods. Moreover, the estimated coefficient of the platform policy index is 0.812, significant at the 1% level, indicating that for every one-unit increase in platform support, the transaction measurement increases by 0.812%. This reflects the significant role of e-commerce platforms institutional arrangements in promoting cross-border transactions. Platforms can effectively reduce transaction costs and enhance market efficiency through policy tools such as commission adjustments and logistics subsidies. This internal policy support from platforms contrasts with national-level tariff policies, highlighting the adaptive adjustment capabilities of market entities in response to trade policy environments.

5.2.4. Robustness Test

In order to ensure the reliability and universality of the empirical results, this study conducts systematic robustness tests from four dimensions: model setting, sample range, variable measurement and endogeneity treatment, and adopts rigorous statistical methods to verify the benchmark regression results in multiple dimensions.

Model Setting Level

By comparing the system GMM and difference GMM estimation methods, it is found that the difference GMM addresses endogeneity issues by eliminating individual fixed effects through first-order differencing. The system GMM combines level and difference equations and introduces lagged variables as instrumental variables, which not only enhances estimation efficiency but also effectively controls for endogeneity. The estimation results show that the signs and significance levels of the core explanatory variables have not changed substantially. Specifically, the log GDP coefficient of the importing country is 0.679 ($p < 0.01$) and 0.683 ($p < 0.01$) under the difference GMM and system GMM, respectively. The log GDP coefficient of the exporting country is 0.718 ($p < 0.01$) and 0.721 ($p < 0.01$), and the log geographical distance coefficient is −0.543 ($p < 0.01$) and −0.547 ($p < 0.01$). Additionally, the tariff rate coefficient is −1.231 ($p < 0.01$) and −1.235 ($p < 0.01$). These findings indicate that the model estimation results are robust across different GMM estimation methods.

Sample Scope

Considering the heterogeneous characteristics of the cross-border e-commerce market at different stages of development, the full sample from 2018 to 2024 is divided into two sub-periods: the growth period from 2018 to 2021 and the maturity period from 2022 to 2024, for separate estimation. During the growth period, cross-border e-commerce experienced rapid expansion in scale, while the maturity period saw structural optimization and business model upgrades. The estimation results show that during the growth period, the log coefficient of the importing countrys GDP is 0.692 ($p < 0.01$), the exporting countrys GDP is 0.735 ($p < 0.01$), geographical distance is −0.538 ($p < 0.01$), and tariff is −1.246 ($p < 0.01$). In the maturity period, these coefficients are 0.678 ($p < 0.01$), 0.712 ($p < 0.01$), −0.552 ($p < 0.01$), and −1.228 ($p < 0.01$), respectively. Although there are slight differences in the coefficients across stages, the direction and significance of the core variables remain stable, indicating that the research conclusions are not significantly affected by the choice of the sample period.

Variable Robustness

This study adjusted the measurement methods for key explanatory variables: converting GDP data from constant price dollars to PPP-adjusted values, and recalculating the logarithms of GDP for each country. It also used the trade policy uncertainty index as a substitute for traditional tariff rate variables to more comprehensively capture the dynamic impact of the trade policy environment. The re-estimation results showed that the coefficient of the logarithm of the GDP of the importing country, after PPP adjustment, was 0.685 ($p < 0.01$), the coefficient of the logarithm of the exporting countrys GDP was 0.723 ($p < 0.01$), the coefficient of the logarithm of geographical distance was −0.549 ($p < 0.01$), and the coefficient of the trade policy uncertainty index was −1.352 ($p < 0.01$). These results are highly consistent with the baseline regression, confirming the robustness of the conclusions regarding the measurement methods of the variables.

Endogeneity of the Model

The core explanatory variable, lagged by three periods, was used as an instrumental variable for the system GMM estimation. The p-value of the over-identification test is 0.234, indicating that the selection of the instrumental variables meets the exogeneity condition. The serial correlation test shows that the p-value for AR (1) is 0.000 (rejecting the null hypothesis of no autocorrelation), and the p-value for AR(2) is 0.123 (accepting the null hypothesis of no second-order autocorrelation), which aligns with the requirements for system GMM estimation. The coefficients and significance levels of the core explanatory variables have not changed substantially after adjustment, further confirming that the model does not suffer from severe endogeneity issues, ensuring the reliability of the estimation results.

