PREDICTIVE MODELLING OF THE IMPACT OF INSURTECH ADOPTION ON FINANCIAL STABILITY IN GLOBAL INSURANCE COMPANIES

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BY

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DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of my own work and that dueacknowledgement has been given in the references to ALL sources of informationbe they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any applicationfor any other degree or qualification of this or any other university, or other institutes of learning.

(3) The word count of this research report is 22,664.

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Finally, I dedicate this work to my family. To my parents and to my siblings, thank you for your understanding and cheerfulness. This achievement is as much yours as it is mine.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
CAR	Capital-to-Asset Ratio
CNN	Convolutional Neural Network
CPI	Consumer Price Index
DID	Difference-in-Difference
DNN	Deep Neural Network
DOI	Diffusion of Innovation
ESG	Environmental, Social and Governance
FinTech	Financial Technology
GDP	Gross Domestic Product
G-SIIs	Global Systemically Important Insurers
HHI	Herfindahl-Hirschman Index
IAIS	International Association of Insurance Supervisors
InsurTech	Insurance Technology
IoT	Internet of Things
KNN	K-Nearest Neighbours
LASSO	Least Absolute Shrinkage and Selection Operator
LSEG	London Stock Exchange Group
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSE	Mean Squared Error
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
RBC	Risk-Based Capital
RBT	Resource-Based Theory
RMSE	Root Mean Squared Error

RNN	Recurrent Neural Network
ROA	Return on Assets
ROC-AUC	Receiver Operating Characteristic- Area Under the Curve
ROE	Return on Equity
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Oversampling Technique
SVM	Support Vector Machine
SVR	Support Vector Regression
TOC	Theory of Operational Capabilities
TOE	Technology–Organization–Environment
VIF	Variance Inflation Factor
XGBoost	Extreme Gradient Boosting

ABSTRACT

While the rapid adoption of InsurTech is reshaping the global insurance industry by enhancing operational efficiency, it also introducing new risks and challenging traditional regulatory frameworks such as Solvency II. This study aims to explore the impact of InsurTech adoption on the financial stability of global insurance companies.

This study utilizes a dataset of the top 100 global insurance companies by market capitalization from 2017 to 2024. InsurTech Adoption Index is constructed to measure the degree of technology integration through principal component analysis (PCA) and textual analysis of annual reports. The analysis employs a series of machine learning algorithms to predict financial stability and utilizes LASSO regression to rigorously address feature selection and mitigate multicollinearity.

Our results indicate that InsurTech adoption is not merely a trend, but a significant driver of financial stability and operational resilience, with Return on Equity (ROE) playing a primary defensive role. The findings show that while excessive capital accumulation increases risk, active leverage can promote stability. Furthermore, the result shown that inflation remains a major destabilizing factor, and increased stability and market concentration has challenged the concentration vulnerability hypothesis.

Methodologically, the XGBoost algorithm has proven to be the most robust predictive model, outperforming linear models and capturing the complex nonlinear relationships revealed by SHAP analysis. These findings suggest that regulators should incorporate predictive analytics into their regulatory frameworks. Insurers should prioritize operational efficiency as well as proactive capital allocation over defensive capital hoarding.

Keywords: InsurTech Adoption; Financial Stability; Predictive Modelling; Global Insurance Companies; Machine Learning

CHAPTER 1: INTRODUCTION

1.0 Research Background

Insurance Technology (InsurTech) means digital technologies in the insurance field. It is changing the industry around the world very fast (Braun & Jia, 2025; Cosma & Rimo, 2024). It includes artificial intelligence (AI), machine learning, big data analytics, blockchain, and Internet of Things (IoT). These tools update old business models and help companies work more efficiently in both established insurers and resilient startups (Widyani, 2023). Finally, these technologies help companies handle risks better (Cosma & Rimo, 2024; Lee & Yim, 2025).

For centuries, high costs, strict rules, and complex products were the reasons stopped the industry from changing (Lee & Yim, 2025). But the 2007–2008 financial crisis showed deep flaws in the system; hence, people needed clear and modern solutions after that event (Casma & Rimo, 2024). This need speeded up the growth of InsurTech (Casma & Rimo, 2024). Since then, startups have received a lot of investment, and big insurance companies also showed they are willing to use digital tools. So, InsurTech became a major force and changing the industry now (Braun & Jia, 2025).

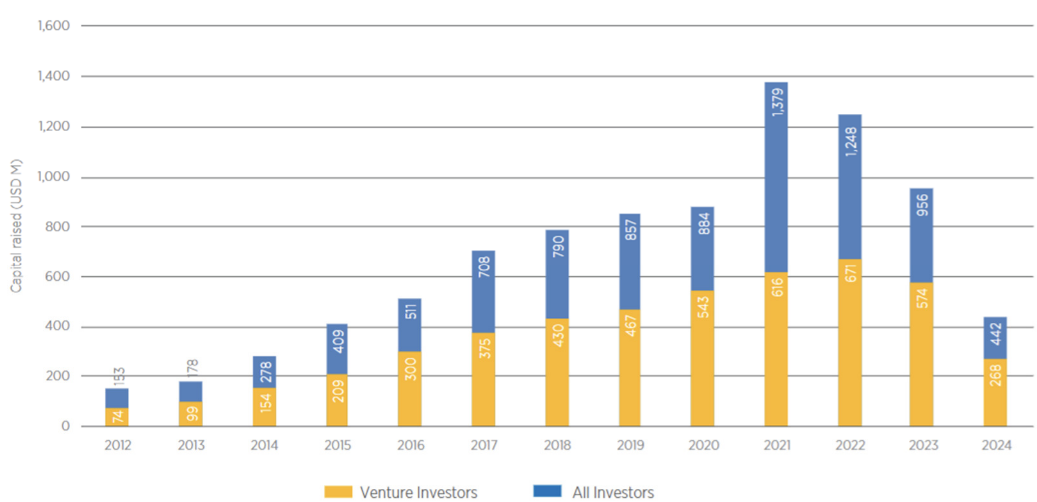
Previous research states that InsurTech funding was less than USD 500 million in 2012. Then, the funding grew quickly. It reached over USD 2.5 billion in 2017 and then rose to USD 4 billion in 2018 (Milken Institute, 2018; Willis Tower Watson, 2019, as cited in Lanfranchi & Grassi, 2021). Ozcan (2024) also further points out that investment started to increase during that time.

The year 2017 was a turning point for InsurTech development. It been recognised by academia, investors, and regulators. Global research on these technologies increased after that year (John et al., 2024). In between 2017 and 2018, major groups such as

OECD and the European Insurance and Occupational Pensions Authority (EIOPA) started to discuss regulations for FinTech and InsurTech (Chatzara, 2019). The International Association of Insurance Supervisors (IAIS) also published a formal definition of InsurTech in 2017 wchich helped the industry understand the concept clearly (Wang, 2021; Chatzara, 2019).

