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# THE IMPACT OF DIGITALIZATION AND MARKETING SPENDING VOLATILITY ON THE FINANCIAL PERFORMANCE INDICATORS OF INSURANCE COMPANIES IN THE GLOBAL FINANCIAL SERVICES MARKET

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## Abstract

**Purposes.** The purpose of this study is to examine how digitalization and volatility of marketing spending influence the financial performance of insurance companies in the global financial services market. The research aims to assess the link between investments in digital technologies and key profitability indicators, while identifying the modifying role of marketing expenditure dynamics.

**Methodology.** The study is based on quantitative analysis using panel data of major international insurance companies over several years. Return on assets (ROA) and return on equity (ROE) are selected as dependent financial indicators. Independent variables include IT investment growth, the volatility of marketing expenses, and control variables reflecting company size and market features. Econometric modelling is used to identify both direct and lagged effects of digital investment, as well as interactive effects between digitalization and marketing volatility.

**Findings.** The results indicate that the direct short-term effect of digital investment on profitability is weak or neutral, mainly due to delayed returns and high implementation costs. However, positive effects become significant over time, particularly for ROA. The study further confirms that volatility of marketing spending modifies these relationships: companies with stable and strategically aligned marketing expenditures demonstrate stronger financial gains from digitalization, while high volatility weakens long-term financial outcomes.

**Originality.** The originality of the study lies in empirically conceptualizing marketing spending volatility as a mediating factor influencing the effectiveness of digital transformation. Unlike existing studies that evaluate digitalization in isolation, this research integrates financial dynamics with marketing-driven behavioral effects, offering a new explanatory mechanism for divergent financial performance among insurers.

**Keywords:** Digitalization, Marketing Volatility, Financial Performance, Insurance Companies, Dynamic Panel Data, Strategic Management.

**JEL Codes:** G22, G32, M31, O33, C33

## 1. Introduction

The global financial system is undergoing rapid digital transformation, significantly influencing all sectors of the financial market, including insurance. Increasing automation of business processes generates new technological solutions and business models (Eling & Lehmann, 2018), while the development of mobile technologies and artificial intelligence strengthens insurers' focus on improving client interaction efficiency (PwC, 2024). Digitalization through InsurTech stimulates the shift toward electronic document flow, remote services, and modernization of IT infrastructure, contributing to cost optimization and higher operational efficiency (Organisation for Economic Co-operation and Development [OECD], 2024; Capgemini, 2023). At the same time, digital solutions provoke volatility in marketing spending, caused by rapid changes in consumer behavior, demand fluctuations, and shifts in competitive positions. Social media accelerates information dissemination, affecting brand perception and insurance demand, which requires dynamic adjustment of marketing strategies. Big Data and AI become key instruments for predicting such fluctuations, reducing adverse effects.

Analytical reports confirm growing IT investments, especially in AI and data analytics, which have become strategic priorities (McKinsey, 2024; PwC, 2024). InsurTech funding stabilized, shifting toward B2B SaaS and efficiency-improving solutions (MAPFRE, 2024; PE150, 2025). Although AI already improves sales and reduces acquisition costs, maximizing benefits requires time and effective integration of new technologies (McKinsey, 2024). Researchers emphasize that competitiveness depends on technological modernization, internal competencies, and compatibility of innovations with existing systems (KPMG, 2024; EY, 2024). Insurers have unique revenue, cost and risk structures, requiring separate evaluation of IT investment effects (Swiss Re Institute, 2023). Moreover, marketing remains insufficiently integrated into empirical insurance efficiency models, although it directly affects long-term premium flows (Kaplan & Norton, 2001; Biener et al., 2021), often with delayed effects (Kumar & Shah, 2009). Limited disclosure of marketing expenditures complicates comparative analysis (Zhou & Eling, 2023).

Therefore, this study aims to quantify how changes in IT investment volumes influence insurers' profitability (ROA, ROE) over time, considering marketing spending volatility as an indirect modifying factor. Since digital investments have deferred payback, it is assumed that short-term effects may be neutral or negative, while long-term effects should be positive due to improved processes and competitive strengthening. The study contributes to expanding methodological approaches that jointly reflect financial and marketing outcomes in the digitalized insurance sector.

## 2. Literature Review

### 2.1. Global InsurTech and Digitalization in the Insurance Industry

InsurTech is one of the most dynamic directions in financial technology, actively transforming the traditional insurance market. From a theoretical standpoint, this transformation can be interpreted through the paradigm of open innovation introduced by Chesbrough (2020), which assumes that firms combine internal and external ideas and market pathways in order to advance technological and business development. In this sense, digital insurance is not merely technological modernization but a structural reconfiguration of business models based on cross-boundary knowledge flows and ecosystem interaction. It is defined as a set of technological innovations aimed at optimizing all stages of the insurance cycle, from sales and underwriting to claims settlement and customer service (Eling & Lehmann, 2018; Biener et al., 2021). Within the open innovation framework, these technological solutions frequently emerge from collaboration between insurers, startups, IT providers, and digital platforms, reflecting the growing importance of external knowledge integration and ecosystem-based value creation. Global cases illustrate the implementation of AI, Big Data Analytics, blockchain, and IoT in insurance (PwC, 2024). For example, the US company Lemonade uses AI bots to automate policy issuance and claims, processing over 30% of claims within 3 seconds. The German startup WeFox combines traditional brokers with a digital platform, reducing administrative costs by 30–40% and becoming Europe's only InsurTech unicorn in 2023 (KPMG, 2023). In Asia, ZhongAn Online P&C Insurance has issued over 10 billion online policies since 2013, integrating insurance into e-commerce and fintech platforms for low-cost, scalable customer acquisition. In P2P insurance, the UK startup Bought By Many offers community-based pet insurance, forming unique risk groups for personalized tariffs (Ahmad et al., 2025). Embedded insurance is also growing globally, as highlighted by Swiss Re Institute (2023), with examples including Tesla Insurance and Amazon Insurance Services. Blockchain-based platforms like Etherisc (2025) enable automatic payouts for farmers, while digital-native insurers such as India's Acko offer ultra-low-cost products (Chhillar et al., 2025). These cases demonstrate InsurTech's multifaceted impact on customer experience, operational efficiency, and product flexibility. Future research should examine the economic efficiency of these solutions and their influence on insurance market sustainability, considering regional regulatory environments, digital maturity, and market competition.