5.2.5. Summary

This section, based on the constructed cross-border e-commerce market measurement space, uses a GMM panel regression model to quantitatively analyze the impact of factors such as GDP, geographical distance, and tariffs on transaction measurements. The model estimation results show that the GDP of both importing and exporting countries has a significant positive effect on transaction measurements, while geographical distance and tariffs have a restraining effect, with the impact of tariffs being much greater than that of geographical distance. After conducting robustness tests using various methods, including different model settings, sample divisions, variable measurements, and endogeneity treatments, the results all confirm the reliability of the benchmark model.

5.3. Empirical Analysis of Machine Learning Models

5.3.1. Architectural Design and Theoretical Logic of Measure-Aware Graph Neural Network

To achieve organic integration of measure theory and deep learning, this study constructs a Graph Neural Network model (MeasureGNN) with measure constraint capabilities. The model takes countries/regions as basic node units and bilateral transaction measure values as edge weights to build a directed weighted graph structure G = (V,E), where edge weights strictly follow the non-negativity and monotonicity characteristics of measures, ensuring the graph structure accurately maps transaction correlations in cross-border e-commerce markets. Node features are extracted from the micro-panel data of cross-border e-commerce transactions from 2018 to 2024. After preprocessing flows such as missing value imputation and outlier removal, a three-dimensional feature matrix including quarters, countries/regions, and product categories is generated, providing the model with input information combining temporal dynamics and spatial correlation.

In the design of core network layers, the measure propagation layer adopts multi-layer graph convolution operations, whose mathematical expression is:

$$h_v^{(l+1)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{\sqrt{|N(v)||N(u)|}} h_u^{(l)} W^{(l)}\right)$$

where $h_v^{(l)}$ represents the feature vector of node v at the l-th layer, N(v) is the set of neighbor nodes of node v, $W^{(l)}$is the learnable weight matrix, and σ is the activation function. Notably, the model introduces a standardization weight mechanism based on measure theory. Through normalization processing of edge weights, it ensures that information propagation strictly satisfies the countable additivity principle of measures, avoiding measure estimation bias caused by weight imbalance.

Additionally, the model innovatively incorporates a completeness regular term:

$$\mathcal{L}_{reg} = \lambda \sum_{M \subseteq N, \mu(N)=0} \left(\hat{\mu}(M)\right)^2$$

This regular term directly reflects the completeness property of the measure space proved in Section 4 by forcing the measure estimation values of subsets of null sets to approach 0, effectively suppressing the overfitting phenomenon of the model for low-probability transaction events and improving the ability to identify null sets and their subsets.

5.3.2. Model Training Strategies and Computational Implementation Details

To ensure the stability and generalization capability of model training, this study adopts a 10-fold cross-validation evaluation scheme, dividing the dataset into training, testing, and validation sets at a ratio of 7:2:1. In the design of the optimization objective, a combined loss function is used:

$$\mathcal{L} = \alpha\mathcal{L}_{mse} + \beta\mathcal{L}_{l1} + \gamma\mathcal{L}_{reg}$$

where $\mathcal{L}_{mse}$ is the mean squared error loss for measuring the overall deviation between predicted and real measures; $\mathcal{L}_{l1}$ is the mean absolute error loss to enhance robustness against extreme values; $\mathcal{L}_{reg}$ is the completeness regular term mentioned above. The weight coefficients are set α = 0.5, β = 0.3, and γ = 0.2, achieving the optimal balance between model accuracy and theoretical consistency by balancing the contributions of different loss terms.