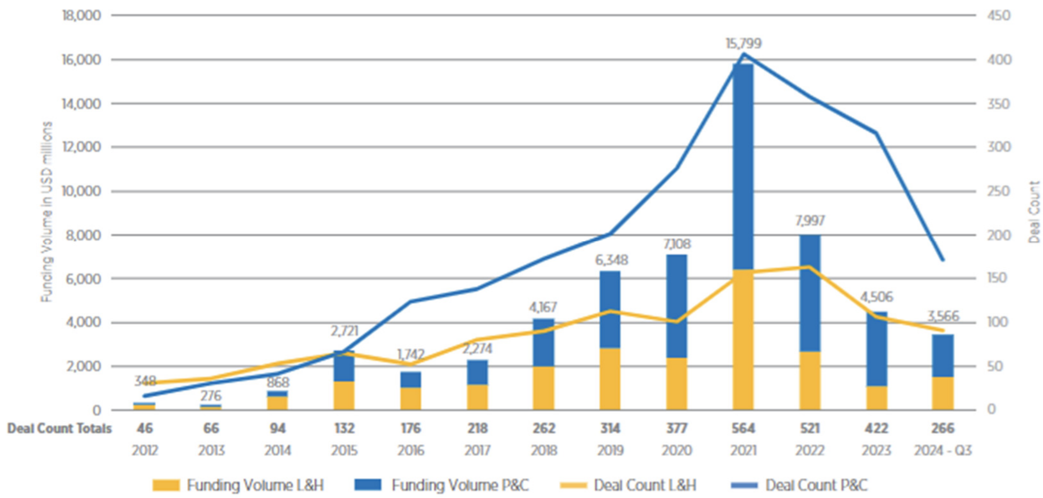
Investments around the world show this shift. The Global InsurTech Report Q3 2024 shows that investor interest was low in 2012 and 2013. However, it began to rise in 2014. Activity reached a peak between 2020 and 2021 (Figure 1.1). There was a small decrease between 2015 and 2016. Yet, total funding hit its highest point in 2021 (Figure 1.2). Funding dropped sharply starting in 2022. By early 2023, investment levels fell by over 50%. Those InsurTech startups' late-stage investments suffered the most, declining by over 60% (Dealroom.co, 2023). TechCrunch reported a similar trend. There that InsurTech stocks fell 59% from their 2021 highs due to lower expected revenue (Wilhelm & Heim, 2023). Failures of over 50 InsurTech firms either shut down or were forced into distress sales further dropped the confidence of investors (PriyaPatel, 2024).

Figure 1.1: Investor in InsurTech



Source: Gallagher Re (2024)

Figure 1.2: Annual Total Insurtech Funding Volume and Transaction Count



Source: Gallagher Re (2024)

InsurTech use differs in every country (Chang, 2023; Widyani, 2023). Small insurance companies often have problems to upgrade their systems because they do not have enough money (Chang, 2023). Besides that, several things such as company size and readiness to change and government rules control the speed of innovation (Chang, 2023). In growing markets like Indonesia, this technology brings dual effect on them (Widyani, 2023). Startups and big companies use technology to make services fast and clear. But some of them may face barriers because of the business models are not ready yet or the management people in the companies do not want to change (Widyani, 2023).

The impact changes based on the local market and the regulations (Koranteng & You, 2024; Cevik, 2024; Vuković et al., 2024). Research also shows that InsurTech has two different effects. InsurTech helps companies operate more efficiently. It also updates the market with new ideas. But, it might cause instability and unfair competition (Lanfranchi & Grassi, 2021; Ozcan et al., 2024; Liu et al., 2023).

1.1 Problem Statement

Financial stability defines insurance company's ability to survive. It helps companies meet their obligation and keep operation even during hard times (Abernikhina et al., 2021; Firouzi et al., 2025). This stability also ensures companies can pay claims fast, compete well (Abernikhina et al., 2021; Firouzi et al., 2025; Kramarić et al., 2019). A company's success, competition and the economy of the country affects its financial stability, (Altuntas & Rauch, 2017). Companies also need strong money reserves, reinsurance plans, different types of investments and accurate reporting to support the stability (Abernikhina et al., 2021; Firouzi et al., 2025; IAIS, 2024).

The industry relies on risk-based solvency frameworks such as Solvency I, Solvency II, and Risk-Based Capital (RBC) (Firouzi et al., 2025; IAIS, 2024). These framework force companies to keep enough money to covers their risks, ensure strong management and clear reporting (IAIS, 2024). These frameworks use different tools such as stress testing and solvency margin ratios (Firouzi et al., 2025). These standards help companies survive financial shocks (Firouzi et al., 2025). But old framework often misses real risks such as cybersecurity problems and the fast changes in technology (Firouzi et al., 2025). Firouzi et al. (2025) suggested a 'Pillar IV' framework which helps manage failing companies safely. But this idea is still just a theory and it do not use it widely yet (Firouzi et al., 2025).

New technologies such as AI, big data, blockchain, and the IoT make things more complex. These tools can improve work speed, lower costs, and customers satisfaction (Cosma & Rimo, 2024). But their tools bring new risks such as cyberattacks, system failures and bias algorithms (Firouzi et al., 2025). Utilising these tools also will cause data leaks which can hurt a company's name, it also hard to manage short-term contracts (Ma, 2024; Tiwari & Sengupta, 2024). AI is doing more tasks now such as handles underwriting and investing, so regulators wonder if current rules are safe enough (IAIS, 2024).

Recent reports show several top Insurtech 50 companies failed, so investors started worry about the survival of digital companies (PriyaPatel, 2024). The Lemonade company is a good example. They admitted that its AI analysed customer videos for 'non-verbal cues' during claims processing, the company faced severe criticism and regulatory scrutiny. This hurt Lemonade's reputation and the stock price went up and down wildly. This case has shown that high-tech tools help companies grow, but they create serious risks (Iceberg.Digital, 2025).

Rules like Solvency II remain important for market stability because they come from a time before digital changes (Chatzara, 2019; Rangu et al., 2024; Firouzi et al., 2025). Recent studies also shown the result that using FinTech and InsurTech can increase financial weakness rather than make systems stronger (Pantielieieva et al., 2018; Stankevičienė & Kabulova, 2022). InsurTech promises benefits such as helps with better decisions, speeds up work and checks risk better (Cosma & Rimo, 2024). Current solvency rules are too slow, so fast growth in technology development created a mismatch (Chang, 2023; Firouzi et al., 2025; Seyam, 2025). Models like Asia's RBC and Europe's Solvency II were designed for a different era and cannot fully account for the dangers of modern technology (Firouzi et al., 2025). This regulatory gap leaves the industry exposed to unexpected vulnerabilities and threatens to weaken overall resilience (Cevik, 2024).

