Research on the Impact of Insurance Technology on the Operating Efficiency of Life Insurance Companies in the Context of Digital Transformation

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Abstract. Insurance technology is the concentrated manifestation of the digital economy in the insurance industry. Based on the panel data of 51 life insurance companies from 2016 to 2021 and the Digital Inclusive Finance Index of Peking University, this paper uses the DEA-Tobit model to analyze the relationship between the operating efficiency of the life insurance industry in China and the development level of insurance technology since the implementation of the Solvency II regulations. The study finds that the application of insurance technology is not yet mature at the current stage, and there is a significant negative correlation between the development level of insurance technology and the operating efficiency of life insurance companies. The overall operating efficiency of the life insurance industry in China is showing an upward and improving trend, but the resource allocation efficiency needs to be strengthened. To promote the high-quality development of the life insurance industry, it is necessary to continuously increase investment in insurance technology, strengthen exchanges and cooperation among industries, and create a healthy environment for the development of the life insurance industry under the guidance of the Solvency II Phase II regulations.

Keywords: Insurance technology, Life insurance company, Operating efficiency

1 Introduction

Insurance plays a crucial role in modern enterprise development through risk management, capital allocation, and product provision, acting as both an economic driver and social stabilizer. It supports national strategies, the real economy, and social welfare by mitigating risks and enhancing resilience. In the digital era, insurers must accelerate the adoption of insurance technology (InsurTech) to enhance operational effectiveness. Although InsurTech has gained academic attention, existing studies are fragmented, often conceptual or case-based, with little empirical analysis or consensus on development metrics. To

I. Bin Abdul Majid et al. (eds.), *Proceedings of the 5th International Conference on Internet Finance and Digital Economy (ICIFDE 2025)*, Advances in Economics, Business and Management Research 352,
https://doi.org/10.2991/978-94-6463-886-8_15

bridge this gap, this study adopts a micro-level empirical approach to examine how InsurTech affects the efficiency of life insurance companies. This not only advances understanding of efficiency drivers in the insurance sector but also offers insights for the digital transformation of traditional insurers amid the evolving digital economy.

In recent years, research on insurance efficiency has evolved considerably, shifting from traditional single-stage models to more sophisticated multi-stage network structures that reflect the complexity of real-world insurance operations. Advanced models such as two-stage parallel-series Data Envelopment Analysis (DEA) allow for a nuanced evaluation of technical efficiency and scale elasticity across key functional areas—particularly underwriting and investment management[1]. Empirical findings across various countries suggest that efficiency in life insurance is not only determined by external regulatory and market conditions but also deeply influenced by internal resource configurations, capital intensity, reinsurance strategies, and technological integration[2-3]. Although technological innovation demonstrates potential for enhancing automation and resource optimization, its impact on efficiency is moderated by implementation costs, organizational readiness, and market maturity[4].

Expanding on this, several studies in emerging and transitional markets offer complementary insights. A DEA window analysis of the Serbian insurance sector revealed persistent underperformance in technical, pure technical, and scale efficiency between 2007 and 2018, particularly post-2015, with only a few firms approaching benchmark levels[5]. This highlights the structural challenges that smaller or less digitally advanced insurers face, including rising administrative costs and scale inefficiencies. In the Chinese context, research has shown that differences in regulatory regimes, institutional arrangements, and environmental constraints have significant implications for insurer performance. Notably, life insurance companies in Taiwan outperformed those in mainland China in terms of pure technical efficiency, largely due to more mature market structures and supportive regulatory frameworks[6]. Domestically, the use of three-stage DEA and DEA-Malmquist methods to evaluate the efficiency of China’s urban medical and pension insurance systems has further demonstrated that regional policy coordination, fiscal investment, and demographic factors all influence performance outcomes[7-8].

Despite these developments, quantitative evaluations of insurance technology's role in efficiency improvement remain limited, especially in emerging markets. Existing literature primarily focuses on mature economies, leaving a gap in understanding how evolving digital capabilities affect efficiency in developing contexts[9]. This study aims to fill that gap by conducting a micro-level empirical analysis of the Chinese life insurance sector in the era of digital economic transformation.

