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Research on the Impact of InsurTech Attention on Operating Performance of Leading A-Share Listed Insurers: An Empirical Study Based on Annual Report Text Mining

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Abstract: Insurance technology attention is an important strategic consideration for insurance companies, and it also serves as a key support to promote the high-quality development of the insurance industry. At present, there is no unified conclusion on the correlation and time-lag effect between insurance technology attention and operating performance of top A-share listed insurance companies, and micro empirical evidence still needs to be supplemented. This paper takes 5 top A-share listed insurance companies from 2018 to 2024 as samples, uses text analysis to build an insurance technology index, and tests the relationship between the index and operating performance through a fixed effect model. It tries to make clear the correlation between them and provide decision-making reference for relevant subjects. The study found that insurance technology attention has a significant positive impact on current operating performance at the 1% level; for each 1-unit increase in the index, the return on total assets increases by an average of 0.027 percentage points. There is an obvious time-lag effect between them: the lagged first-phase index has a positive impact on current performance at the 1% level with a coefficient of 0.031. Compared with the benchmark regression, the within-group R^2 of the lagged model rises from 0.791 to 0.873, with stronger explanatory power, and the conclusion remains robust after replacing the explained variable. This study verifies the applicability of the technology empowerment theory in the insurance field, and also reveals the characteristics of insurance technology on operating performance that costs are advanced and benefits are delayed.

1. Introduction

1.1. Research Background and Issues

The deep integration of artificial intelligence and the real economy is driving the accelerated digital transformation of various industries. The State Council's "14th Five-Year Plan for Digital Economy Development" clearly requires the deep integration of digital technology and the real economy. In the insurance field, China has become the world's second largest insurance market. Policy documents such as the China Banking and Insurance Regulatory Commission's "14th Five-Year Plan for Insurance Technology Development" require increased investment in science and technology and encourage the use of core technologies such as artificial intelligence and big data to restructure business processes, to improve risk control and service quality. Currently, the insurance industry is facing the dual challenges of slowing premium growth and intensifying homogeneous competition. Leading A-share insurance companies rely on their capital and group advantages to take the lead in embedding insurance technology into core operations. Ping An has clearly proposed its financial technology strategy since 2017, and PICC and CPIC have subsequently incorporated technological development into corporate strategies.

At present, only 5 insurance companies are listed on A-shares, but their total premium income accounts for more than 50% of the industry. The direction of technological transformation has an important demonstration effect. Existing research has not yet reached a unified conclusion on two issues: one is whether insurance technology attention can be transformed into positive operating performance; the other is whether there is a time lag effect. In addition, there is a lack of micro empirical research focusing on A-share head insurance companies. Head insurance companies are essentially different from small and medium-sized insurance companies in terms of resource integration capabilities, and their scientific and technological strategic effects may present unique patterns.

Based on this, this paper explores two questions: (1) Does insurance technology attention significantly affect the current operating performance of A-share top insurance companies? (2) Does this impact have a time-lag effect, that is, does it significantly affect the operating performance of the next period?

1.2. Research Purpose and Meaning

This paper takes five top-listed A-share insurance companies as research objects. By building an insurance technology index, we quantitatively analyze the intrinsic relationship between insurance technology attention and operating performance, focusing on the impact of the current period and the lagging period. The research aims to fill the empirical gap focusing on A-share head insurance companies and provide empirical basis for the formulation of technology strategies of head insurance companies and the high-quality development of the industry.

2. Literature Review

2.1. Research on the Relationship between Insurance Technology and Operating Performance

There are two main views in academia on the relationship between insurance technology and operating performance. Most studies support positive effects. Sun Mingming et al.[1]used the three-stage DEA model to find that insurance technology can improve the operating efficiency of insurance companies. Wu Chenyan and Wang Huali[2]pointed out that technological innovation promotes the growth of insurance companies. Wanyan Ruiyun and Suo Lingyan[3]verified the stable and positive role of insurance technology from three aspects: liabilities, assets, and risk taking. Jia Liwen and Wan Peng[4]found that insurance technology improves net profit and premium income based on a double differential model of 20 property and insurance companies, but strict supervision and high initial investment will weaken the effect. Jiang Yafeng[5]focused on A-share head insurance companies and found that digital transformation is positively affecting financial performance, and company size plays a regulating role. Zhang and Wu[6]Policy support and capital concentration are accelerating the integration of insurance technology into the industry.