1.2 Research Questions

Based on the problem statement, the research questions are listed below.
RQ1: How about the relationship between InsurTech adoption and the financial stability of global insurance companies?

RQ2: How firm-specific characteristics affect the stability outcomes of InsurTech adoption?

RQ3: How does industry-level factor affect the stability effect of InsurTech adoption?

RQ4: How do macroeconomic factors in the relationship between InsurTech adoption and financial stability?

1.3 Research Objectives

The main objective of this study is to examine the relation between Insurtech adoption. The three objectives have generated are as below:
RO1: To investigate the relationship between InsurTech adoption and the financial stability of global insurance companies.

RO2: To analyse how firm-specific characteristics affect the stability outcomes of InsurTech adoption.

RO3: To investigate how does industry-level factor affect the stability effect of InsurTech adoption.

RO4: To examine how do macroeconomic factors in the relationship between InsurTech adoption and financial stability.

1.4 Significance of the Study

Even though financial technology is becoming more important, there is a distinct lack of hard evidence regarding how InsurTech specifically affects financial stability. Most existing studies rely on general reviews or theoretical discussions rather than data analysis methods (Pantielieieva et al., 2018; Braun & Jia, 2025). Furthermore, while there are some general ways to track technology, very little effort has been made to measure adoption at the individual company level using annual reports (Dicuonzo et al., 2023; Koranteng & You, 2024). As a result, it remains very difficult to accurately measure how widely this technology is being used and what its real-world effects are.

Predictive modelling and machine learning are powerful tools which analyse risk well; however, insurance research rarely uses them in current research (Farag et al., 2025; Chang, 2023). Researchers and policymakers cannot see the links between technology and stability without these tools. This study fills that gap by showing how technology helps assess risk right away. This makes the analysis accurate and helps regulators respond to new threats effectively.

The main contribution of this study is building 'InsurTech Score'. We use text software called AntConc and scan company reports. This creates a fair measurement and adds hard evidence to our knowledge of Insurtech. We combine this score with machine learning models to let us look deep into the link between InsurTech and financial stability. It applies advanced computer methods to the industry and pushes the insurance field forward.

This study also gives useful ideas to insurance executives. They can see how InsurTech affects financial stability. We compare different machine learning algorithms so they can use this to check their stability and see the results of different investments in technology. We also use SHAP analysis. This makes complex models easier to understand, and decision-makers can see exactly what factors drive the predictions.

Finally, these findings show something important to regulators and policymakers. They highlight the need for data tools such as using text analysis and machine learning in their systems. This helps them manage the fast changes in InsurTech.

1.5 Outline of the Study

- Chapter 1: Introduction
  Provides the background, problem statement, research questions, objectives, significance, and overall structure of the study.

- Chapter 2: Literature Review
  Reviews relevant literature on FinTech and InsurTech adoption, financial stability in insurance, machine learning applications in finance, and regulatory challenges.

- Chapter 3: Research Methodology
  Describes the research design, data sources, InsurTech Score development, machine learning models employed, and methods for feature interpretation.

- Chapter 4: Results and Analysis
  Presents the empirical findings, model performance comparisons, SHAP analysis, and interpretation of results.

- Chapter 5: Conclusion and Recommendations
  Summarises key findings, discusses implications for theory and practice, highlights limitations, and suggests directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter reviews existing research about the topic of InsurTech and financial stability in the insurance industry. First, the chapter explains the development of InsurTech and shows how researchers measure its use. Next, the chapter defines financial stability. It looks at evidence of how InsurTech affects this stability. It also outlines the methods from previous studies. Then, it compares them with newer machine learning techniques. Finally, the chapter finds important theories and gaps in the current research. It uses this information to form the hypotheses for this study.

2.1 Financial Stability in Global Insurance

Financial stability describes an insurance company's ability to handle shocks that come from inside or outside the company. Stability ensures the company can keep its promises to policyholders. It also allows the company to support the wider financial system (Pantielieieva et al., 2018). This idea became very important after the 2008 financial crisis. Regulators and policymakers focused on it more (Casma & Rimo, 2024). The IAIS states the main goal of supervision is to protect policyholders and keep the insurance market fair and safe (Chatzara, 2019). Finally, it helps maintain financial stability (Kramarić et al., 2019).

2.1.1 Key indicators of financial stability

The Z-score is a very popular tool to measure if a financial company is close to bankruptcy (Kramarić et al., 2019). A high Z-score means the company is strong. A low score means the company is weak (Kramarić et al., 2019). Researchers calculate the Z-score using three components, which are Return on Assets (ROA), the Capital-to-Asset Ratio (CAR), and the standard deviation of ROA (Cevik, 2024; Stankevičienė & Kabulova, 2022). The score combines profit, capital, and risk to show how much profit can drop before the company loses all its money (Safiullah & Paramati, 2022). So, it is useful for predicting money problems (Sattar et al., 2025). Other tools like CARAMELS and CAMELS exist which look at management and cash flow, but these are hard to use for studies across different countries (Kalyani & Pathak, 2020; Tsvetkova, 2019). Data rules differ in each country, so the Z-score is the best choice for insurance research to helps compare stability in different places clearly (Kramarić et al., 2019; Safiullah & Paramati, 2022).

Past studies also list important factors for an insurer's health. Company size is a big factor (Altuntas & Rauch, 2017; Stankevičienė & Kabulova, 2022). Big insurers often save money and spread out their risks because of their size, but some researchers worry about very big firms that might take big risks due to the reason 'too big to fail' (Altuntas & Rauch, 2017; Stankevičienė & Kabulova, 2022). Profit is also important to helps insurers strengthen their position, and researchers usually measure this by Return on Equity (ROE). They use money from premiums and investments (Altuntas & Rauch, 2017). Capital and debt levels matter too (Kramarić et al., 2019). High capital makes a firm strong, but too much debt makes it weak (Kramarić et al., 2019; Stankevičienė & Kabulova, 2022). Liquidity is another key factor to keep safe because they can pay debts quickly and not need to sell other assets in a hurry (Nyika, 2021). Finally, operational efficiency shows how well managers run the company (Altuntas & Rauch, 2017). Low expenses mean better efficiency. This usually leads to better financial stability (Altuntas & Rauch, 2017; Kalyani & Pathak, 2020; Shamsuddin, 2024).