Against this backdrop, further investigation is warranted. Despite growing consensus that digital technology can enhance operational models and service delivery in the insurance sector, few studies have quantitatively assessed its actual efficiency effects—particularly in the Chinese context. Challenges such as rising investment costs, heightened regulatory oversight, financial risk containment, and slowing premium growth all raise questions about the true return on technological investments. To this end, this study seeks to provide empirical evidence through two focal points: (1) examining the operational efficiency of China's life insurance sector since the implementation of the Solvency II framework, using a DEA-Malmquist index model, in light of the regulatory transition from functional to institutional supervision and back; and (2) exploring whether the current stage of InsurTech development can indeed promote operational efficiency across the Chinese life insurance industry.

2 Theoretical Analysis and Research Hypotheses

Since the enforcement of the Solvency II regulations in 2016, they have exerted a positive influence on advancing the modernization of insurance supervision, bolstering the industry's risk - prevention capabilities, facilitating industry transformation and upgrading, and enhancing the international standing of China's insurance market and supervision.Simultaneously, with the ongoing evolution of insurtech, the degree of technological empowerment in the insurance industry has been steadily increasing. Through the integration of emerging technologies such as big data, artificial intelligence, the Internet of Things, and blockchain, the insurance industry has been propelled towards high - quality development. For instance, during the product development phase, insurance companies can customize and accurately price insurance products according to diverse customer segments. In the marketing phase, intelligent customer service and advisors can rapidly identify policyholders' needs and offer product recommendations. At the underwriting and coverage stage, automated underwriting enabled by big data and identity verification via artificial intelligence streamline the underwriting process and enhance the accuracy of risk assessment. In the claims settlement phase, intelligent loss assessment and mobile claims processing improve compensation efficiency and boost customer satisfaction. Evidently, insurtech has gradually permeated every aspect of the insurance business.Nonetheless, in the broader financial domain, consumer satisfaction within the insurance industry remains relatively low, and the digitalization level lags behind. As per the complaint data of life insurance companies released by the National Financial Regulatory Administration, sales disputes and surrender disputes account for a significant proportion of complaint categories. The practical application of insurtech in the life insurance business remains relatively limited.Although new technologies offer robust support for the high - quality development of the insurance industry, the question of how to effectively leverage these technologies to enhance operational efficiency is a pressing issue that the insurance industry must address. The integration of new technologies and business operations necessitates continuous substantial investments in human resources, materials, and finances. Such large - scale investments not only consume other corporate resources but also entail significant uncertainty regarding returns. Currently, life insurance companies often hesitate to invest in new technologies. Insufficient resource allocation frequently results in delayed technological output, which adversely affects the improvement of a company's operational efficiency.Based on these considerations, this paper formulates the following hypotheses:

Hypothesis1: Following the implementation of the Solvency II regulations, the operational efficiency of the life insurance industry has been on a continuous upward trend.

Hypothesis 2: The current state of insurtech development has a detrimental impact on the operational efficiency of life insurance companies.

3 Data

3.1 Sample Selection and Data Sources

In order to explore the alterations in the operational efficiency of China's life insurance industry subsequent to the implementation of the Second Solvency Directive, and taking into account data availability, this research designates the period from 2016 to 2021 as the study period. The company data employed in this study is sourced from the "China Insurance Yearbook" spanning from 2017 to 2022 and the publicly disclosed information of various insurance companies.To guarantee the integrity and reliability of the data, the sample data undergoes the following processing steps:Exclude life insurance companies established after 2016. Remove life insurance companies with a substantial number of missing statistical data indicators. Eliminate life insurance companies with significant inaccuracies in their disclosed data. Following this screening procedure, the sample data of 51 life insurance companies are ultimately obtained.