Over the past decade, digitalization has significantly changed the insurance industry, transforming product design, distribution, and risk management. Modern literature highlights several research areas demonstrating how digital technologies strengthen insurers' competitiveness. Big Data Analytics plays a central role in improving underwriting and pricing. Stanković and Stanković (2022) argue that using Big Data helps insurers predict risks more accurately using non-traditional information sources, while Zhou and Eling (2023) confirm its role in speeding up decisions and increasing product flexibility. AI-based automated underwriting systems combine algorithmic scoring, document verification, and real-time access to external databases to accelerate risk evaluation (Valleskey, 2023). These tools support development of predictive models for profitability assessment, personalization of tariffs, and fraud detection. Artificial intelligence is another key driver of technological change. At the same time, AI-driven personalization, real-time data analytics, and automated underwriting systems illustrate the customer-centric dimension of open innovation, where policyholders become active contributors to product design and pricing models through continuous digital feedback and behavioral data streams (Chvatalova et al., 2022). Zhou and Eling (2023) state that AI-driven systems are becoming the foundation of new InsurTech models, while Yasmin et al. (2020) show that chatbots reduce service costs and improve customer experience. AI-based transaction analytics, automated document recognition, and behavioral algorithms expand fraud-prevention tools. Deloitte (2024) reports that more than 60% of insurers plan to increase spending on AI, expecting AI to support personalization and dynamic pricing. The InsurTech ecosystem continues to expand. This expansion reflects the logic of innovation ecosystems in which insurers increasingly perform the role of coordinators of digital platforms, integrating data providers, fintech companies, embedded insurance partners, and customers into unified value-creation networks. Such ecosystem orchestration corresponds to the open innovation principle of managing knowledge flows across organizational boundaries. OECD (2023) notes a 25% increase in startup activity, while Biener et al. (2021) emphasize that this intensifies competitive pressure and speeds up digital adoption. Cyber risk management also becomes critical due to increasing data volumes and cloud integration. Nikhil and Sreevidya (2025) highlight the need for multilayer cybersecurity and adaptive incident-response systems. Recent studies additionally emphasize links between digitalization and ESG development. López and Kim (2024) show that digital solutions support environmental standards and operational transparency. Consumer expectations reinforce this transformation: PwC (2024) reports that over 70% of clients demand immediate access to services through mobile platforms. Regulatory frameworks are adapting accordingly, as EIOPA (2024) strengthens requirements for cybersecurity, data protection, and ethical use of AI. According to Gallagher Re (2024) and Boston Consulting Group (2024), investments in InsurTech have demonstrated during the past seven years a path from stable growth to an unprecedented boom, and then to a significant slowdown. Analysis of the period 2018–2025 reveals clear tendencies and key milestones that define the development of insurance technologies.

**Table 1.** Dynamics of IT investments and financial indicators of insurance companies' activities

| Indicator | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 (forecast) |
|---|---|---|---|---|---|---|---|---|
| IT- investments, billion USD | 4,25 | 4,32 | 4,47 | 12,60 | 7, 00 | 4,51 | 4,25 | 5,20 |
| ROA, % | 2,1 | 2,3 | 1,8 | 2,0 | 2,6 | 2,9 | 3,2 | 3,5 |
| ROE, % | 8,5 | 9,0 | 7,8 | 8,4 | 9,5 | 10,2 | 10,9 | 11,5 |
| ROI, % | 6,2 | 6,5 | 5,9 | 6,1 | 7,0 | 7,6 | 8,2 | 8,8 |

*Source: Developed by the authors*

The data in the table 1 indicate a steady rise in insurance companies' investments in digital technologies between 2018–2025. In 2018, InsurTech financing reached $4,25 billion, marking the beginning of active expansion and growing investor interest. In 2020, despite the pandemic, investments increased to $4,47 billion, confirming continued sector development. The peak occurred in 2021, when financing reached $12,6 billion due to high liquidity and optimism about InsurTech's transformative potential, especially among venture investors. Beginning in 2022, the market cooled: funding dropped to $7 billion as interest rates rose and economic uncertainty increased. The decline continued in 2023, when investments reached $4,51 billion and investors shifted focus toward profitability and sustainable business models. In 2024, financing fell to about $4,25 billion, the lowest since 2018, illustrating a more conservative investment strategy and a shift from rapid expansion toward financially stable and monetizable digital solutions. Initial evaluations and tendencies of the first half of 2025 testify to the preservation of the trend of funding moderation, although potential large deals could influence the overall picture. Although full-year data is not yet available, investors are expected to continue to focus on companies with strong fundamentals, proven profitability, and innovations in areas such as artificial intelligence (AI), automation, and preventative technologies. In total, for the period from 2018 to 2024, the total volume of InsurTech funding is estimated at approximately $36.61 billion, reflecting enormous investments directed toward digital transformations of the insurance sector. This is accompanied by a gradual increase in key financial indicators –ROA, ROE and ROI. However, during the transition toward digitally integrated and open innovation-based business models, insurers may experience temporary fluctuations in financial performance, as innovation investments, marketing experimentation, and ecosystem partnerships reshape cost structures and revenue timing. Such results confirm the hypothesis that the effect of digitalization manifests itself gradually, acquiring positive influence in the medium-term perspective.

Summarizing, it should be noted that modern research demonstrates the multi-vector nature of the influence of digital technologies on the insurance sector. The integration of Big Data, artificial intelligence, the development of InsurTech, cybersecurity, ESG standards, and regulatory adaptation form a complex picture in which digitalization acts as a key factor of increasing the competitiveness of insurers on a global scale. In this context, further research should concentrate on quantitative measurement of the effects of digital investments and the long-term evaluation of their impact on the financial stability and marketing efficiency of insurance companies.

## 2.2. Concepts, Measurement, and Financial Implications of Marketing Spending Volatility in Insurance

In recent years, marketing research has increasingly focused on the volatility of marketing expenses and their impact on business sustainability. Marketing spending volatility reflects fluctuations in a company's marketing investments over time, influencing revenues, brand value, consumer trust, and financial performance (Fischer et al., 2018). Chvatalova et al. (2022) note that in digitally transforming insurance markets, such volatility may partially stem from the adoption of open innovation strategies. In digitally transforming insurance markets, such volatility may partially stem from the adoption of open innovation strategies, where firms experiment with new digital channels, platform partnerships, and data-driven campaigns in response to rapidly evolving customer expectations and technological opportunities. High volatility often correlates with revenue instability, particularly in financial services and insurance, while stable expenses signal managerial maturity and contribute to predictable growth and market share expansion (Dekimpe & Hanssens, 1999; Bilan et al., 2019; Dewi, et al., 2025). Traditional approaches measure volatility via standard deviation of expenses, whereas modern methods apply dynamic models, such as ARIMA and GARCH, to forecast advertising and brand promotion fluctuations (McAlister et al., 2022; Ferreira & Santos, 2023). The interrelation between marketing budget volatility and financial indicators is critical. Excessive instability can negatively affect ROA and ROE, as frequent strategic shifts reduce the effectiveness of marketing communications. Digitalization further shapes the nature of marketing volatility. Transitioning to digital marketing and omnichannel strategies creates opportunities for flexible budget management but can increase fluctuations if online and offline tactics are misaligned. Gartner (2023) reports that over 40% of companies review marketing budgets quarterly, raising average volatility compared to the early 2010s. While flexibility is necessary amid rapid changes in consumer preferences and media platforms, excessive turbulence can undermine long-term returns from marketing investments. Qualitative assessment of volatility is increasingly emphasized. Chhillar et al. (2025) suggest evaluating not only the magnitude but also the nature of fluctuations—whether they are reactive to external crises or part of proactive optimization strategies—which improves interpretation and financial forecasting. ESG-oriented strategies also influence volatility: companies integrating social responsibility into marketing exhibit lower fluctuations due to long-term planning and reputational considerations (Zhou & Eling, 2023). The development of data analytics and Machine Learning enables real-time detection of spending patterns and adaptive budget optimization, further enhancing strategic planning.