Risk management is just as important as financial metrics. Reinsurance is a key tool to reduces the impact of huge losses, but researchers debate its effect (Altuntas & Rauch, 2017; Kramarić et al., 2019; Shim, 2015, cited in Kramarić et al., 2019). Some say reinsurance improves stability by spreading out the risk, and others say too much reliance on it is bad because it shows that the company takes too many risks (Altuntas

& Rauch, 2017; Kramarić et al., 2019; Shim, 2015, cited in Kramarić et al., 2019). Claims and losses are also important signs because too many claims can drain money fast and stable underwriting results usually mean higher stability scores (Kramarić et al., 2019; Altuntas & Rauch, 2017). Fast growth in premiums can be risky too because aggressive expansion often leads to instability (Kim et al., 1995, cited in Kramarić et al., 2019). Lastly, investment income shows the success of a strategy because some studies say it helps performance, but others find it has a small effect when investments are diverse and underwriting is careful (Altuntas & Rauch, 2017; Liu et al., 2023; Sugandi & Gantyowati, 2024).

The structure of the market matters at the industry level. Research supports the 'concentration-fragility' idea, which suggests that a highly concentrated market is bad for stability (Altuntas & Rauch, 2017; Shim, 2015, cited in Kramarić et al., 2019). Altuntas and Rauch's (2017) results show that the 'Top 3 concentration ratio' is the most efficient ratio to examine the relation between financial stability and. Finally, the wider economy, such as growth in Gross Domestic Product (GDP) and inflation, plays a big role (Altuntas & Rauch, 2017). These things lower the value of assets and create uncertainty about future returns and debts (Kramarić et al., 2019; Altuntas & Rauch, 2017).

2.1.2 Importance of stability for global insurance companies

Everyone agrees that financial stability is vital for insurance companies because it is a main part of global financial policy (Abernikhina et al., 2021). This is important not only for single companies but also affects the health of financial markets and national economies and impacts the well-being of customers everywhere (Puławska, 2021). Basically, firm stability is good for the public because it ensures insurers can pay claims fully and on time as well as keep customer trust and protect people's way of living (Puławska, 2021). Regulators want to keep companies stable as their main goal. This prevents bankruptcy. It also protects policyholders from losing money (Altuntas &

Rauch, 2017). On the other hand, instability can cause bad effects and it will spread across society and the economy (Tsvetkova, 2019; Rangu et al., 2024).

Financial stability is not only for protecting insurance buyers but also for supporting the whole financial system and helping the economy grow (Firouzi et al., 2025). So, a stable insurance sector helps development, manages risks well and builds up money for the economy (Puławska, 2021). Unstable companies cause the stopping of the flow of capital and slow down economic growth (Altuntas & Rauch, 2017). International regulators such as IAIS highlight the need for strong markets (Puławska, 2021). They identify the largest insurers as Global Systemically Important Insurers (G-SIIs) and subject them to stricter rules to prevent a market collapse (Puławska, 2021).

For companies, financial stability is key for long-term survival and success (Abernikhina et al., 2021). Regulatory frameworks play a big role to ensure insurers have enough money and can manage risks wisely to avoid bankruptcy (Ziemele & Voronova, 2013). Increasing usage of technology like AI and automation makes work faster, but they also bring new challenges such as technical risks and operational risks (Chang, 2023). Regulators emphasise the need to balance innovation and safety, which further maintains market stability (IAIS, 2024).

For companies, financial stability is key for survival. It is also key for long-term success (Abernikhina et al., 2021). Regulatory frameworks play a big role here. Solvency II is one example. These rules ensure insurers have enough money. They also make sure insurers manage risks wisely. This helps them avoid bankruptcy (Ziemele & Voronova, 2013). But the increased usage of technology brings new challenges. They also bring new technical risks. Operational risks appear too (Chang, 2023). So, regulators emphasize the need for strict watch. They want to balance innovation and safety. This maintains market stability (IAIS, 2024).

2.2 InsurTech Adoption in the Insurance Industry

The word 'InsurTech' combines 'insurance' and 'technology'. It refers to the use of new technology, including AI, big data, cloud computing, the IoT, and blockchain to change the insurance industry. For example, it can help for updating old business models, products, and operation processes (Braun & Jia, 2025; Cosma & Rimo, 2024; Liu et al., 2023).

2.2.1 Adoption patterns and drivers in global markets

Insurers adopt InsurTech for several reasons, such as to improve efficiency, cut costs, serve customers better and compete with digital companies (Eti et al., 2024 Liu et al., 2024). Technologies like blockchain and smart contracts do tasks automatically. These tasks include paying premiums and submitting claims (Bian et al., 2023). Also, selling insurance online reduces the need for agents and allows companies to reach customers anywhere (Bian et al., 2023). This helps small and medium non-life insurers the most (Bian et al., 2023). But digital changes cost money (Braun & Jia, 2025). Setting up new systems is expensive and it can lower work speed at first (Braun & Jia, 2025). This happens mostly in the non-life sector (Eti et al., 2024; Lee & Yim, 2025). Life insurance has seen fewer gains because its products are complex and still need human agents (Eti et al., 2024; Lee & Yim, 2025).

InsurTech has changed the customer experience, which focuses on serving customer needs and does not just sell products anymore (Chatzara, 2019). For example, mobile apps help customers get services fast and cheap and customers can manage policies and claims anytime (Eti et al., 2024; Liu et al., 2023). It also improves risk assessment and fraud detection because it is a advanced tools collect data on behaviour and the environment in real time (John et al., 2024; Eti et al., 2024). This lets insurers check risk quickly and even predict or prevent losses (Eti et al., 2024; Ma, 2024). Moreover, It makes pricing fairer and reduces common problems like bad risks to make the market more reliable (Ma, 2024; Braun & Jia, 2025).

InsurTech also can drive new ideas and competition because it creates new products, improves services and makes a company stronger in the market (Chang, 2023; Liu et al., 2023). But this usually helps big companies the most because they have the money to invest in digital changes, while small firms might struggle to keep up (Chang, 2023). Financially, InsurTech helps by closing information gaps and reduces risky behaviour (Sosa & Sosa, 2025; John et al., 2025). This makes it easier for companies to get money and encourages them to do research and development (Sosa & Sosa, 2025; John et al., 2025). It boosts profit by cutting costs (Eti et al., 2024). But some studies give a warning that this fast change can hurt the profits of firms that adapt slowly (Shamsuddin, 2024). InsurTech affects sectors differently; for example, in the non-life sector, it creates a fair chance for small insurers, but in the life sector, the impact is small because these products rely heavily on trust and reputation (Bian et al., 2023).