3.2 Variable Definitions

Dependent Variable. Regarding efficiency indicators, Farrell put forward the "frontier efficiency analysis method" for efficiency assessment, classifying overall efficiency into technical efficiency and allocative efficiency. Charnes et al. extended the single-input and single-output model to a multi-input and multi-output model, namely the Constant Returns to Scale (CRS) Data Envelopment Analysis (DEA) model. Nevertheless, in practical operations, not all decision-making units operate at the same scale. Hence, Banker et al. modified the CCR model and developed it into a Variable Returns to Scale (VRS) DEA model.In this study, the comprehensive technical efficiency (TE) of each life insurance company is computed using the VRS DEA method and serves as the dependent variable.

In the selection of input and output variables within the DEA model, the approaches for determining input and output indicators mainly include the production approach, the intermediation approach, and the value-added approach. These three methods generally utilize labor, capital, and expenses as input indicators. However, there is no unified consensus regarding the selection of output indicators.

Under the production approach, financial institutions primarily offer production services to account holders. For insurance companies, they generate insurance policies and claim rights by inputting relevant variables. In the intermediation approach, financial institutions mainly function as intermediaries between depositors and lenders. For insurance companies, they act as intermediaries between policyholders and insured individuals, effectively safeguarding the uncertain risks of the insured through the premium payments of policyholders. Thus, in this approach, the main output indicators are incurred claims payments and changes in reserves.

The value-added approach posits that all assets and liabilities possess output characteristics. When assets and liabilities exhibit significant value addition, they should be regarded as crucial outputs, while factors leading to value reduction should be considered as inputs.

In alignment with current research, this paper also employs labor, operating expenses, and financial capital as input variables. Output variables are considered separately from the insurance and investment perspectives, with premium income, claim payments, and investment income serving as output variables. The indicator explanations are presented in Table 1. It is noteworthy that some companies have negative investment income. To ensure the model's smooth operation, this indicator is normalized using the maximum-minimum normalization method.

Table 1. Explanation and Descriptive Statistics of Input-Output Indicators

Input-Output Indicators		**Indicator Description**	**Mean**	**Standard Deviation**	**Maximum Value**	**Minimum Value**
Input	Labor Input	Total number of employees in the company	52780.29	158827.1	1480043	118
	Operating Expenses	Business and management expenses + handling fees and commissions + business taxes and surcharges (million)	6543.69	16478.37	125334	100.57
	Financial Capital	Registered capital + capital reserve (million)	8456.672	12893.81	83407	481.06
Output	Premium Income	Insurance business income (million)	33554.17	82717.31	618327	6.92
	Claim Payments	Insurance claim payments (million)	7608.945	24740.16	205143	2.49
	Investment Income	Company investment income (million)	8312.298	25401.71	241814	-111.42

Based on the above indicator system, an input-output model was constructed, and the operating efficiency of 51 life insurance companies from 2016 to 2021 was calculated using DEAP2.1 software. The specific results are shown in Table 2. Overall, the comprehensive technical efficiency of life insurance companies showed a trend of first decreasing and then increasing after the implementation of the Solvency II rules. Life insurance companies need a certain adaptation period to apply the Solvency II rules. When decomposing the comprehensive technical efficiency, from the perspective of pure technical efficiency and scale efficiency, although the level of pure technical efficiency is constantly improving, the average scale efficiency is still higher than the average pure technical efficiency. This indicates that the overall operating efficiency of life insurance companies brought about by the scale effect is more significant, and there is still considerable room for improvement in resource allocation and technical management level.

Table 2. Average DEA Calculation Results of Life Insurance Companies from 2016 to 2021

	2016	2017	2018	2019	2020	2021
Comprehensive Technical Efficiency (TE)	0.632	0.601	0.568	0.611	0.697	0.710
Pure Technical Efficiency (PTE)	0.713	0.655	0.622	0.667	0.744	0.782
Scale Efficiency (SE)	0.887	0.913	0.915	0.924	0.929	0.906