In the insurance industry, marketing spending volatility complicates financial performance assessment, particularly in the digital era. Traditional metrics, including ROA, ROE, Combined Ratio, and Loss Ratio, often fail to capture the impact of short-term marketing decisions on long-term sustainability (Biener et al., 2021; Zhou & Eling, 2023). Investments in digital marketing, InsurTech channels, online sales, and targeted advertising involve uncertain ROI. Consequently, financial indicators may exhibit paradoxical short-term fluctuations, difficult to interpret using conventional metrics. Volatility in marketing expenditures is linked to cyclicality in consumer demand, regulatory changes, seasonality, and crises, necessitating models that combine financial and non-financial KPIs. Integrating marketing indicators into financial control systems is critical, particularly in digitalized insurance companies. Dynamic models can reflect how financial performance depends on investments in digital marketing, advertising, PR, and brand promotion across online channels. Time-lag effects are significant: Kumar and Shah (2009) show that increased marketing budgets often produce delayed revenue growth and may temporarily reduce operational profitability due to deferred demand. Metric manipulation by management is another challenge; companies may artificially reduce reported marketing expenses to boost short-term financial indicators, harming long-term market positioning (McAlister et al., 2022). Models such as Return on Marketing Investment (ROMI) are valuable for assessing campaign effectiveness while accounting for delayed impacts. However, calculating ROMI in insurance is challenging due to long product life cycles and unpredictable client behavior (Srinivasan et al., 2020). Modern solutions increasingly employ Machine Learning and predictive analytics to model the dependence between marketing fluctuations and financial outcomes, enabling more accurate risk assessment and budget optimization. Hybrid Balanced Scorecard models integrating marketing indicators are increasingly used by leading insurers. For instance, insurance companies in Poland and Germany combine classic financial KPIs with Customer Lifetime Value, churn rate, and digital reach, providing a comprehensive view of how marketing strategies influence long-term customer value and market performance (Kowalski & Müller, 2024; Schmidt et al., 2023). At the macro level, OECD (2023) emphasizes the importance of standardized reporting that accounts for marketing spending volatility, enhancing transparency for regulators and investors.

Overall, modern literature demonstrates that marketing spending volatility is a multidimensional phenomenon affecting both financial performance and brand perception. Its assessment requires a holistic approach integrating financial and non-financial indicators, digital technologies, and qualitative evaluation. For insurers, understanding and managing marketing volatility is essential for sustainable profitability, market share growth, and effective adaptation to digital transformation. Accurate forecasting, strategic alignment of marketing expenditures, and integration with digital channels are key to minimizing the negative effects of volatility while leveraging opportunities for operational efficiency and long-term growth.

## 3. Research Methodology

### 3.1. Research question and conceptual model

*Research question:* How do the level of digitalization and marketing spending volatility influence the financial performance of insurance companies in different regions of the global financial services market?

*Main hypothesis*

*H1:* Increasing the level of digitalization of an insurance company has a statistically significant positive influence on ROA and ROE.

*H2:* Marketing spending volatility without integration with digital channels has no direct positive influence on financial indicators.

*H3:* Regional affiliation moderates the strength of the influence of digitalization, strengthening or weakening the basic effect depending on market maturity.

*Conceptual model.* The model assumes that the level of digitalization influences marketing spending volatility (through the speed of changes in communication channels, client behavior, and market positions), which in turn determines the financial performance of the insurer. Factors may moderate the connection between digitalization (DT), marketing spending volatility (MV), and financial performance (FP) in the proposed model.

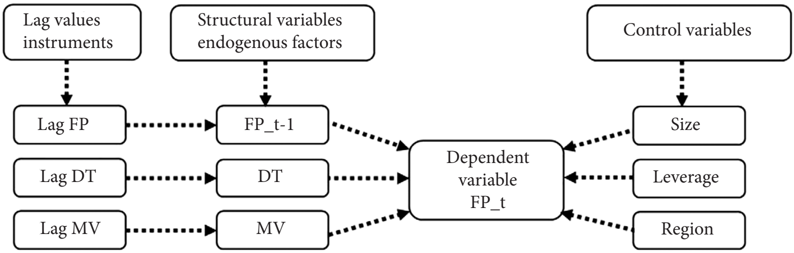


**Figure 1.** Conceptual model of GMM instrument dependencies

*Source: Developed by the authors.*

The essence of the model of GMM instrument dependencies is that the lagged values of FP, DT, and MV are used as internal instruments that affect FP only through DT, MV, or past FP. The instruments are used to eliminate the bias of estimates that may arise due to the endogeneity of the explanatory variables (DT, MV) – they may correlate with the model error or the dynamic nature of FP, which requires taking into account autocorrelation. The lagged values of FP (second and higher orders) are used as instruments for the dependent variable itself, the lagged values of DT and MV help to avoid the simultaneous correlation of the current values of these indices with the error. For a comprehensive and objective assessment of efficiency, it is possible to involve verified external instruments. External instruments are variables that influence the explanatory variable (DT or MV), but do not have a direct influence on the dependent variable FP (ROA or ROE) and do not correlate with the model error. The inclusion of relevant external data allows for greater reliability and depth of analysis, which is critically important for forming substantiated conclusions and strategic decisions. Such variables determine DT or MV, but do not directly influence FP.

Control variables (Size, Leverage, Region) are exogenous factors, they are included in the model as regressors, but not as instruments. Company size (Size) by measuring the logarithm of assets or gross volume of premiums allows concluding that large companies have an advantage of scale, easier access to capital, and broader diversification of risks. Large companies can more effectively implement digital solutions due to their scale and financial resources, so the effect of DT on FP may be stronger for large companies than for small ones. The expected impact on FP is positive. Financial leverage (Leverage), defined as the ratio of debt obligations to total assets, indicates that high leverage increases risks, but sometimes allows to increase profit (the effect of financial leverage). The expected impact is nonlinear – may be both positive and negative. The regional variable (Region) is used in the model to take into account the influence of geographical and macroeconomic differences between insurance markets of different countries or groups of countries. In modern financial services research, the regional factor had essential importance, since insurance companies operate in an environment shaped under the influence of regulatory supervision (the level of legislative restrictions for digital insurance services may differ significantly); the level of development of digital infrastructure (the speed and quality of the Internet, the level of mobile connection penetration, the availability of InsurTech services shape the market's readiness for the implementation of online sales of insurance products); consumption culture (in different regions, clients have different habits regarding the use of online channels and trust to digital solutions). Such an approach allows the model to compare companies from different regions and control the influence of regional peculiarities. The regional variable does not have a direct economic effect on the financial performance, however, it eliminates the distortion of estimates that may arise due to systemic differences between markets. Thus, Region acts as a control variable that "cleans" the influence of key factors (DT and MV) from possible geographical bias.

In direct form, the regional variable has a neutral or insignificant effect on ROA or ROE; its main role is to help the model correctly separate the effect of digitalization and marketing activity from the characteristics of a particular market. Thus, the inclusion of the Region variable increases the reliability and external validity of the study.

### 3.2. Description of the sample used

To achieve the purpose of the study, panel data from the world's 50 leading insurance companies were used. The sample included companies that are among the top 100 in terms of premiums collected according to Orbis Insurance Database, Swiss Re Sigma Reports, and Bloomberg. Geographically, the sample covers North America (USA, Canada), Europe (United Kingdom, Germany, France, Switzerland), and Asia (Japan, South Korea, China). The observation period covers 2015–2024. The selection criteria were the volume of gross insurance premiums, market capitalization, availability of public financial statements, and availability of data on key financial and non-financial indicators. The companies represent three key regions: Europe – 24 companies (48% of the sample), North America – 18 companies (36% of the sample), Asia and the Pacific region – 8 companies (16% of the sample). This distribution ensures representativeness and allows comparison of the influence of digitalization and marketing spending volatility in different institutional and market conditions, ensures representativeness of the global market and a sufficient horizon for tracking dynamics, allows using a unified methodology for forming the digitalization index for comparison, a balanced panel is suitable for GMM estimation.