The hyperparameter optimization links adopt the Bayesian optimization algorithm. After multiple iterations, the optimal network architecture is determined: a three-layer structure with hidden layer dimensions of 256-128-64, a learning rate of 0.001, an L2 regularization coefficient of 0.001, and a dropout rate of 0.3. The model training relies on 4 NVIDIA A100 GPUs for parallel computing, with a single training epoch taking approximately 15 min. Batch

Normalization technology is used to alleviate the gradient vanishing problem, combined with the Early Stopping strategy to avoid overfitting in the training process. The following is a core Python code snippet of the model implementation, clearly demonstrating the specific realization of the measure constraint mechanism in the network layer:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
# Define the Measure-Aware Graph Neural Network model
class MeasureGNN(nn.Module):
    def __init__(self, node_features, hidden_channels, out_channels, dropout = 0.3):
        super(MeasureGNN, self).__init__()
        # Measure propagation layer (GCN convolution) for multi-order neighborhood information aggregation through three convolution layers
        self.conv1 = gnn.GCNConv(node_features, hidden_channels)
        self.conv2 = gnn.GCNConv(hidden_channels, hidden_channels)
        self.conv3 = gnn.GCNConv(hidden_channels, out_channels)
        # Measure standardization weight layer to learn the measure mapping relationship of edge weights through an MLP network
        self.edge_mlp = nn.Sequential(
            nn.Linear(1, 64),
            nn.ReLU(),
            nn.Linear(64, 1)
        )
        # Activation function and regularization modules to improve model generalization
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(dropout)
        self.batch_norm = nn.BatchNorm1d(hidden_channels)
    def forward(self, x, edge_index, edge_attr):
        # Edge weight standardization: constrained by the countable additivity of measure theory
        edge_weights = torch.sigmoid(self.edge_mlp(edge_attr))
        # Normalization processing to ensure the sum of edge weights is 1, conforming to the additivity principle of measures
        edge_weights = edge_weights/(torch.sum(edge_weights, dim = 0, keepdim = True) + 1e-8)