Explanatory Variables. Taking into account the comprehensiveness of coverage and the consistency of data, this paper uses the insurance business sub-index of the China Digital Financial Inclusion Index compiled by the Digital Finance Research Center of Peking University as the basis, and measures the level of fintech development at the provincial level using provincial-level data, in order to explore whether there is a statistically significant impact between the level of fintech development and the operating efficiency of life insurance companies. Due to the different business scopes of different life insurance companies, this paper uses the proportion of provincial premium income of life insurance companies in total premium income as the weight to calculate the weighted insurance business sub-index of each insurance company, and based on the overall situation of the sample data, the weighted insurance business sub-index divided by 100 is used as a substitute variable for insurance technology. It should be noted that the statistics of market share of each insurance company in the "China Insurance Yearbook" include five plan-designated cities: Shenzhen, Dalian, Ningbo, Xiamen, and Qingdao. To ensure consistency with the provincial-level data statistics of the China Digital Financial Inclusion Index, the premium income of Shenzhen is included in Guangdong Province, the premium income of Dalian is included in Liaoning Province, the premium income of Ningbo is included in Zhejiang Province, the premium income of Xiamen is included in Fujian Province, and the premium income of Qingdao is included in Shandong Province.

Control Variables. Based on existing research results and in combination with the availability, completeness, and accuracy of relevant data, company size, leverage ratio, profit level, and establishment time are selected as control variables. Generally speaking, the larger the company size and the longer the establishment time, the greater the scale efficiency and experience effect, which will lead to cost reduction and quality improvement, and help promote the improvement of operating efficiency. Leverage ratio and profit level respectively reflect the financial situation and operating results of the company, and will also have an impact on the overall operating efficiency of the company. Main variable explanations are shown in Table 3.

Table 3. Meanings of Key Variables

Variable Type	Variable Name	Variable Symbol	Variable Description
Dependent Variable	Insurance Company Operating Efficiency	TE	Comprehensive technical efficiency calculated through DEA
Independent Variable	Insurance Technology Development Level	Insurance	Weighted average insurance business sub-index based on provincial data of China's digital inclusive finance index
Control Variables	Company Size	Size	Natural logarithm of the end-of-year total assets
	Leverage Ratio	Lev	End-of-year total liabilities / total assets Profitability Level
	Profitability Level	ROA	Net profit / end-of-year total assets
	Establishment Age	Time	Time The establishment age of the company

3.3 Model Construction

Based on the aforementioned variables, the following model is set up for analysis:

$$TE_{it} = \alpha + \beta_1 Insurance_{it} + \beta_2 Size_{it} + \beta_3 Lev_{it} + \beta_4 ROA_{it} + \beta_5 Time_{it} + \varepsilon_{it}$$

In the formula, i represents the 51 life insurance companies, and t ranges from

2016 to 2021. Since the operating efficiency values are "aggregated data" and their value range is between 0 and 1, they belong to the restricted model of explained variables. Therefore, a panel Tobit regression was selected to analyze the model.

4 Empirical Results

4.1 Analysis of the Impact of Insurance Technology on the Operating Efficiency of Life Insurance Companies

The LR test was conducted on the sample data, and the P-value was less than 0.001. Therefore, a random effect was adopted for the regression. The regression results of the sample companies are shown in the (1) column of Table 4. From the regression results, the development level of insurance technology is significantly at the 10% level, indicating that insurance technology has a significant impact on the operating efficiency of life insurance companies. However, the regression coefficient of this variable is negative. At the current stage, there are still significant challenges for life insurance companies in applying insurance technology in China. A large amount of human and financial investment has increased their cost pressure and reduced their operating efficiency. Moreover, the insurance ecosystem has not yet been formed, and the intelligent application of insurance technology is limited to specific scenarios. In addition, life insurance companies need to pay particular attention to the issue of security when using technological means, including data security, data ethics, and privacy protection. How to enable insurance technology to empower the development of the life insurance industry and improve its operating efficiency is an urgent problem for the life insurance industry.