These changes show that InsurTech is reshaping the whole insurance value chain (Shamsuddin, 2024). It affects product design, changes risk assessment and updates how companies sell policies and manage claims (Shamsuddin, 2024). Startups often act as 'disruptors' and introduce new ideas that customers like and traditional insurance giants are responding to this as they use their deep knowledge of rules and their large size combined with the speed and creativity of InsurTech partners (Braun & Jia, 2025).

2.2.2 Measurement of InsurTech Adoption

Recent studies show new ways to measure InsurTech use even though this field is still growing (Bian et al., 2023; Liu et al., 2023). One common method checks a company’s digital presence (Bian et al., 2023). Researchers see if an insurer sells products online and check if the company works with digital partners, so they know how much a specific company uses technology (Bian et al., 2023). Researchers also count patent applications and trademark registrations to help estimate how much a company innovate and developing new technologies (Liu et al., 2023).

Another method is analysing text in official documents (Seyam, 2025). This method counts how often technology words appear in reports (Seyam, 2025). For example, Seyam (2025) tracks words like AI, big data, blockchain, and the IoT for analysing the Saudi insurance market. The study scanned annual reports and counted terms to identify how much the industry focused on these technologies and major trends in the industry (Seyam, 2025; Tiwari & Sengupta, 2024).

As InsurTech is a branch of FinTech, the methods for measuring FinTech work well here. Dicuonzo et al. (2023) made a FinTech Index for banks by analyzing annual reports and counting keywords like 'AI' and 'Blockchain'. Kharrat et al. (2024) did the same for banks in the MENA region. Both studies used a tool called AntConc (Dicuonzo et al., 2023; Kharrat et al., 2024). First, researchers turn annual reports into text files and use a tool called AntConc to scan these files (Dicuonzo et al., 2023). It counts the keywords and gives a clear number for technology use (Dicuonzo et al., 2023).

2.3 Impact of InsurTech on Financial Stability

2.3.1 Positive and Negative Impact of InsurTech on Financial Stability

According to Braun & Jia (2025), they say digital innovations make insurance companies stronger. These technologies, which include AI, the IoT, cloud computing, and blockchain, improve clarity, help companies spread out their work, and allow companies to do key tasks such as checking risks and managing claims automatically (Braun & Jia, 2025). By automating these processes, companies cut costs significantly this way and improve their work speed (Braun & Jia, 2025).

However, using InsurTech fast brings new risks that will threaten financial stability. Relying on digital platforms increases systemic risk because financial systems are very connected today and problems spread fast, leading to market trouble and cash flow issues (Altuntas & Rauch, 2017; IAIS, 2024). Cybersecurity data leaks and technical failures are another big worry (Ma, 2024). Also, strong competition forces small companies to take bad risks because they try to keep up with leaders and big traditional companies also face huge costs to update their systems (John et al., 2024; Braun & Jia, 2025). Finally, government rules are often slow; hence, they create uncertainty about fair prices and data safety and also affect customers who do not use digital tools (Chatzara, 2019; Firouzi et al., 2025).

2.3.2 Empirical Evidence from Global Insurance Markets

Studies show that InsurTech has different effects in different places. In China, it reduced the power of big companies in the non-life insurance market because non-life products are simple and standard (Bian et al., 2023). So, digital tools help small and medium insurers reach customers easily, lower costs and also solve problems with distance (Bian et al., 2023). But the life insurance sector changed very little because life insurance products are complex, and companies still need human agents to compete and a strong brand reputation (Bian et al., 2023). Hence, InsurTech lowered costs for non-life companies because it made marketing and claims digital and helped new companies enter the market, but life insurers did not see these benefits as much (Bian et al., 2023).

Other research also studies the link between InsurTech and risk (Ma, 2024). Research in China been suggested that using InsurTech increases risk-taking, especially during crises like the COVID-19 pandemic; hence, companies need to manage risk carefully (Ma, 2024). However, studies in the banking sector show that some technologies help reduce risk for a firm (Koranten & You, 2024). InsurTech also changes competition a lot (Chang, 2023). For example, smaller insurance companies face big pressure because they often lack money to invest in technology, but larger insurers are usually stronger because they have the resources to use technology well (Chang, 2023).

2.4 Methodologies Employed in Examining the Relationship between Financial Stability and InsurTech

Econometric methods such as Ordinary Least Squares (OLS) and panel regressions are common to test the link between InsurTech and financial stability. Researchers use them to check the impact of InsurTech on the market and often use variables from the past to solve timing problems (Bian et al., 2023; Stankevičienė & Kabulova, 2022). Researchers also use advanced methods such as Instrumental Variables approach and Two-Stage Least Squares to help solve cause-and-effect problems. They use specific data like the number of mobile phone users and Patent applications which relate to InsurTech use (Bian et al., 2023). The Generalised Method of Moments estimator is another common tool which works well for data that changes over time and handles hidden differences and long-term effects (Daud et al., 2021; Shamsuddin, 2024).

Some studies use the Difference-in-Difference (DID) model to find causal effects by comparing different groups over time especially useful during big events like the COVID-19 pandemic (Ma, 2024). Studies of many countries also use the Global Vector Autoregressive model combined with the use of a Bayesian version to capture changing relationships and see how effects spread between growing markets (Vuković et al., 2024). Finally, researchers' use of case studies and expert interviews is useful to see real-world applications and help explain InsurTech business models and market changes (Braun & Jia, 2025; Pantielieieva et al., 2018).

2.5 Research Gaps

Digital innovation grows fast in the insurance sector, but there is little hard evidence about its effect on financial stability. People often praise benefits like lower costs; however, recent events suggest a different reality (Eti et al., 2024). For example, the Lemonade company faced controversies and also several top 50 InsurTech firms collapsed, which shows that digital models might cause instability (PriyaPatel, 2024; Iceberg.Digital, 2025). Most research relies on general reviews, theories, or qualitative discussions, so studies fail to measure the real impact of InsurTech and do not know if it makes the industry safe or risky (Pantielieieva et al., 2018; Braun & Jia, 2025).

There is a major obstacle, which is the lack of a standard way to measure InsurTech adoption for each company. General indices exist for the FinTech sector, but researchers rarely create specific measures from insurance companies' annual reports (Dicuonzo et al., 2023; Koranteng & You, 2024). Researchers cannot link technology to financial performance without a clear tool. This leaves a big gap in the industry.

Old rules like Solvency II came before AI and Big Data, so they often miss new threats such as cybersecurity problems and algorithm errors (Firouzi et al., 2025; IAIS, 2024). Machine learning is a promising tool for predicting these risks. But researchers use it very little right now (Farag et al., 2025; Chang, 2023). This slow analysis prevents regulators from accessing the 'near real-time' assessments to update the rules. So, it is creating a dangerous gap between outdated supervisory tools and the operational reality of the modern InsurTech landscape.