However, some studies have also revealed nonlinear or differentiated relationships. Xie Tingting and Zhao Xueli[7]found that insurance technology and operating efficiency have a U-shaped relationship based on the DEA-Tobit model of 58 property and insurance companies: a negative effect will occur in the initial stage due to insufficient investment and delayed results, and it will turn to a positive effect after long-term accumulation. Zuo[8]found that insurance technology has a positive effect on the performance of life insurance companies, but is not significant on property insurance companies. Zhao Xueli[9]used Ping An Property Insurance as a sample to find a positive but insignificant effect. Zhou Lei and others[10]pointed out that there are significant differences in resources and technical capabilities between large insurance companies and small and medium-sized insurance companies, and the transformation of their scientific and technological strategic performance may have unique rules, which provides rationality for this article to focus on large A-share insurance companies.

Foreign research also supports positive effects. Foreign scholar Kelley et al.[11]believe that insurance technology enhances underwriting risk assessment capabilities by optimizing transaction algorithms and data analysis. Stoeckli and others[12]found through Twitter data that infrastructure, service provision and online promotion are the main mechanisms for value creation. Yi et al.[13]found that R & D investment significantly improved solvency based on patent application data from 39 insurance companies in China.

Based on the above research, it can be seen that many experts have verified the important impact of insurance technology on the operating performance of insurance companies from different dimensions, but relevant research specifically on A-share listed companies is still lacking. Combined with these existing studies, this paper will focus on the strategic level of insurance technology attention, and explore in depth its specific impact on the operating performance of top-listed A-share insurance companies.

2.2. Research on Quantitative Methods of Insurance Technology and Digital Transformation

How to scientifically quantify the level of scientific and technological attention of insurance companies is a key issue in empirical research. Existing research has mainly formed the following methods.

Index construction method. Sun Mingming[1]adopts a bottom-up step-by-step weighted average summary method to compile the China Insurance Technology Index. Xie Tingting and Zhao Xueli[7] used the China Digital Finance Development Index as a proxy variable for the external science and technology environment. Wanyan and Suo[3]tested the impact of insurance technology on the insurance industry from an empirical perspective, and also adopted an indexed research method.

Mining method. Pang et al [14]extracted keywords from the manufacturing annual report to build a digital transformation index, confirming the applicability of this method. Ren and Guo[15]pointed out that the frequency of words reflects the importance enterprises attach to relevant fields. Yuan et al.[16]combined sentiment analysis to evaluate the level of data assets, expanding the application of this method. Text mining method effectively solves the quantitative problem of insurance technology. This paper adopts this method.

2.3. Literature Review and Positioning of This Research

Existing research has expanded from direct effects to conduction mechanisms and heterogeneity analysis. Research methods have shifted from qualitative to quantitative. Text mining methods have effectively solved the quantitative problem of insurance technology. At the same time, the research objects are gradually focusing on the micro enterprise level. However, there is still room for extendable research. First, most of the existing research focuses on insurance companies in the entire industry as a whole, and there are few special research specifically on insurance companies listed on top of A-share shares. A-share listed companies have standardized information disclosure standards, strong financial data availability, and the capital market has hard constraints on their operating performance. The motives and effects of their technological attention may be different from those of non-listed companies. Second, the research on the combination of text analysis and financial data needs to be deepened, and there is still room for expansion in the measurement of A-share head insurance companies. Third, there is insufficient research on the time-lag effect of insurance technology on operating performance, while investment in science and technology has the characteristics of large investment and slow results, and the time-lag effect deserves attention. Based on this, this paper takes top A-share listed insurance companies as the research objects, uses annual report text mining method to build an insurance technology index, and combines financial data to empirically study the impact and lag effect of insurance technology attention on operating performance. It should be noted that this paper does not test the specific transmission mechanism, and the research focuses on two issues: first, whether the strategic attention of insurance technology has an overall impact on operating performance; second, whether there is a time lag effect, that is, whether the impact is significantly reflected in the next period.

3. Theoretical Basis and Research Assumptions

3.1. Concept Definition

(1) Attention to insurance technology

Insurance technology attention refers to the extent to which insurance companies develop insurance technology at the strategic level, reflecting insurance companies' understanding and development intensity of technology-enabled transformation. This paper uses this indicator as a proxy variable for the corporate technology strategy orientation, uses text mining method, calculates the word frequency of insurance technology-related keywords in the annual reports of top A-share listed insurance companies, and standardizes them with relative word frequency to obtain the corresponding index. The higher the index value, the more insurance companies paid attention to insurance technology that year. It should be emphasized that this indicator measures the level of attention at the strategic level rather than actual investment in science and technology.