For other control variables, (1) the size of life insurance companies is positively correlated with their operating efficiency at the 1% significant level, which is consistent with the above DEA calculation results. Currently, the life insurance industry still has a scale effect, and the expansion of scale can promote the improvement of its operating efficiency. (2) The leverage ratio of life insurance companies is negatively correlated with their operating efficiency at the 1% significant level. High debt will affect the asset allocation of the company and bring pressure to its term matching, thereby affecting the operating efficiency. (3) The return on total assets is positively correlated with the operating efficiency of life insurance companies at the 1% significant level. An increase in the level of returns can promote the improvement of operating efficiency. (4) The establishment time of life insurance companies has no significant impact on their operating efficiency.

To examine how insurance technology influences the operational efficiency of insurance companies, this study divides 51 life insurers into three groups—large, medium, and small—based on firm size. The top 17 firms are classified as large, the middle 17 as medium, and the bottom 17 as small. Regression results reveal significant scale heterogeneity. Specifically, for medium-sized insurers, the coefficient of the insurance technology index is -0.047 and significant at the 10% level, indicating a notable negative impact on efficiency. This may result from their limited technological capacity and resource constraints—they lack both the scale advantages of large firms and the flexibility of small ones—making them more prone to inefficiencies during technological transition. In contrast, large insurers, though well-equipped with resources and data infrastructure, often face longer implementation cycles due to organizational complexity, delaying observable benefits. Small insurers are still at an early stage of technology adoption, and the effects remain limited due to insufficient investment. These findings suggest that differentiated, size-sensitive strategies are needed to promote effective digital transformation across the insurance industry.

Table 4. Regression Results of the Impact of Insurance Technology on the Operating Efficiency of Life Insurance Companies

variables	(1)	(2)	Large companies	medium-sized companies	small companies
Insurance	-0.029* (-1.919)	-0.041** (-2.088)	-0.013 (-0.665)	-0.047* (-1.834)	-0.019 (-0.884)
Size	0.150*** (7.143)	0.121*** (4.158)			
Lev	-0.528*** (-3.108)	-0.202 (-0.973)	1.239** (2.275)	0.895** (2.112)	-0.351** (-2.151)
ROA	1.621*** (2.827)	1.481** (2.140)	5.287** (2.103)	4.530*** (4.921)	1.886*** (2.911)
Time	0.001	0.006	0.013*	0.016	0.008

	(0.200)	(0.684)	(1.869)	(1.405)	(1.137)
_cons	-0.268	-0.133	-0.442	-0.031	0.812***
	(-1.257)	(-0.478)	(-0.919)	(-0.089)	(4.281)

Note: The values in parentheses are t-values; ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2 Robustness Test

To ensure the robustness of the research conclusions and the reliability of the indicator selection, this paper uses the variable substitution method and the DEA model to calculate the pure technical efficiency obtained from the model as the alternative variable for the model regression analysis. The regression results are shown in the (2) column of Table 4. From the robustness test regression results, it can be seen that after changing the measurement indicators of operating efficiency, the regression results of the model did not undergo substantial changes. This further verifies that the development level of insurance technology has a significant negative impact on the operating efficiency of life insurance companies.

4.3 Further Analysis of Operating Efficiency Changes

To calculate the dynamic changes in the operating efficiency of commercial banks, this paper analyzes the sample data from 2016 to 2021 through the Malmquist index. The change in the M value represents the dynamic situation of production efficiency or operating efficiency. If $M < 1$, it indicates a decrease in productivity and a decline in operating efficiency; if $M = 1$, it means that the enterprise's operating efficiency remains unchanged; if $M > 1$, it indicates an increase in the operating efficiency. The Malmquist index is calculated through DAEP2.1 software based on output orientation, and the calculation results are shown in Table 5.