2.6 Predictive Modelling in Insurance Industry

Researchers recently started to use Machine Learning with traditional economic methods, which improves their analysis (Farag et al., 2025). This combination helps them make accurate predictions and find hidden patterns, so researchers can handle huge datasets but traditional methods struggle with them (Farag et al., 2025). Finally, this approach gives a deep understanding of trends. It shows what affects financial stability (Farag et al., 2025).

2.6.1 Feature Selection Techniques

Lasso regression is a useful tool to select the right variables in complex datasets (Wasserbacher & Spindler, 2021). This method improves the accuracy of a model and makes the model easier to understand (Wasserbacher & Spindler, 2021). It works by shrinking the influence of small factors to zero and removing them from the calculation (Enwere et al., 2023). Lasso is good at handling multicollinearity by selecting one variable from a similar group and ignores the others, which traditional methods like OLS struggle with (Enwere et al., 2023).

Experts also use Lasso regression for classification tasks, which is called 'Lasso Logistic', to sort data into categories and does not just predict a number (Pan & Xu, 2021; Yan et al., 2020). Researchers use it to predict financial stability because it can handle complex problems with many categories well (Zizi et al., 2021; Yang et al., 2022). It can select the important clues and keep the model simple to help prevent overfitting, which happens when a computer memorises data instead of learning the pattern (Wasserbacher & Spindler, 2021).

2.6.2 Machine Learning Models in Financial Prediction

Machine learning tools are essential for financial predictions because they offer data-driven ways to find complex patterns (Hoang & Wiegratz, 2022). Supervised algorithms learn from datasets that already have the correct answers, which experts use widely to predict bankruptcy and score credit, forecast profits and find errors (Gao et al., 2024). These algorithms fit into two main groups. One group is classification models, which predict specific categories and the other group is regression models, which predict continuous numbers (Gupta et al., 2022).

Classification models like Support Vector Machines (SVMs) show strong performance at predicting financial instability even when the data is complex (Damrongsakmethee & Neagoe, 2017; Kayakus et al., 2023; Farag et al., 2025). Logistic Regression is also a common choice because it is simple and easy to explain and works well for "yes or no" tasks like predicting default (Sizan et al., 2025). Naïve Bayes similarly used a classification function to help with credit scoring and sentiment analysis (Hoang & Wiegratz, 2022). Other statistical methods such as Linear Discriminant Analysis and Quadratic Discriminant Analysis are still useful for smaller datasets (Belesis et al., 2023; Seyam, 2025).

Regression models are usually the best choice for predicting exact numbers (Schenkelberg et al., 2020; Gupta et al., 2022). Linear regression is the most basic type, but it has a major weakness, as it assumes that data follows a straight line, limiting its accuracy in the complex world of finance (Kinaneva et al., 2021). So, researchers use advanced versions such as Ridge, Lasso, and Elastic Net regression to fix this because these models are better at preventing 'overfitting' and also handle variables that are too similar to each other (Jiang et al., 2020; Hoang & Wiegratz, 2022). Support Vector Regression (SVR) is also powerful because it often predicts profits better than old methods (Kayakus et al., 2023; Pabuccu & Barbu, 2024). Finally, polynomial regression is useful when relationships are curved (Kinaneva et al., 2021).

Tree-based and ensemble methods are also popular in financial prediction (Bakumenko & Elragal, 2022). Decision Trees are valuable because they are easy to understand and capture complex links in credit scoring (Bao et al., 2019; Belesis et al., 2023). However, single trees often make mistakes by memorising data too closely, so researchers use ensemble algorithms like Random Forest (Ileri, 2025). It can combine many trees, so it can create strong and accurate predictions (Farag et al., 2025). XGBoost is also an advanced analytic tool because it improves accuracy and speed (Sizan et al., 2025; Olowe, 2024). Other models like AdaBoost, LightGBM, and CatBoost similar with XGBoost optimise speed and control errors (Villar & De Andrade, 2024).

K-Nearest Neighbours (KNN) can use to predicts outcomes by looking at similar data points nearby (Gao et al., 2024). It is flexible, so researchers use it for credit scoring and fraud detection (Bao et al., 2019). But it has a downside, such as it needs a lot of computer power for big datasets (Gao et al., 2024). Still, it is a great basic method because it finds unusual trends well. and groups financial entities with similar risks (Gao et al., 2024).

Neural Networks and Deep Learning help a lot with financial predictions (Gao et al., 2024). Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) can find hidden patterns in financial data, so they are powerful for predicting business failures (Bao et al., 2019; Sizan et al., 2025). For data that changes over time, researchers used Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks because these models remember past information and capture the flow of time well (Yang et al., 2022). Hybrid models like LASSO-LSTM combine different techniques can manage complex data and time trends together (Yang et al., 2022). Finally, Convolutional Neural Networks (CNNs) can spot patterns in financial charts, so researchers traditionally use them for recognising images (Gao et al., 2024).

2.6.3 Model Optimization, Evaluation, and Interpretability

Hyperparameter tuning is the first step in optimisation which involves choosing the best settings to control how the model learns from data (Sizan et al., 2025). Researchers evaluate the models by using appropriate statistical performance metrics after this step (Sizan et al., 2025). Regression models use standard performance metrics such as R-squared (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) (Seyam, 2025; Farag et al., 2025; Jones et al., 2023). Classification models use different metrics such as accuracy, precision, recall, the F1 score and the ROC-AUC (Farag et al., 2025).

Complex machine learning models are hard to understand, so researchers use tools to explain them, such as Shapley values, variable importance scores and partial dependence plots (Shamsuddin, 2024; Seyam, 2025; Jones et al., 2023). The SHAP framework provides a consistent approach to explain predictions from different models (Boukrouh et al., 2024). D'Amato et al. (2023) stated that SHAP values are generated by calculating the contribution of each feature and show if a feature had a positive or negative impact on the prediction.

2.7 Theoretical Frameworks and Models

Past studies used different ideas to analyse InsurTech and financial stability (Nyika, 2021; Shamsuddin, 2024). One key idea is Disruptive Innovation Theory, which explains how startups begin by serving customers that big firms ignore and slowly take over the main market (Christensen Institute, n.d.). In the insurance sector, startups use new technologies such as big data, the IoT, blockchain, and AI to change traditional tasks like risk assessment and claims management (Chang, 2023; Shamsuddin, 2024). This shift has good and bad points, as innovation helps companies compete better but companies who are slow to adopt new technologies will lose their place in the market (Liu et al., 2023).