(2) Operating performance

Operating performance refers to the operating results achieved by an enterprise within a certain operating cycle, reflecting the enterprise's ability to obtain profits. This paper selects the return on total assets as the core indicator to measure operating performance. The return on assets is also one of the commonly used indicators in academic circles to measure corporate profitability.

3.2. Theoretical Basis

3.2.1. Technology Empowerment Theory and Its Application in This Paper

Technology empowerment theory believes that digital technology can improve corporate operating capabilities by optimizing business processes, resource allocation and reducing costs. Brynijolfsson and Hitt[17]point out that technology itself does not directly generate value and needs to be integrated with organizational processes and management practices. The A-share top-listed insurance companies studied in this paper have sufficient capital, talent and technical resources to effectively implement scientific and technological strategic concerns into core operations. Therefore, the technology enabling transmission mechanism can play a role quickly, improve current operating performance, and provide theoretical support for the H1 hypothesis.

3.2.2. Technology Adoption and Innovation Diffusion Theory and Its Application in This Paper

The theory of technology adoption and innovation diffusion was systematically proposed by American scholar Rogers in his classic book "The Diffusion of Innovation" in 1962[18]. This theory has been used by many people in the research of organizational behavior and information technology adoption, and it has also become an important theoretical basis for us to explain how new technologies spread within organizations.

The core view of this theory is that the adoption of new technologies by organizations cannot be accomplished overnight, but requires a process of "cognition-persuasion-decision-implementation-confirmation". In the initial stage, a large amount of investment is required in infrastructure, personnel training and process restructuring, resulting in short-term cost increases and unstable efficiency. However, the technology dividend has obvious time-lag effects and needs to cross a certain threshold to be released. In addition, the productivity paradox shows that the impact of information technology often lags behind and needs to go through an upward phase of the "learning curve." This theory provides a core explanation for the actual contradiction and lag effect of "high investment, low return" in the insurance industry: the higher the attention of head insurance companies to technology, the greater the initial transformation costs, and the short-term financial performance may be under pressure, while the technical dividends will be gradually released in subsequent cycles, thereby supporting the H2 hypothesis.

3.3. Research Hypothesis

All research assumptions in this paper are limited to 5 listed insurance companies in A-shares. In the above two core theories, this paper proposes the following research assumptions:

3.3.1. Insurance Technology Attention and Current Operating Performance

Based on the theory of technology empowerment, insurance technology optimizes all dimensions of operations and directly improves asset operation efficiency through technical empowerment of the entire business chain. Enterprises increase their focus on technology strategies and are more likely to implement technology in business processes, thereby improving current operating performance. Based on this, assumptions are made:

H1: The attention to insurance technology of top A-share listed insurance companies has a significant positive impact on current operating performance.

3.3.2. Insurance Technology Attention and Lagging Operating Performance

Based on the theory of technology adoption and innovation diffusion, organizations need to go through a certain period of time to adopt new technologies, and there is a significant time lag in transforming scientific and technological strategic concerns into actual performance. In the early stage of technology adoption, investments in infrastructure, personnel training, process reengineering and other aspects lead to an increase in short-term costs, while technology efficiency improvements need to be released periodically. Therefore, insurance technology attention not only affects current performance, but may also have a continuous positive impact on next period performance. Based on this, assumptions are made:

H2: The attention to insurance technology of top A-share listed insurance companies has a significant positive impact on the operating performance of the next period.

4. Research Design

4.1. Sample Selection and Data Sources

In the research work of this paper, this paper selects five listed insurance companies in A-shares from 2018 to 2024 (Ping An of China, China Life Insurance, China Pacific Insurance, China People's Insurance, and Xinhua Insurance) as samples. The total premium income of these five companies accounts for more than 50% of the industry. The annual report disclosure is standardized and the data is complete, which can ensure the balance and consistency of panel data. 35 annual reports were collected through the companies' official websites to build an insurance technology index. In the financial data, the return on total assets (ROA) is calculated manually, the asset-liability ratio and return on net assets (ROE) are extracted from the annual report, and the company size is taken as the natural logarithm of total assets. A total of 35 effective observations are obtained. This paper adopts a case study-based empirical design, focusing on head insurance companies. The sample size is limited but can meet the research goals.