From the perspective of total factor productivity, from 2016 to 2021, except for the period of 2016-2017 and 2017-2018, the total factor production index between adjacent years was greater than 1. The overall operating efficiency of 51 life insurance companies showed an upward and improving trend, with an average Malmquist index value of 1.042. Decomposing the total factor productivity index, from the perspectives of technical efficiency change and technological progress change, the technical efficiency change index was greater than 1 except for the periods of 2016-2017 and 2017-2018. In China, the operating efficiency of life insurance companies has been continuously improving, while the technological progress change index was less than 1 in the periods of 2016-2017 and 2018-2019, indicating that the technological progress of life insurance companies is not stable and the technological progress ability is relatively weak. Further decomposing the technical efficiency change into pure technical efficiency change and scale efficiency change, the pure technical efficiency change index showed an overall upward trend, except for the periods of 2016-2017 and 2017-2018, which was greater than 1. This indicates that the resource allocation management level of life insurance companies is continuously improving. Overall, the development of the life insurance industry in China is constantly improving, but the exogenous technological progress ability is relatively weak. In the current context of rapid development of the digital economy, the life insurance industry still faces significant challenges.

Table 5. Overall Operating Efficiency M Index and Its Decomposition Items of 51 Life Insurance Companies in China from 2016 to 2021

year	effch	techch	pech	sech	tfpch
2016~2017	0.919	0.989	0.881	1.043	0.909
2017~2018	0.925	1.04	0.923	1.001	0.961
2018~2019	1.127	0.95	1.107	1.018	1.07
2019~2020	1.167	1.041	1.161	1.005	1.215
2020~2021	1.027	1.027	1.066	0.963	1.055
mean	1.033	1.0094	1.0276	1.006	1.042

5 Conclusion and Recommendations

5.1 Conclusion

This paper uses the sample data of 51 life insurance companies in China from 2016 to 2021. The weighted average insurance business sub-index calculated based on the provincial data of China's digital inclusive finance index is used as a substitute variable for the level of insurance technology development. A panel Tobit model is constructed to analyze the impact of the level of insurance technology development on the operating efficiency of the life insurance industry. The dynamic changes in the operating efficiency of the life insurance industry after the implementation of the Solvency II rules are measured using the Malmquist index. The main conclusions are as follows:

First, the level of insurance technology development has a significantly negative correlation with the operating efficiency of life insurance companies. At the current stage, the application of insurance technology is not yet mature, and a large amount of human and financial investment has, to a certain extent, increased its cost pressure and reduced the operating efficiency.

Second, company size, leverage level, and profit level have a significant impact on the operating efficiency of life insurance companies. Among them, the larger the company size and the higher the profit rate, the higher the operating efficiency; while the higher the leverage ratio, the greater the risk, the greater the asset allocation pressure, and the lower the operating efficiency.

Third, since the implementation of the Solvency II rules, the operating efficiency of the life insurance industry in China has generally shown an upward trend. The level of insurance technology development has been continuously improving, but the resource allocation efficiency needs to be strengthened. The Solvency II Phase II rules were officially implemented in 2022, which emphasizes the goal of guiding the insurance industry to return to its fundamental role of providing protection and enhancing the ability to serve the real economy. This will further promote the high-quality development of the life insurance industry in China and enhance the operating efficiency.

5.2 Recommendations

Based on the above conclusions, this paper proposes the following recommendations:

First, adhere to the general direction of digital strategic transformation. In the long term, using technological means to achieve the transformation and upgrading of life insurance companies and the improvement of their operating efficiency is the inevitable path for their development. Life insurance companies should insist on optimizing the industrial chain through insurance technology means, increasing investment in insurance technology, and providing strong support for technological innovation in terms of organizational structure, resource allocation, and corporate culture.

Second, strengthen cooperation among industries and build a high-quality insurance technology ecosystem. Large insurance companies should further master emerging technologies, increase their independent research and development capabilities, combine insurance technology with products, services, and customers, and build core competitiveness through insurance technology. Small and medium-sized insurance companies can choose to cooperate with technology companies and internet companies, reducing investment risks while ensuring the economic benefits of their insurance business.

Third, fully implement the Solvency II regulatory requirements, enhance risk management capabilities, establish a major risk prevention mechanism, adhere to the bottom line of not causing systemic financial risks, and create a healthy environment for the development of the life insurance industry.

Acknowledgments

This study was funded by The Project for Improving the Basic Research Ability of Young and Middle-aged Teachers in Guangxi Universities in 2025 (grant number 2025KY0936).

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