The Diffusion of Innovation (DOI) Theory offers another view in explaining how technological innovations spread in the industry (Nyika, 2021). Ozcan et al. (2024) describe five stages of innovation, which are knowledge, persuasion, decision, implementation, and confirmation. They also group people into categories which are innovators, early adopters, and laggards (Ozcan et al., 2024). Shamsuddin (2024) also used DOI to show that InsurTech adoption follows an S-shaped curve which reflects the gradual acceptance of new products.

The Theory of Operational Capabilities (TOC) shows how that technology improves internal work and ultimately leads to better efficiency and financial stability

(Shamsuddin, 2024; Chatzara, 2019). Uasage of digital tools like AI and blockchain can automate processes, cut costs and improve decision-making (Eti et al., 2024; Braun & Jia, 2025; Bian et al., 2023). So, it can make workflows smoother and let companies perform better as well as become more resilient (John et al., 2024; Shamsuddin, 2024).

Resource-Based Theory (RBT) emphasises a company's own resources and skills as the main drivers of success (Nyika, 2021; Jurevicius, 2023). Specific InsurTech tools such as special analytics systems and digital platforms are valuable resources (Wang, 2021). Companies must combine these tools with their existing skills because this boosts efficiency, helps get funding and encourages new ideas (Wang, 2021). Using these resources well leads to better financial health (Braun & Jia, 2025).

The Technology–Organization–Environment (TOE) framework emphasises how the organisation, the technology, and the environment are important to affect innovation (Seyam, 2025). The organisational context includes firm size, financial capacity, and top management support. The technological context includes the advantage, compatibility, and complexity of the new tool. The environmental context includes market dynamics, regulatory influence, and competitive intensity (Gupta et al., 2022). Research in the insurance sector supports that technology and organisational factors affect decisions the most (Annisa & Sutjipto, 2025).

Research on financial stability often uses Signaling Theory. This theory says financial ratios are signs, and investors use them to judge a company's health (Sugandi & Gantyowati, 2024). Insurers show their strength through these numbers, such as high profit, which is a good sign and a high RBC ratio builds trust as it shows good risk management (Connelly et al., 2024; Sugandi & Gantyowati, 2024). Also, steady growth in premiums shows the company is stable because it can handle difficult market situations (Sugandi & Gantyowati, 2024).

2.8 Hypotheses Development

This study examines how InsurTech affects the financial health of insurance firms. On one hand, digital tools can make companies stronger, improve work speed and also help firms compete in fast-changing markets, but these tools also bring new dangers as companies might face more market ups and downs and also face risks from cyberattacks (Cevik, 2024; Koranteng & You, 2024). The model uses several variables, such firm-specific features, industry-level concentration, and macroeconomic conditions to explain financial stability. It (Kramarić et al., 2019; Altuntas & Rauch, 2017).

Past research says InsurTech improves stability because it helps companies spread out their work, increases efficiency, fills gaps in information and lowers running costs (Cevik, 2024; Koranteng & You, 2024). This helps answer the first research question which asks how much InsurTech affects the stability of global insurance companies. It makes the industry more stable, helps assess risks accurately and also simplifies tasks like underwriting and claims (Liu et al., 2023; Eti et al., 2024). We use Disruptive Innovation Theory and Resource-Based Theory (RBT) to support this reseach question. This is because InsurTech acts as a special digital skill, is a strategic asset and also improves solvency and stability. At the same time, it changes traditional ways of company operation (Wang, 2021; Liu et al., 2023). So, we formulate the first hypothesis:
H_1: InsurTech adoption positively affects financial stability.

The second research question asks how specific company features change the effect of InsurTech on financial stability. Past studies show that these specific features are important because they affect a company's financial health. They also affect how well a company uses new technologies (Kramarić et al., 2019). Big companies can invest in InsurTech better because they have more money and resources to help them get more stability benefits (Chang, 2023). Profit and safe debt levels act as a cushion to help companies pay for new technology; hence, it leads to long-term stability (Liu et al., 2023). Research proves that the impact of technology varies, as it depends on the size and health of the firm (Bian et al., 2023; Liu et al., 2023; Safiullah & Paramati, 2022). Two theories support this idea, which are the TOE framework, highlighting the role of company structure and readiness and the Resource-Based Theory (RBT), focusing on how internal resources can drive success (Seyam, 2025; Nyika, 2021). So, we formulate the second hypothesis:

H_2: Firm-specific characteristics influence the stability effect of InsurTech adoption.

Existing research emphasises the significance of industry structure in influencing insurers' financial results in order to answer the third research question, which asks how industry-level factors impact the stability effect of InsurTech adoption (Altuntas & Rauch, 2017). The "concentration-fragility" hypothesis suggests that high market concentration lowers financial stability in the insurance sector (Altuntas & Rauch, 2017; Shim, 2015, cited in Kramarić et al., 2019). This means the level of competition matters because it changes how well InsurTech supports stability. The TOE framework supports this idea, as it shows that environmental factors like competition affect technology choices (Seyam, 2025). So, we formulate the third hypothesis:

H_3: Industry-level factors affect the stability effect of InsurTech adoption.

Previous studies help answer the fourth research question. This question looks at macroeconomic factors which ask how they change the relationship between InsurTech and financial stability. Factors like inflation and GDP growth are affecting the financial health of insurers (Kramarić et al., 2019; Ma, 2024). High inflation creates problems as it raises prices and reduces the benefits of digital efficiency. However, strong economic growth helps because it allows companies to invest more in InsurTech and brings clear stability benefits. The environmental part of the TOE framework explains this link. TOE usually focuses on the decision to adopt technology and environmental factors decide if the technology works well (Seyam, 2025; Gupta et al., 2022). So, we formulate the fourth hypothesis.

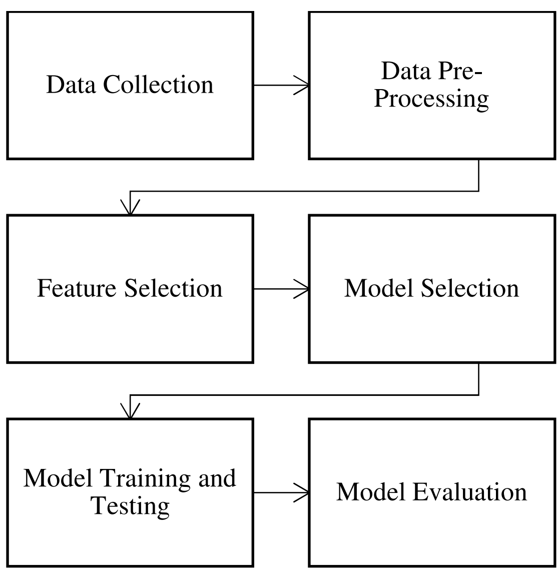
H_4: Macroeconomic factors affect the stability effect of InsurTech adoption.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter explains the research methods for this study, which examines the impact of InsurTech on financial stability. Figure 3.1 shows the steps we followed. The method provides a structured framework to meet the research objective. It lists the research design, data sources, feature selection, and analytical techniques. We also describe the data collection process, such as the sources, coverage period, and preprocessing steps. Second, we define the target and features clearly with the explanation of the reasons in both theoretical and empirical terms. Following this, the model specification is outlined, where the decision to employ machine learning regression and classification models. The Model training, testing and evaluation step also be mention in this chapter.