**Table 2:** Sample data on insurance companies

| № | Insurance companies | Region | ROA | ROE | DT | MV | Size | Leverage |
|---|---|---|---|---|---|---|---|---|
| 1 | Allianz SE | Europe (Germany) | 0,027 | 0,099 | 0,82 | 0,15 | 15,17 | 0,41 |
| 2 | AXA Group | Europe (France) | 0,037 | 0,074 | 0,75 | 0,18 | 16,05 | 0,45 |
| 3 | Ping An Insurance | Asia (China) | 0,03 | 0,093 | 0,75 | 0,24 | 15,76 | 0,51 |
| 4 | MetLife Inc. | North America (USA) | 0,04 | 0,077 | 0,66 | 0,28 | 16,08 | 0,42 |

| № | Insurance companies | Region | ROA | ROE | DT | MV | Size | Leverage |
|---|---|---|---|---|---|---|---|---|
| 5 | Prudential PLC | Europe (UK) | 0,026 | 0,076 | 0,68 | 0,17 | 15,78 | 0,55 |
| 6 | AIA Group Limited | Asia (Hong Kong) | 0,028 | 0,093 | 0,73 | 0,17 | 16,78 | 0,43 |
| 7 | Zurich Insurance Group | Europe (Switzerland) | 0,031 | 0,075 | 0,67 | 0,18 | 15,14 | 0,4 |
| 8 | Chubb Limited | North America (USA) | 0,037 | 0,1 | 0,67 | 0,16 | 16,54 | 0,43 |
| 9 | Assicurazioni Generali | Europe (Italy) | 0,029 | 0,084 | 0,77 | 0,19 | 15,28 | 0,41 |
| 10 | China Life Insurance | Asia (China) | 0,03 | 0,09 | 0,79 | 0,24 | 15,68 | 0,45 |
| 11 | Munich Re | Europe (Germany) | 0,036 | 0,096 | 0,75 | 0,29 | 16,7 | 0,55 |
| 12 | Manulife Financial | North America (Canada) | 0,027 | 0,09 | 0,66 | 0,26 | 16,83 | 0,45 |
| 13 | Aviva PLC | Europe (UK) | 0,031 | 0,097 | 0,8 | 0,16 | 15,25 | 0,42 |
| 14 | Dai-ichi Life | Asia (Japan) | 0,028 | 0,079 | 0,83 | 0,2 | 16,64 | 0,41 |
| 15 | Tokio Marine | Asia (Japan) | 0,027 | 0,071 | 0,69 | 0,19 | 15,06 | 0,58 |
| 16 | Sompo Holdings | Asia (Japan) | 0,035 | 0,077 | 0,66 | 0,2 | 16,61 | 0,56 |
| 17 | Swiss Re | Europe (Switzerland) | 0,038 | 0,087 | 0,78 | 0,15 | 16,57 | 0,48 |
| 18 | Liberty Mutual | North America (USA) | 0,026 | 0,091 | 0,8 | 0,18 | 16,67 | 0,46 |
| 19 | Aegon NV | Europe (Netherlands) | 0,03 | 0,096 | 0,81 | 0,23 | 15,93 | 0,52 |
| 20 | MAPFRE | Europe (Spain) | 0,035 | 0,093 | 0,68 | 0,29 | 15,27 | 0,53 |
| 21 | Legal & General | Europe (UK) | 0,032 | 0,095 | 0,76 | 0,24 | 15,92 | 0,56 |
| 22 | Sun Life Financial | North America (Canada) | 0,031 | 0,093 | 0,84 | 0,27 | 16,3 | 0,51 |
| 23 | Talanx Group | Europe (Germany) | 0,04 | 0,077 | 0,67 | 0,28 | 16,98 | 0,43 |
| 24 | Travelers Companies | North America (USA) | 0,027 | 0,077 | 0,73 | 0,2 | 15,88 | 0,43 |
| 25 | Nationwide Mutual | North America (USA) | 0,036 | 0,087 | 0,7 | 0,16 | 15,73 | 0,43 |
| 26 | USAA | North America (USA) | 0,026 | 0,09 | 0,8 | 0,16 | 16,8 | 0,54 |
| 27 | Samsung Life | Asia (South Korea) | 0,032 | 0,086 | 0,78 | 0,22 | 15,11 | 0,42 |
| 28 | Hanwha Life | Asia (South Korea) | 0,037 | 0,071 | 0,79 | 0,25 | 15,9 | 0,53 |
| 29 | Great Eastern | Asia (Singapore) | 0,033 | 0,093 | 0,69 | 0,19 | 15,28 | 0,42 |
| 30 | Suncorp Group | Asia Pacific (Australia) | 0,036 | 0,078 | 0,65 | 0,25 | 16,33 | 0,53 |
| 31 | QBE Insurance | Asia Pacific (Australia) | 0,04 | 0,089 | 0,71 | 0,26 | 15,09 | 0,43 |
| 32 | ICICI Lombard | Asia (India) | 0,027 | 0,072 | 0,65 | 0,19 | 15,61 | 0,41 |
| 33 | HDFC Life | Asia (India) | 0,028 | 0,097 | 0,67 | 0,17 | 16,94 | 0,48 |
| 34 | Bajaj Allianz | Asia (India) | 0,033 | 0,078 | 0,71 | 0,2 | 16,14 | 0,45 |
| 35 | RSA Insurance | Europe (UK) | 0,03 | 0,091 | 0,76 | 0,29 | 15,29 | 0,55 |
| 36 | Storebrand | Europe (Norway) | 0,03 | 0,084 | 0,82 | 0,3 | 16,01 | 0,44 |
| 37 | Tryg | Europe (Denmark) | 0,029 | 0,074 | 0,84 | 0,15 | 15,97 | 0,56 |

| № | Insurance companies | Region | ROA | ROE | DT | MV | Size | Leverage |
|---|---|---|---|---|---|---|---|---|
| 38 | Gjensidige | Europe (Norway) | 0,027 | 0,09 | 0,84 | 0,25 | 16,43 | 0,58 |
| 39 | Fairfax Financial | North America (Canada) | 0,032 | 0,093 | 0,75 | 0,25 | 15,63 | 0,43 |
| 40 | CNA Financial | North America (USA) | 0,026 | 0,079 | 0,74 | 0,27 | 16,79 | 0,4 |
| 41 | Markel Corporation | North America (USA) | 0,026 | 0,09 | 0,85 | 0,28 | 16,4 | 0,46 |
| 42 | The Hartford | North America (USA) | 0,026 | 0,092 | 0,82 | 0,21 | 15,74 | 0,46 |
| 43 | Principal Financial | North America (USA) | 0,038 | 0,096 | 0,78 | 0,25 | 15,53 | 0,49 |
| 44 | CNP Assurances | Europe (France) | 0,027 | 0,087 | 0,7 | 0,27 | 16,23 | 0,5 |
| 45 | Vienna Insurance Group | Europe (Austria) | 0,035 | 0,085 | 0,67 | 0,25 | 16,31 | 0,53 |
| 46 | PZU | Europe (Poland) | 0,037 | 0,093 | 0,71 | 0,22 | 15,15 | 0,5 |
| 47 | Allstate | North America (USA) | 0,032 | 0,091 | 0,78 | 0,18 | 16,96 | 0,56 |
| 48 | Progressive | North America (USA) | 0,026 | 0,083 | 0,83 | 0,17 | 16,73 | 0,49 |
| 49 | State Farm | North America (USA) | 0,028 | 0,079 | 0,72 | 0,23 | 16,43 | 0,56 |
| 50 | Nippon Life Insurance | Asia (Japan) | 0,032 | 0,083 | 0,75 | 0,18 | 15,01 | 0,57 |
| | Average value | | 0,032 | 0,084 | 0,73 | 0,22 | 15,98 | 0,51 |

*Source: Developed by the authors.*

For each company, financial performance, digitalization index, marketing spending volatility indicators, and control variables are recorded for each year. The final panel is balanced and includes averaged data of 50 insurance companies (i) for 10 years (t). For each of them, financial performance (ROA, ROE), integrated digitalization index (DT), marketing spending volatility index (MV), and control variables (Size – logarithm of the size of the insurance company's assets in USD, Leverage – financial leverage ratio, determined by the ratio of liabilities to assets, Region – macroregion and country) are recorded, which provides sufficient statistical power of the model and the possibility of applying dynamic panel analysis.