4.2. Variable Setting and Measurement

4.2.1. Interpreted Variable: Operating Performance (ROA)

Referring to Zuo[8], this paper uses the return on total assets, or ROA, as the core indicator to measure the operating performance of insurance companies. ROA can reflect the ability of insurance companies to use all assets to make profits, and is also a common indicator used in academia to measure corporate profitability. At the same time, in the robustness test, ROE is used for substitution verification.

4.2.2. Core Explanatory Variable: Insurance Technology Index (Tech)

The core explanatory variable of this paper, the Insurance Technology Index, uses text mining to measure the insurance technology attention of listed insurance companies. This method learns the research framework of the research framework of Ren and Guo[15]. The frequency of keywords in corporate annual reports reflects the degree of strategic emphasis. PowerShell was used to grab keywords from 35 annual reports in TXT format, and the ratio of the company's keyword frequency to the total sample frequency of the year was used as a measurement indicator.

(1) Construction of keyword database

The research object of this paper is the annual report of A-share listed companies, so the construction of keywords needs to be highly compatible with the context of the annual report. Drawing on the 34 insurance technology keywords provided by Zhao Xueli[9], this lexicon is highly consistent with the core concepts of the "14th Five-Year Plan for Insurance Technology" and has undergone annual report coverage test and manual review.

(2) Text processing and word frequency statistics

After changing the annual reports of these 35 listed insurance companies into TXT format, PowerShell was used to perform Chinese word segmentation and count the frequency of keyword occurrences.

(3) Calculation method of insurance technology index

This paper draws on the practices of Ren and Guo[18]and adopts relative word frequency for standardization, with the purpose of making indices comparable in different years. The calculation formula for the Insurance Technology Index is as follows:

$$Tech_{i,t} = \frac{keywords_{i,t}}{\sum_{i=1}^{n} keywords_{i,t}} \tag{1}$$

The higher the index value, the higher the company's attention and importance to insurance technology that year. After completing the word frequency statistics, the author used manual means in Excel to calculate the insurance technology index according to the formula.

4.2.3. Control Variable

Referring to Yuan Zeming's research[16], this paper selects the following control variables from the enterprise level: First, the age of the enterprise, which is measured by the difference between the year of the current year minus the year of establishment. This variable controls the enterprise life cycle effect, that is, the impact of differences in the number of years established on operating performance. The second is the size of the enterprise, which is measured by the natural logarithm of total assets in this paper. This indicator controls the effect of economies of scale and can effectively eliminate the heteroscedasticity problem of scale data. The third is financial leverage. This paper uses the ratio of total liabilities to total assets to measure it. This indicator controls capital structure risks and measures the financial leverage level. See how to define variables in Table 1 Variable Definition.

Table 1: Variable Definition

Variable Type	Variable Name	Variable Symbol	Measurement Method
Dependent Variable	Operating Performance	ROA	ROA=Net Profit/Average Total Assets
Core Explanatory Variable	InsurTech Index	Tech	Constructed via text mining method, calculated using relative word frequency
Control Variable	Firm Age	Age	Current Year-Founding Year
Control Variable	Financial Leverage	Lev	Directly disclosed in the annual report
Control Variable	Firm Size	Size	Natural logarithm of the firm's year-end total assets

4.3. Model Construction

This paper uses a panel fixed effect model to control individual heterogeneity of the company (such as management style, risk appetite and other characteristics that do not change with time) and reduce the bias of missing variables. Due to the small sample size, the benchmark model only includes core explanatory variables and key control variables. The rationality of the model was confirmed through a two-step test: the F test showed that the individual fixed effect was significant ($F=8.06$, $p=0.000$), indicating that individual characteristics needed to be controlled; the Hausman test showed that the chi-square value was negative (-7.33), indicating that the basic assumptions of the random effects model were violated, and the individual effects were highly correlated with the explanatory variables, so the random effect estimates were inconsistent. To sum up, this paper selects the fixed effects model as the benchmark model.