        # Multi-layer measure propagation process for layer-wise aggregation of neighborhood transaction measure information
        x = self.conv1(x, edge_index, edge_weight = edge_weights)
        x = self.batch_norm(x)
        x = self.relu(x)
        x = self.dropout(x)
        x = self.conv2(x, edge_index, edge_weight = edge_weights)
        x = self.batch_norm(x)
        x = self.relu(x)
        x = self.dropout(x)
        x = self.conv3(x, edge_index, edge_weight = edge_weights)
        return x.squeeze()
```

5.3.3. Model Performance Evaluation and Comparative Analysis

In terms of measure estimation accuracy, the model achieves a Mean Squared Error (MSE) of $9.8 \times 10^4$and a Mean Absolute Error (MAE) of 765.32 yuan on the validation set, demonstrating precise characterization of transaction measures. Comparing the performance of traditional GNN models, Random Forest models, and Gradient Boosting Tree models (as shown in Table 2), the measure-aware graph neural network shows significant advantages on training, validation, and test sets: the training set MSE is reduced by 35.6% compared with traditional GNN, the validation set MAE is reduced by 24.4%, and the test set MSE is improved by approximately 35.8% compared with traditional GNN models. This result fully verifies the effectiveness of integrating measure theory with graph neural networks. In particular, the introduction of the completeness regular term significantly improves the model's ability to handle low-probability transaction events such as null sets, avoiding estimation biases in traditional models due to the lack of measure constraints.

Table 2. Comparative Results of Model Performance Evaluation**.**

Types of Models	Data Set	MSE	MAE
Measurement of perceptual graph neural network	training set	8.7×10^4	682.5
	validation set	9.8×10^4	765.3
	test set	1.02×10^6	792.1
GNN model	training set	1.35×10^5	925.7
	validation set	1.48×10^5	1012.4
	test set	1.55×10^6	1056.2
Random forest model	training set	1.12×10^5	853.6
	validation set	1.21×10^5	901.3
	test set	1.28×10^6	937.5
Gradient boosting tree model	training set	1.05×10^5	812.8
	validation set	1.13×10^5	864.2
	test set	1.19×10^6	898.6

5.3.4. Model Interpretability Analysis Based on SHAP Values

To deeply understand the contribution of each feature in the model's decision logic, this study uses the SHAPvalue method for interpretability analysis. The results show that among the key features affecting transaction measure estimation, the mean SHAP value of importing country GDP is 0.283, and that of exporting country GDP is 0.275, indicating that economic scale is the core factor driving transaction measures. The SHAP value of tariff rate is −0.312, with the largest absolute value, confirming the strong inhibitory effect of tariff policies on cross-border transactions. The SHAP value of geographical distance is −0.214, reflecting the weakening effect of digital trade on spatial constraints. The SHAP value of the platform policy index is 0.187, indicating that the support policies of e-commerce platforms can effectively promote the improvement of transaction measures. This conclusion is highly consistent with the results of the GMM panel regression, which not only verifies the reliability of the model but also further confirms the effectiveness of measure theory in describing the dynamic relationships in cross-border e-commerce markets from the perspective of machine learning.

6. Conclusions

6.1. Core Theoretical Contributions

This study successfully applied the Karchiorod expansion theorem to construct a complete measurement space (X, M, μ) of cross-border e-commerce market, and its core innovation points are as follows:

(1) Spatial structure: The market base set is defined as a topological product space $X = \prod_{t \in T} X_t$, and a semi-

ring *S* is constructed by column sets. In which the transaction amount space adopts a left-open and right-closed interval semi-ring, and the discrete dimension adopts a power set semi-ring, so as to realize the structured representation of multi-dimensional market data;

(2) Measure expansion: Define a σ-finite predictive measure μ_0 on the semicircle *S*. By using Lebesgue and counting measures to characterize the trading weights across different dimensions, and through the outer measure μ^* and the Kallar-Scholze condition, construct the σ-algebra *M*. This proves that the measure μ is the unique complete extension of μ_0;

(3) Completeness proof: Through the verification of the monotonicity, subadditivity and Karchiorodri condition of zero-measure subsets of the outer measure, it is confirmed that "the subset of zero-measure must be measurable" in the measure space, which provides a theoretical guarantee for market quantitative analysis.

6.2. Empirical Application Value

Based on the constructed measurement space, this study carried out empirical analysis and model construction, and drew the following key conclusions:

(1) Data compatibility: Through Kolmogorov-Smirnov test (D = 0.032, p = 0.12) and zero set verification; ($\mu(N) \approx 0$, $\mu(M) \approx 0$), it is confirmed that the theoretical measurement is highly consistent with the cross-border e-commerce data from 2018 to 2024;

(2) GMM Model Analysis: For the importing country, a 1% increase in GDP leads to a 0.683% rise in transaction measures; for the exporting country, a 1% increase in GDP results in a 0.721% increase in transaction measures; a 1% increase in geographical distance decreases transaction measures by 0.547%; and a 1% increase in tariff rates reduces transaction measures by 1.235%, indicating that tariffs remain a significant barrier.

(3) Machine learning application: A measure-perception graph neural network was constructed to force the measure of zero-measure subsets to be 0 through completeness regularization. The model measure estimation MSE reached 9.8×10^5, and MAE was 765.32 yuan, significantly better than the traditional model, which verified the effectiveness of the measure theory in improving the accuracy of the algorithm.

In summary, this study establishes a comprehensive measurement system for the cross-border e-commerce market using the Kardiaorodis expansion theorem. Theoretically, it achieves rigorous mathematical derivation from basic space to measurement completeness, filling the gap in the application of mathematical theory in the cross-border e-commerce sector. Empirically, it verifies the adaptability and practical value of the measurement space through multi-dimensional analysis, providing a mathematical tool that is both theoretically rigorous and practically applicable for market quantitative analysis, dynamic modeling, and risk assessment.

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References

1 Cheng Q, Zhang D, Wei G, *et al*. *Foundations of Real Analysis and Functional Analysis*, 4th ed.; Higher Education Press: Beijing, China, 2019.

2 Yan J. *Lectures on Measure Theory,* 2nd ed.; Science Press: Beijing, China, 2013.

3 Doob JL. *Measure Theory*; Springer: New York, NY, USA, 1994.

4 Halmos PR. *Measure Theory;* Springer: New York, NY, USA, 1974.

5 Royden HL, Fitzpatrick PM. *Real Analysis*; Pearson Education: London, UK, 2010.

6 Evans LC, Gariepy RF. *Measure Theory and Fine Properties of Functions*; CRC Press: Boca Raton, FL, USA, 1992.

7 Davidson R, MacKinnon JG. *Estimation and Inference in Econometrics*; Oxford University Press: New York, NY, USA, 1993.

8 Chen Q. *Advanced Econometrics with Stata Applications*, 3rd ed.; Higher Education Press: Beijing, China, 2019.

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