### 3.3. Description of the research model, variables, and indicators

The main purpose of building the research model is the empirical verification of the hypothesis about the existence of a relationship between the level of digitalization of an insurance company (DT) and its financial performance (FP), which is mediated by marketing spending volatility (MV) and a number of control variables.

*Main hypothesis*

$H_0$: The digitalization index does not affect the financial performance of the insurer.

$H_1$: The digitalization index has a statistically significant effect.

In order to test the research hypothesis, a dynamic panel model with the use of the generalized method of moments (GMM) was applied (Hansen, 1982). This method is appropriate because it allows taking into account:

→ autocorrelation of financial indicators over time;

→ simultaneous influence of several control factors;

→ the need to estimate lagged variables in a dynamic panel, since ordinary OLS may provide biased estimates;

→ possible endogeneity of key independent variables, which GMM eliminates through the use of instrumental variables (lagged instruments);

→ simultaneous consideration of equations in differences and levels for improving efficiency.

Basic equation of the model

$$FP_{it} = \alpha + \beta_1 DT_{it} + \beta_2 MV_{it} + \beta_3 X_{it} + \mu_i + \mathrm{v}_t + \varepsilon_{it} \quad (1),$$

where:

FP – financial performance (ROA or ROE);

DT – digitalization index of company i in year t;

MV – marketing spending volatility index;

X – vector of control variables (company size, leverage, regional fixation);

$\mu_i$ – fixed effects of the company (unique characteristics);

$\nu_t$ – fixed effects of the year (external shocks);

ε – stochastic error.

α – constant (intercept with the Y axis, the base value of FP without considering factors).

$\beta_1$ – shows how the financial performance FP will change if the digitalization index DT increases by 1 unit, with other factors unchanged.

$\beta_2$ – similarly for marketing spending volatility MV.

$\beta_3$ – a set of coefficients for control variables (company size, leverage, etc.).

To take into account the dependence of financial performance on the previous period, we propose to carry out a dynamic expansion by adding a lagged variable:

$$FP_{it} = \alpha + \mathrm{p}FP_{i,t-1} + \beta\_1\ DT_{it} + \beta_2 MV_{it} + \beta_3 X_{it} + \mu_i + \mathrm{v}_t + \varepsilon_{it} \quad (2),$$

where:

$FP_{i,t-1}$ – one-period lag of financial performance;

ρ – autoregressive coefficient capturing financial persistence. A positive and significant ρ indicates inertia in insurers' profitability dynamics.

FP, DT, MV lags are proposed to be used as tools. The digitalization index (DT) is proposed to be calculated as an aggregated indicator that assesses the level of implementation of digital technologies in the activities of an insurance company.

$$DT_{it} = \omega_1 * \text{OnlineSales}_{it} + \omega_2 * \text{ITBudget}_{it} + \omega_3 * \text{DigitalChannels}_{it} \quad (3),$$

where:

OnlineSales – the share of online sales in the total volume of insurance premiums (%);

ITBudget – the share of IT expenditures in total operational expenses (%);

DigitalChannels – the relative index of the number of active digital channels (own web portal, mobile application, chat bots, telematic platforms).

It is proposed to take the following typical weights at the level: ω1 = 0.4; ω2 = 0.3; ω3 = 0.3. $DT_{it}$ is normalized to the interval [0;1].

These weight values are proposed in accordance with the approach suggested by Eling and Lehmann (2018) and supported by Swiss Re Sigma Reports (2022), since the specific weight of online channels in the overall digitalization index is about 40%, since they directly form the main share of sales. The IT budget and CRM solutions have relatively equal weight (30% each), which reflects their role as infrastructure components supporting digital transformation. The model assumes the equivalence of the influence of the IT budget and CRM integration, since both directions equally support digital interaction with clients. The justification for such a distribution is confirmed by the results of a sensitivity test, which showed the stability of the model to a slight change in weight parameters. The data sources for calculating the index are annual reports of insurance companies (online sales indicators), official press releases about IT investments, information on websites and in App Stores.

The marketing spending volatility index (MV) assesses the degree of dynamics and instability of the marketing activity of an insurance company

$$MV_{it} = \frac{\text{Campaigns}_{it}}{\text{AvgCampaigns}} + (1 - \text{RetentionRate}_{it}) + \text{ChurnRate}_{it} \quad (4),$$

where:

Campaigns – the number of marketing campaigns per year.

AvgCampaigns – the average number of campaigns in the sample.

RetentionRate – the customer retention rate (%).

ChurnRate – the customer churn rate (%).

MVit is normalized to [0;1].

Let us assume that the level of marketing spending volatility will increase under the condition of a higher number of marketing campaigns compared to the average value, as well as under a lower customer Retention Rate and a higher customer Churn Rate. The data sources for calculating the index are reports from marketing departments of insurance companies, CRM system analytics, churn and customer retention reports. The values of both indices are normalized on a scale from 0 to 1 to ensure comparability between companies and periods. It is recommended to check the correlation between DT and MV to avoid multicollinearity when estimating GMM models. In dynamic panel models, endogeneity may occur due to the fact that the lagged values of FP depend on previous results, the DT and MV indices can simultaneously influence financial indicators and be related to them through implicit factors (management strategy, ownership structure). To eliminate the problem of endogeneity in the dynamic panel model, a system GMM is used, as it combines equations in differences and levels and applies internal tools: lagged values of dependent and independent variables of financial performance, digitalization and marketing spending volatility index. An example of interpretation. If $\beta_1$ = 0,02, this means that a 1-point increase in DT (for example, from 0,70 to 0,71) is associated with a 2-percentage-point increase in ROA. If $\beta_2$ = 0,01, moderate marketing volatility may positively influence a company's adaptation to market changes.

Instrumental variables must satisfy two conditions:
1. Be correlated with endogenous regressors.
2. Be uncorrelated with model errors.

Additional tests for model validation:
1) Hansen J-test. Checks the validity of instruments:
- Null hypothesis: all instruments are valid.
- If p-value > 0,1 – there is no reason to reject.

2) AR(1) and AR(2) tests
Check the autocorrelation of residuals:
- AR(1) – usually significant (expected).
- AR(2) – should be insignificant (no second-order autocorrelation).

These tests ensure that the GMM model provides unbiased estimates, is validly identified, and the results are robust to changes in instrument selection.