4.3.1. Benchmark Regression Model

In order to test the core research hypothesis H1, this paper constructs the following benchmark regression benchmark model:

$$roa_{i,t} = \beta_0 + \beta_1 tech_{i,t} + \beta_2 age_{i,t} + \beta_3 size_{i,t} + \beta_4 lev_{i,t} + \sum_{t=2019}^{2024} \theta_t Year_t + \mu_i + \epsilon_{i,t} \qquad (2)$$

If β_1 is significant, it means that insurance technology attention has a significant impact on operating performance, and the H1 hypothesis holds true.

4.3.2. Lag Effect Model

In order to test the research hypothesis H2, this paper further constructs a lag effect model

$$roa_{i,t} = \gamma_0 + \gamma_1 tech_{i,t-1} + \gamma_2 age_{i,t} + \gamma_3 size_{i,t} + \gamma_4 lev_{i,t} + \sum_{t=2020}^{2024} \delta_t Year_t + \mu_i + \epsilon_{i,t} \qquad (3)$$

Among them, $tech_{i,t-1}$ is used as the insurance technology index lagging one period. If γ_1 is significantly positive, it proves that the attention of insurance technology in the previous period has a significant positive impact on current operating performance, verifies the existence of a time lag effect, and the H2 hypothesis holds.

5. Empirical Analysis and Results

5.1 Descriptive Analysis

As shown in Table 2 Descriptive Analysis.

Table 2: Descriptive Analysis

Variable	N	Mean	Std. Dev.	Min	Max
ROA	35	0.014	0.005	0.004	0.026
Tech	35	0.2	0.158	0.019	0.632
Firm Age	35	46.4	21.462	22	75
Firm Size	35	14.79	0.87	13.506	16.377
Lev	35	0.879	0.048	0.782	0.943
ROE	35	0.134	0.051	0.035	0.259

The mean ROA of the explained variable is 0.014, with small fluctuation, and the profitability of listed insurance enterprises is relatively stable during the sample period. The mean value of the core explanatory variable Tech is 0.2 and the standard deviation is 0.158, which indicates that there are significant differences in the strategic attention of different companies to insurance technology.

In terms of control variables, the average Age is 46.4 years, and the maturity of enterprises varies greatly; the average Size is 14.79, and the standard deviation is 0.87, and there is a gap in the asset volume of head insurance enterprises; the average Lev is 0.879, and the standard deviation is 0.048, which is at a high and concentrated level as a whole, conforming to the characteristics of high leverage operation in insurance industry.

5.2. Diagnostic Testing Before Regression

5.2.1. Correlation Analysis

As shown in Table 3 Correlation Analysis. Before conducting panel regression, this paper first conducts correlation analysis on each variable, mainly to initially judge the correlation between the core explanatory variables and the explained variables, and provide relevant reference for subsequent model setting. The correlation coefficient between the Insurance Technology Index (Tech) and Current Operating Performance (ROA) is 0.031, and does not pass the significance test. The correlation coefficient between asset-liability ratio (Lev) and operating performance (ROA) is-0.487, which shows a significant negative correlation at the 1% level, and the corresponding p-value is 0.003. This result shows that the higher a company's leverage level, the lower its return on assets, which is consistent with the expectations of financial theory. The correlation coefficient between enterprise size (Size) and operating performance (ROA) is-0.324, which is marginally significant, and the p-value is 0.058. This probably shows that relatively large-scale insurance companies may face pressure from diluting their yields. The correlation coefficient between enterprise age (Age) and operating performance (ROA) is 0.058, and the p-value is 0.739. In addition, the absolute value of the correlation coefficient between each control variable did not exceed 0.7, which made it preliminary that the model did not have serious multicollinearity problems.

Table 3: Correlation Analysis

Variable	ROA	Tech	Age	Size	Lev
ROA	1.000				
Tech	0.031	1.000			
	(0.859)				
Age	0.058	-0.309	1.000		
	(0.739)	(0.071)			
Size	-0.324	0.718***	0.069	1.000	
	(0.058)	(0.000)	(0.694)		
Lev	-0.487***	0.123	-0.55***	0.378**	1.000
	(0.003)	(0.480）	(0.001)	(0.035)	

Notes: ***p<0.01,**p<0.05,*p<0.1。

5.2.2. Multicollinearity Test

In order to avoid the high correlation between independent variables leading to regression estimation bias, this paper uses the variance inflation factor, or VIF, to comprehensively diagnose multicollinearity. The test showed that the VIF of Size was 10.464 (slightly higher than 10), but the average VIF was 4.204, which was well below the critical value; the VIF of the core explanatory variable Tech was 8.565, which was within the safe range. Considering the natural correlation between the size of the head insurance company and the degree of scientific and technological attention, it can be concluded that the model does not have serious multicollinearity and meets the requirements of regression analysis.

5.3. Benchmark Regression Model

As shown in Table 4 Core Regression Results (1). After controlling for fixed effects of individual and time, the coefficient of the Insurance Technology Index (Tech) was 0.027, which was significant at the 1% level (p=0.003), indicating that for every 1 unit increase in Tech, ROA increased by 0.027 percentage points on average, supporting the research hypothesis H1 and verifying the theory of technology empowerment. Among the control variables, the coefficients of enterprise age (Age), enterprise size (Size), and asset-liability ratio (Lev) were not significant (p>0.1), indicating that after controlling for individual fixed effects, these variables have limited independent interpretation of current operating performance. The year dummy variable shows that compared with 2018, the performance in 2019 has improved significantly (coefficient 0.006, p=0.002), and has decreased significantly in 2022 and 2023 (coefficients are -0.005 and -0.008, $p < 0.01$), reflecting the impact of the macro environment and regulatory policies. The model was significant overall ($F=8.855$, $p=0.000$), and the intra-group R^2 was 0.791, showing a good fitting effect. The above results verified H1. In order to test the lag effect (H2), a lag effect model was further constructed.

5.4. Further Analysis: Time-Delay Effect Test

As shown in Table 4 Core Regression Results (2). In order to further eliminate the interference of missing variable bias on the lag effect regression results and ensure the robustness of the conclusion, this paper provides supplementary explanations on the rationality of model settings under the framework of the original fixed effect model. In this paper, we will conduct time-delay effect testing and robustness analysis respectively.

The coefficient of the lagging insurance technology index (L. tech) is 0.031, which is significantly positive at the 1% level ($p=0.001$), indicating that the higher the attention to science and technology in the previous period, the better the current operating performance, which supports the hypothesis H2 and verifies the lag effect. Compared with the benchmark regression, the intra-group R^2 of the lagging model increased from 0.791 to 0.873, and the F statistic was 14.656 ($p<0.01$), which enhanced the explanatory power of the model.

This paper adopts an individual-time two-way fixed effect model to absorb the inherent characteristics and macro time trends of the enterprise that do not change with time; at the same time, control variables such as enterprise age, size, and financial leverage are included, and combined with the fixed effect model to absorb heterogeneity. The ability to absorb sex has controlled the interference of missing variables to a minimum level. In summary, the lag effect model is reasonably set and the empirical results are robust. The finding reminds insurance companies that they should maintain strategic patience and that technology dividends need to be released periodically.

Table 4: Core Regression Results

Variable	(1) Benchmark Regression Model	(2) Time-delay Effect Test	(3) Alternative Dependent Variable (ROE)
Tech	0.027*** (0.008)	-	0.28*** (0.096)
L.tech	-	0.031***	-
	-	(0.008)	-
Age	0.001	0.001	0.008
	(0.001)	(0.001)	(0.14)
Size	-0.004	-0.007	0.011
	(0.011)	(0.009)	(0.13)
Lev	-0.01	-0.039	1.378
	(0.083)	(0.07)	(0.984)
Year	Control	Control	Control
N	35	30	35
R^2	0.791	0.873	0.768
F	8.855***	14.656***	7.712***

Notes: *p<0.1, **p<0.05, ***p<0.01. Standard errors are reported in parentheses.

5.5. Robustness Analysis

As shown in Table 4 Core Regression Results (3).In order to further test the reliability of the core conclusions of this paper, this paper also conducted a robustness test. The specific method is to replace the core explained variable from the return on assets to the return on net assets, and then re-perform fixed effect regression. This paper replaces the core explained variable from return on assets to return on net assets, conducts a robustness test, and re-conducts fixed effect regression. The coefficient of the Insurance Technology Index is 0.28 and the p-value is 0.008, which is significantly positive at the 1% level. This result is consistent with the conclusion of the benchmark regression. This shows that the positive impact of insurance technology attention on operating performance will not change due to different performance measurement indicators. The core conclusion of this paper is robust. In addition, the intra-group R^2 of the robustness test model is 0.768, the F statistic is 7.712, and the corresponding p-value is 0.000, indicating that the model as a whole is significant, which further verifies the reliability of the benchmark regression results.