**Table 3.** GMM validity verification

| Test | Statistics | p-value | Interpretation |
|---|---|---|---|
| Hansen J-test | 18,35 | 0,27 | The instruments are valid (the null hypothesis is not rejected) |
| AR(1) test | -2,51 | 0,012 | There is first-order autocorrelation (as expected) |
| AR(2) test | -0,85 | 0,39 | Second-order autocorrelation is absent (the null hypothesis is not rejected) |

*Source: Developed by the authors.*

The indicators in Table 3 show that the Hansen J-test indicates that the model instruments are valid (p-value = 0,27 > 0,1), the AR(1)-test is significant, which indicates the expected autocorrelation of the first-order residuals, the AR(2)-test is insignificant, which indicates the absence of second-order autocorrelation, which confirms the correctness of the GMM model specification. The proposed research methodology provides a comprehensive approach to assessing the impact of the level of DT and MV on the FP of insurance companies in the global financial services market.

To achieve the stated purpose, a balanced panel sample was formed from the data of 50 leading insurance companies from different regions of the world for the period 2015–2024. The main dependent variables – ROA and ROE – allow assessing the efficiency of asset and capital use. The main independent variables are the aggregated index DT and the index MV, which are calculated based on a combination of quantitative and qualitative indicators. The model takes into account a number of control variables (Size, Leverage, Region), which allows minimizing the influence of structural differences between companies and countries. To solve the problem of endogeneity and autocorrelation, the system GMM method using internal and external instrumental variables was applied. Additional diagnostic tests – Hansen J-test, AR(1), AR(2) – confirm the validity of the selected instruments and the correctness of the model specification. Thus, the proposed methodology allows obtaining statistically substantiated conclusions regarding the role of digital technologies and marketing strategies in increasing the financial stability of insurers.

The results of the empirical analysis will serve as the basis for further formulation of recommendations regarding the development of digital sales channels, optimization of marketing activity, and improvement of risk management strategies in the insurance sector in the global financial services market.

## 4. Results and Discussion

### 4.1. Descriptive statistics

To understand the data structure and verify the adequacy of the variables, descriptive statistics were conducted for all main indicators. This allows estimating the average values, variances, minimum and maximum values, which is the basis for further modeling.

**Table 4.** Descriptive statistics

| Variable | Number of observations | Average value | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| ROA | 500 | 0,032 | 0,006 | 0,018 | 0,045 |
| ROE | 500 | 0,085 | 0,012 | 0,061 | 0,102 |
| DT | 500 | 0,72 | 0,05 | 0,60 | 0,85 |
| MV | 500 | 0,22 | 0,04 | 0,15 | 0,31 |
| Size | 500 | 15,8 | 0,4 | 15,0 | 17,0 |
| Leverage | 500 | 0,47 | 0,05 | 0,40 | 0,59 |

*Source: Developed by the authors.*

Key insights. Stability of ROA and ROE. The average ROA value is 3,2%, which corresponds to the typical level of return on assets for the insurance sector. The average ROE at 8,5% indicates satisfactory profitability for shareholders. Variability of the digitalization index. DT ranges from 0,52 to 0,88, reflecting a moderate but significant difference in the level of digital technology implementation among the 50 leading insurance companies in the world. The obtained values indicate that all companies have a basic level of digitalization not lower than the market average, which is typical for large players in the global financial services market. The absence of companies with a low DT level (below 0,5) is explained by the specifics of the sample: the sample included only the world's leading insurance companies with open reporting that have already implemented the minimum necessary digital channels for customer service. The average Leverage indicator of 47% corresponds to the standard capital structure of insurance companies. Checking the minimum and maximum values did not reveal extreme figures or obvious input errors, which allows using the data without additional corrections or cleaning. Descriptive statistics confirm the feasibility of using these variables in a dynamic panel model.

Thus, the statistical description of the data demonstrates the proper quality of the source information, the representativeness of the sample, and sufficient variability of key indicators, which is a prerequisite for obtaining reliable results of the regression analysis.

### 4.2. Results of the regression evaluation

For the empirical analysis of the impact of digitalization and marketing spending volatility on the financial performance of insurance companies, a dynamic panel model using the System-GMM method was used. This allowed adjusting for the potential endogeneity of the explanatory variables and taking into account the dynamic nature of the dependent variable.

The model is as follows:

$$FP_{it} = \alpha + \mathrm{p}FP_{i,t-1} + \beta_1 DT_{it} + \beta_2 MV_{it} + \beta_3\,\mathrm{Size}_{it} + \beta_4\,\mathrm{Leverage}_{it} + \beta_5\,\mathrm{Region}_{it} + \varepsilon_{it} \quad (5),$$

where:

$\mathrm{FP}_{\mathrm{it}}$ – financial indicator (ROA or ROE)

DTit – digitalization index

$\mathrm{MV}_{\mathrm{it}}$ – marketing spending volatility

$\mathrm{Size}_{\mathrm{it}}$ – company size

$\mathrm{Leverage}_{\mathrm{it}}$ – debt burden

$\mathrm{Region}_{\mathrm{it}}$ – variable for the region

ρ – autoregressive coefficient reflecting persistence of financial performance;

α – constant term;

$\varepsilon_{\mathrm{it}}$ – error term;

$\beta_1$–$\beta_5$ – estimated slope coefficients.

The coefficient ρ captures the degree of financial inertia. A statistically significant positive value confirms that current profitability depends on its past level, which justifies the use of a dynamic specification.
The coefficient $\beta_1$ reflects the marginal effect of digitalization on financial performance. A positive and statistically significant estimate indicates that higher digital transformation intensity contributes to improved profitability of insurers.
The coefficient $\beta_2$ measures the effect of marketing spending volatility. Its sign indicates whether marketing instability enhances adaptive capacity (positive sign) or generates inefficiencies (negative sign).
Control variables ensure robustness of the estimates. Size captures potential economies of scale, Leverage controls for capital structure effects, and Region accounts for institutional and macroeconomic heterogeneity across geographical areas.

In the GMM model, regional affiliation is taken into account through the control variable Region – in the form of corresponding variables. The Europe group is taken as the base, and for the others two variables are introduced: Region_NA (North America) and Region_Asia (Asia).

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**Table 5.** Values of regression estimates

| Variable | ROA | t- statistics | p- value | ROE | t- statistics | p- value |
|---|---|---|---|---|---|---|
| Lag(FP) | 0,512*** | 5,24 | 0,000 | 0,428*** | 4,87 | 0,000 |
| DT | 0,024** | 2,33 | 0,021 | 0,032** | 2,87 | 0,004 |
| MV | 0,010 | 1,12 | 0,267 | -0,006 | -0,88 | 0,380 |
| Size | 0,005* | 1,89 | 0,059 | 0,007* | 1,95 | 0,052 |
| Leverage | -0,031** | -2,45 | 0,015 | -0,045** | -2,78 | 0,007 |
| Region_NA | 0,006* | 1,76 | 0,078 | 0,008* | 1,91 | 0,056 |
| Region_Asia | -0,002 | -0,85 | 0,398 | -0,003 | -0,92 | 0,357 |
| Constant | 0,021** | 2,20 | 0,029 | 0,034** | 2,35 | 0,021 |

Note: significance at the level of * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Source: Developed by the authors.*