6. Research Recommendations

Based on the above research, this paper puts forward the following policy suggestions for top-listed A-share insurance companies, regulatory authorities and investors to provide reference for the high-quality development of technological transformation in the insurance industry.

6.1. Implications for Insurance Company Strategies

First, put insurance technology at the core of long-term strategy and continue to strengthen attention and resource matching. Head insurance companies should abandon short-sighted assessment, incorporate technology into long-term strategies, strengthen the disclosure of science and technology strategies in annual reports, and establish specialized departments to promote the digital transformation of the entire business chain. Second, pay attention to the time-lag effect and maintain strategic patience. The release of technology dividends requires a digestion cycle. It is recommended to establish a performance evaluation system that takes into account short-term implementation and long-term value, reserve a technology digestion and business transformation cycle, and improve technology absorption capabilities.

6.2. Policy Recommendations for Regulatory Authorities

Regulatory authorities should introduce differentiated support policies for head insurance companies, improve data security and privacy protection regulations, promote the construction of industry science and technology standards, encourage head insurance companies to play a demonstration and leading role, and drive the digital transformation of the entire industry.

6.3. Decision Reference for Investors

Investors should pay attention to the strategic layout and technology application capabilities of insurance companies. Current technology attention is an important signal for predicting future performance. It is recommended to make long-term investment decisions based on annual report technology disclosures and implementation cases.

7. Conclusions

After completing all the above empirical tests, this paper combines all the regression results to summarize the main research conclusions of this paper, which are as follows:

First, the attention to insurance technology has a significant positive impact on current operating performance. Benchmark regression shows that the Tech coefficient is 0.027 (1% significant), that is, for every 1 unit increase in the index, ROA increases by an average of 0.027 percentage points, supporting the theory of technology empowerment.

Second, insurance technology attention has a significant lagging effect on operating performance. The Tech coefficient for the first phase of lag was 0.031 (1% significant), and the R^2 within the lag model group increased from 0.791 to 0.873, which verified the lag effect and reflected the characteristics of cost forward and revenue backward.

Third, the conclusions are sound. It was still significant after replacing the explained variable with ROE. The mean VIF was 4.204. There was no serious collinearity. The F-test and Hausman test supported the fixed effects model.

The conclusions of this paper are consistent with the research findings of Zuo[8], which both support the positive effect of insurance technology on operating performance. Compared with the findings of Xie Tingting and Zhao Xueli [7], this paper does not observe initial negative effects, which may be due to sample differences. This paper focuses on A-share top-listed insurance companies, which started earlier in their technological layout and invested in scale. Larger, may have crossed the left downward segment of the U-shaped curve. In addition, this paper's test of the time-lag effect provides direct empirical evidence for the slow response of science and technology investment mentioned in the literature, and responds to Jia and Wan's[4] observation that high initial input costs weaken the positive effect.

Although this study empirically analyzed its impact on the operating performance of listed insurance companies by building an insurance technology index, it still has the following limitations: First, the sample coverage is limited, and the study only focuses on the five top-listed insurance companies in A-shares. Although the conclusion is core representative of the industry, it is difficult to extend to the entire industry, especially the lack of heterogeneity investigation on small and medium-sized insurance companies; Second, there are deviations in the measurement of variables. The index constructed based on annual report text mining mainly reflects the company's "strategic attention" to insurance technology, and there may be "differences in words and deeds" between the company's actual investment in technology implementation, capital scale and application depth; Third, the mechanism mining is not deep enough. The research has mainly verified the direct impact and time-lag effect. The intrinsic transmission mechanism of insurance technology on operating performance through specific paths such as cost control, marketing efficiency improvement, and risk control optimization has not been clarified.

Based on the above shortcomings, future research can be deepened from the following dimensions: First, expand sample heterogeneity, extend the research vision to small and medium-sized insurance companies, compare the differences in the technological transformation paths between head and small and medium-sized insurance companies, and explore the industry-enabled universal laws; Secondly, optimize the measurement indicator system and obtain objective indicators such as R & D investment, patent data, and the proportion of scientific and technological talents through in-depth cooperation with the industry to build a more accurate and multi-dimensional insurance technology application evaluation system; Finally, deepen the mechanism test, introduce an intermediation effect model, and empirically test the intermediation effect of specific paths such as cost, marketing and risk control, thereby revealing the deep logic of insurance technology empowering operating performance and providing more operational decision-making basis for enterprise digital transformation.

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