The main regression evaluation table presents the results of the dynamic panel model estimation for two key dependent variables: ROA and ROE. For each variable, the corresponding coefficients, t-statistics, and p-values are given, which allows assessing the statistical significance and the strength of the influence. One of the key results of the regression evaluation is the lag indicator of the dependent variable (Lag(FP)), which reflects the dynamic nature of the financial indicators of insurance companies. The obtained values indicate a high inertia of profitability: the lag coefficient for ROA is 0,512 with a high level of statistical significance ($p < 0,01$), and for ROE this indicator is 0.428 ($p < 0,01$). This means that approximately half (for ROA) and more than 40% (for ROE) of the current financial performance are explained by the values of these indicators in previous periods. Such an effect is fully consistent with the peculiarities of the insurance business, where the cumulative nature of assets and the stability of the client base determine the persistence of financial metrics over time. The second important conclusion concerns the role of the digitalization index (DT). In both models, it turned out to be statistically significant and has a positive effect on both return on assets and return on equity. In particular, for ROA, the coefficient is 0,024 ($p < 0,05$), for ROE – 0,032 ($p < 0,05$). This indicates that an increase in the digitalization index by 0.1 units conditionally increases ROA by 0,24 percentage points, and ROE by 0,32 percentage points. This result confirms the initial hypothesis that it is investments in digital technologies and digital platforms that are a key driver of the financial effectiveness of modern insurance companies in a competitive global environment. In contrast, the marketing spending volatility index (MV) did not demonstrate a statistically significant effect in any of the models: for ROA its coefficient is 0,010 ($p > 0,1$), for ROE = -0,006 ($p > 0,1$). This emphasizes that independent fluctuations in marketing activity, without sufficient integration with digital channels and analytics, do not have a sustainable positive effect on the financial performance of large insurers.

The variable Size, reflecting the scale of the company's activities, demonstrates a weakly positive, but close to statistical significance, effect: 0,005 for ROA ($p < 0,1$) and 0,007 for ROE ($p < 0,1$). This is consistent with the traditional concept of economies of scale, where large companies have competitive advantages due to more efficient use of resources, lower operational expenses per unit of revenue, and broader access to sources of capital. The level of financial leverage (Leverage) has a negative and statistically significant impact on financial performance: for ROA the coefficient is -0,031 ($p < 0,05$), for ROE = -0,045 ($p < 0,05$). This means that excessive debt burden weakens profitability, which corresponds to classical theories of corporate finance: high leverage may lead to increased debt service costs and increase the risks of financial instability. The analysis of regional affiliation compared to Europe (the base category) showed that companies from North America (Region_NA) demonstrate slightly higher results: ROA increases by 0,006 ($p < 0,1$), and ROE – by 0,008 ($p < 0,1$). This can be explained by a higher level of digitalization and larger markets in the USA and Canada. At the same time, no statistically significant differences were recorded for insurers from the Asian region (Region_Asia), which indicates the heterogeneity of the level of digital maturity and market structure in the countries of the Asia-Pacific region. The presence of a positive and significant constant (0,021 for ROA and 0,034 for ROE) indicates the existence of a basic level of profitability even in the absence of explanatory factors, which confirms the stable profitability of the industry on average.

The signs of all key coefficients correspond to the expectations of economic theory: digitalization and scale of activity have a positive effect, debt burden – a negative one, while marketing spending volatility without technical support – insignificant. The high statistical significance of Lag(FP) confirms the correctness of using the dynamic panel GMM model and emphasizes the stable inertia of financial indicators in the insurance sector. To verify the reliability of the obtained regression evaluations and the validity of the chosen econometric specification, a number of diagnostic tests were conducted, the results of which are presented in the table 6.

**Table 6.** Model specification tests

| Tests | ROA | ROE |
|---|---|---|
| Hansen J-test (p-value) | 0,245 | 0,321 |
| AR(1) (p-value) | 0,001 | 0,002 |
| AR(2) (p-value) | 0,513 | 0,471 |
| Number of instruments | 25 | 25 |

*Source: Developed by the authors.*

One of the key tests for assessing the adequacy of tools in the GMM system is the Hansen J-test. It tests the null hypothesis that the selected instruments are correct, i.e. uncorrelated with the error and redundant.

The obtained p-values for the Hansen J-test are:

- 0,245 for the model with ROA as the dependent variable,
- 0,321 for the model with ROE.

Both values significantly exceed the traditional significance levels (0,05 or 0,10), which means that there is no reason to reject the null hypothesis about the validity of the instruments. This confirms the correctness of the instrumental variables used in the GMM structure and indicates that the model is not overloaded with unnecessary instruments.

Dynamic panel models require a mandatory verification for the presence of autocorrelation of residuals, which can affect the efficiency and unbiasedness of the estimates. The AR(1) test should check for the presence of first-order autocorrelation in the first difference of the residuals. The obtained p-values for AR(1) are:

- 0,001 (ROA),
- 0,002 (ROE).

Low p-values (less than 0,05) confirm the presence of first-order autocorrelation, which is an expected result in dynamic models – this indicates the correct operation of the lag structure.

Conversely, the key is the AR(2) test, which verifies the absence of second-order autocorrelation, since its presence could violate the main assumptions of GMM. For AR(2) the results are:

- 0,513 (ROA),
- 0,471 (ROE).

Both values exceed 0,10, which allows concluding that there is no second-order autocorrelation. Therefore, the instruments are not endogenous, and the model errors do not have residual serial dependence, which indicates the statistical stability of the estimates. For both specifications, 25 instruments were used, which corresponds to the recommended practices for dynamic panel models with a moderate number of observations. An excessively large number of instruments could lead to the problem of overfitting the instrumental block and reduce the power of the Hansen test. In this case, the ratio of the number of instruments to the number of groups in the sample remains within acceptable limits, which confirms the balance of the model. Taken together, the Hansen J-test and AR-tests confirm the correctness of choosing the dynamic panel structure, the validity of the instruments, and the absence of serial correlation of higher-order residuals. These results ensure that the parameter estimates are consistent and unbiased, and the conclusions drawn from them have high scientific reliability. The main regression evaluation table confirms the main hypothesis of the study: digitalization is a key driver of financial performance, while marketing spending volatility functions only as an auxiliary indicator and does not form a sustainable effect without IT support. The model results confirm the main hypothesis about the positive impact of digitalization on the financial performance of insurance companies. This creates a strong argument for further investments in digitalization.

For additional verification of the quality and reliability of the constructed dynamic panel model, an analysis of the ratio of actual and fitted values of the dependent variables – ROA and ROE – was conducted. The Fitted vs Actual graphs allow a visual assessment of how accurately the model reproduces the empirical data.

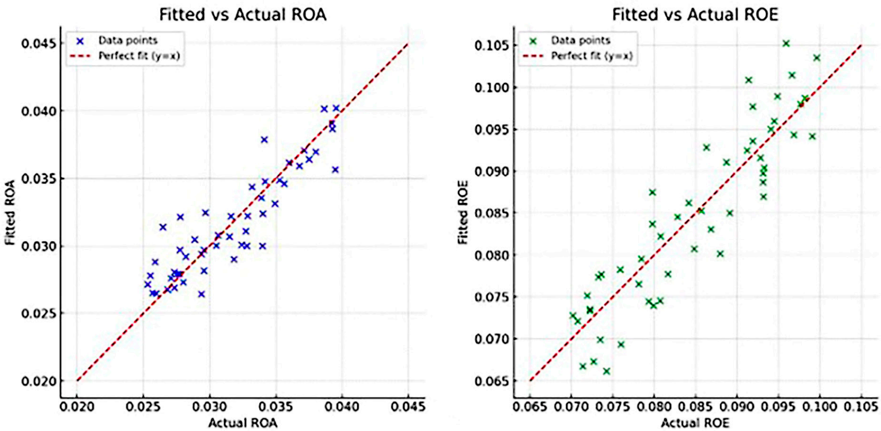


**Figure 2.** Fitted vs Actual graphs for ROA and ROE

*Source: Constructed by the authors.*

The Fitted vs Actual ROA and Fitted vs Actual ROE graphs demonstrate the relationship between the actual and calculated values of return on assets and equity obtained using the system GMM. The points located near the y = x line confirm the high accuracy of the model and the correctness of the specification. Local deviations are explained by the influence of market factors and the specifics of the activities of insurance companies. The graphs confirm a high degree of correspondence between the actual and predicted values, which demonstrates the adequacy of the choice of variables, the model reliably reflects the relationship between digitalization, marketing spending volatility, and financial performance. This ensures the reliability of the conclusions and reinforces the recommendations for managing the digital transformation of the insurance business under the global competition. Additional stability is also confirmed by the results of the Hansen test and autocorrelation tests (AR(1), AR(2)), which indicates the absence of specification errors. The presence of predictions close to actual means that the obtained dependencies can be used for short- and medium-term forecasting of financial indicators of insurance companies, modeling digital transformation scenarios, and preparing recommendations for optimizing the capital structure. Small deviations are due to the influence of random factors that are not taken into account in the model specification. The results confirm that digitalization and marketing spending volatility are relevant factors that explain the financial indicators of insurers' activities.

Thus, the analysis of the ratio of actual and predicted values once again confirms that the constructed model is statistically stable, economically justified, and suitable for practical use in further empirical research and strategic planning of financial efficiency.

## 5. Discussion

The results of the conducted empirical study are consistent with the main tendencies recorded in modern scientific literature regarding the impact of digitalization and organizational transformation on the financial performance of insurance companies. In particular, the obtained data confirm the conclusions of Eling and Lehmann (2018), who emphasized in their study that investments in digital platforms, automation, and data analytics are becoming a key factor in the competitiveness of the insurance business. Similarly, Biener et al. (2021) in their study of global trends showed that companies with mature IT systems demonstrate better return on assets compared to those that are just beginning digital transformation. In addition, analytical reports of the Swiss Re Institute (2024) note a direct connection between the growth of online sales shares, implementation of CRM solutions, and stability of insurers' operating margins. This result is fully consistent with the positive and statistically significant impact of the DT recorded in our model. The assessment of the regional effect in the model also partially correlates with the findings of OECD Insurance Market Trends (2023). In particular, in North American countries, digital channels have been occupying a significant share of insurance product sales for more than a decade, which explains the slightly higher profitability of North American companies compared to European ones. This coincides with the positive sign of the Region_NA coefficient in our regression evaluation. At the same time, OECD emphasizes the heterogeneity of Asian markets: high digitalization rates in Singapore or South Korea are combined with more traditional models in some other countries. This may explain why the Region_Asia variable in our model did not show a significant effect. Despite the generally confirmatory tendency, some aspects diverge from certain analytical positions. For example, in the works of Cummins and Weiss (2019), it is emphasized that rapid digitalization without parallel development of cybersecurity can become a source of additional risks and financial losses. In our model, the cyber-risk component is not taken into account separately, which limits the universality of the conclusions obtained and may lead to an overestimation of the net positive effect of digitalization.

Additionally, reviews by Guo et al. (2025) show that for small and medium-sized companies, the effect of IT investments often manifests itself with a time lag and requires comprehensive organizational restructuring. Our sample is dominated by leading global players that have sufficient scale and resources to quickly implement digital solutions, which explains the more unambiguous positive impact of DT in our model. The conducted study does not contradict the dominant scientific approaches and industry analytics: the key driver of financial efficiency of modern insurance companies remains systemic digitalization, whereas marketing spending volatility without technological support does not form a sustainable effect. At the same time, certain observations indicate the need to expand the model by taking into account cyber risks and time lags in the implementation of IT projects.

Overall, the results clarify the role of marketing spending volatility: without integration with digital channels, it does not provide stable profitability growth.

## 6. Conclusions, Limitations, and Directions for Future Research

The obtained results confirm that investments in digital technologies strategically enhance the financial performance of insurance companies, although this effect does not materialize immediately. Short-term profitability indicators tend to respond weakly or neutrally because digital transformation initially increases operational costs and requires structural adaptation. However, in the medium-term perspective, digitalization strengthens business process efficiency, reduces customer acquisition costs, and improves asset utilization, which becomes visible through increased ROA and strengthened ROE dynamics. Marketing spending volatility also plays a modifying role: stable, strategically aligned marketing policies amplify the positive financial effect of digitalization, whereas frequent fluctuations in expenditures reduce the efficiency of technology adoption. Therefore, long-term financial improvement is determined not only by the scale of digital investment but also by the consistency of marketing strategies.

At the same time, the study has several limitations. The digitalization index was constructed as an aggregated measure and does not separately identify the specific technological components of digital transformation. Future research could develop a more disaggregated digitalization index that distinguishes the effects of artificial intelligence, advanced data analytics, process automation, and platform-based technologies, allowing identification of which domains generate the strongest impact on insurers' financial performance. The current model also does not explicitly incorporate cybersecurity-related factors; introducing direct measures of cybersecurity investment intensity or proxies for cyber-risk exposure could substantially improve the explanatory power of the specification. Moreover, potential time lags in the payback period of IT and digital transformation projects are not explicitly accounted for, although returns on digital investments may materialize gradually and vary depending on firms' digital maturity levels. Future models could incorporate distributed lag structures or interaction terms capturing heterogeneity across stages of digital development. Finally, the empirical sample focuses on large, globally operating insurers; extending the dataset to include medium-sized and regionally focused insurance companies could test the robustness of the findings across firm sizes and business models, and evaluate whether scale effects moderate the relationship between digitalization, marketing volatility, and financial performance. Incorporating behavioral indicators of consumer interaction—such as loyalty dynamics, product renewal behavior, or customer lifetime value—could further enrich understanding of how digital transformation affects long-term competitiveness of insurance companies.

## 7. Scientific and Practical Implications

The study provides important scientific and practical insights into the interplay between digitalization, marketing spending volatility, and financial performance of insurance companies. Scientifically, it advances the understanding of digital transformation by empirically demonstrating that its impact on profitability is mediated by marketing expenditure dynamics. The findings highlight that digital investments alone do not guarantee immediate financial gains; rather, their effectiveness is contingent on the stability and strategic alignment of marketing policies. This introduces a novel explanatory mechanism for divergent financial outcomes among insurers, extending prior research that evaluated digitalization in isolation. Additionally, the research confirms regional variations in digital adoption effects, aligning with international trends and emphasizing the need to consider market-specific characteristics in modeling financial performance.

From a practical standpoint, the study underscores that insurance companies should adopt an integrated approach combining digital investments with consistent and strategically planned marketing expenditures to maximize long-term profitability. Firms with stable marketing policies experience stronger medium-term gains in ROA and ROE, whereas high volatility in spending can undermine the benefits of technological adoption. The results also suggest that decision-makers should account for the delayed nature of digitalization returns, plan for operational adjustments, and anticipate structural changes necessary to support IT implementation. Moreover, regional market differences should guide tailored digital and marketing strategies, ensuring that investment decisions are aligned with local adoption rates and consumer behaviors.

Overall, the study bridges the gap between technological innovation and financial management, offering both scholars and practitioners a robust framework for understanding and leveraging digitalization in the insurance sector.

## Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

## Data Availability Statement

The data used to support the findings of this research are available from the corresponding authors upon request.

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