Figure 3.1: Process of Methodology

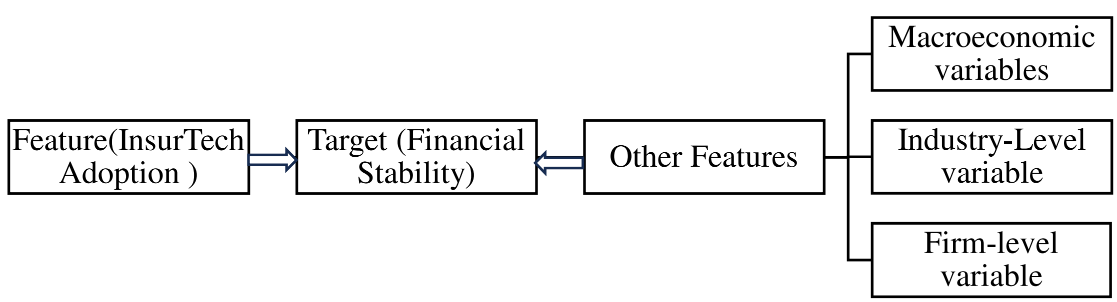


Source: Developed for the research

This study uses a conceptual framework which focuses on the relationship between using InsurTech and the financial stability of global insurance companies. The main concepts are InsurTech adoption and financial stability. The framework also includes three extra factors which change the relationship between adoption and stability. First, firm-specific features such as size, profit, and debt levels matter because they affect how well insurers invest in InsurTech. The Resource-Based Theory (RBT) and the TOE framework support this because they emphasise that a company's resources and readiness determine success (Kramarić et al., 2019; Safiullah & Paramati, 2022). Second, the industry level is important because market concentration changes the results of InsurTech adoption. Past research highlights the "concentration–fragility" hypothesis. It says that high concentration often reduces stability (Altuntas & Rauch, 2017; Shim, 2015). Third, macroeconomic factors play a role as GDP growth and inflation change the link between InsurTech and financial stability. Previous studies alsp using the TOE framework to highlight industry and macroeconomic factors (Kramarić et al., 2019; Ma, 2024).

Figure 3.1 shows the conceptual framework. It sets financial stability as the target. InsurTech adoption acts as the main feature. Several other features include firm-specific characteristics, industry-level conditions, and broader macroeconomic factors is influence this relationship.

Figure 3.2: Conceptual Framework



Source: Developed for the research

3.1 Data Collection

We collected the data for this study from the London Stock Exchange Group (LSEG) database. It provides reliable financial information on listed companies. The data covers the years from 2017 to 2024. We chose this time period to capture the fast growth of InsurTech investment. Funding grew from less than USD 500 million in 2012 to over USD 2.5 billion in 2017 and went over USD 4 billion by 2018 (Milken Institute, 2018, as cited in Lanfranchi & Grassi, 2021; Willis Tower Watson, 2019, as cited in Lanfranchi & Grassi, 2021). Research by Ozcan (2024) confirms this trend. Investment started to rise a lot in 2016 compared to earlier years. So, this timeframe covers the most important phase of change in the insurance sector.

We selected the insurance companies based on market capitalisation rankings. We focused on the top 100 global insurers. Researchers often use market capitalisation to measure firm size and show systemic importance (Roosmawarni et al., 2023). Roosmawarni et al. (2023) highlight that the big companies with high market value affect the industry more because they influence sustainability, risk management, and financial stability. Also, past research used the top 100 companies as a sample for other topics. For example, Kengkathran (2019) used them to study Environmental, Social and Governance (ESG) issues.

Table 3.1 shows the list of insurance firms for this study. Table 3.2 displays the percentage of firms in each nation. The findings show the United States makes up nearly 35% of the sample, following with Canada, Japan, China, and other nations. Figure 3.3 shows these ratios as a pie chart. It gives a picture of each nation's share.

Table 3.1: List of Insurance Companies

Company Name	Market Cap (Σ=Avg)	Country of Exchange
Allianz SE	156,680,887,065.13	Germany
Progressive Corp	153,391,278,427.38	United States of America
Allianz SE (Labuan Branch)	151,985,211,062.38	Canada

China Life Insurance Co Ltd	136,957,879,634.76	China
Ping An Insurance (Group) Co of China Ltd	131,352,096,051.21	China
Chubb Ltd	113,725,955,646.60	United States of America
AXA SA	108,214,265,915.76	France
Marsh & McLennan Companies Inc	105,975,886,620.80	United States of America
Zurich Insurance Group AG	102,277,148,962.75	Switzerland
AIA Group Ltd	97,974,467,920.73	Hong Kong
Muenchener Rueckversicherungs-Gesellschaft in Muenchen AG	85,668,393,654.79	Germany
Arthur J. Gallagher & Co.	81,465,410,000.00	United States of America
Tokio Marine Holdings Inc	80,849,196,074.34	Japan
Aon PLC	76,606,844,600.16	United States of America
Life Insurance Corporation Of India	69,883,763,433.15	India
Travelers Companies Inc	59,843,613,446.18	United States of America
Aflac Inc	56,535,250,577.96	United States of America
Assicurazioni Generali SpA	55,017,730,454.31	Italy
MetLife Inc	54,140,169,666.90	United States of America
Manulife Financial Corp	53,874,726,327.86	Canada
Allstate Corp	52,433,865,990.00	United States of America
Swiss Re AG	52,025,811,098.62	Switzerland
People's Insurance Company Group of China Ltd	49,426,694,061.88	China
American International Group Inc	47,939,151,026.80	United States of America
China Pacific Insurance Group Co Ltd	45,108,104,857.18	China
PICC Property and Casualty Co Ltd	43,693,271,290.00	Hong Kong
Fairfax Financial Holdings Ltd	43,247,880,774.32	Canada
Fubon Financial Holding Co Ltd	42,473,501,972.34	Taiwan
Intact Financial Corp	40,779,252,133.85	Canada
Prudential Financial Inc	38,614,320,000.00	United States of America
Hannover Rueck SE	37,875,126,322.32	Germany
Sun Life Financial Inc	36,544,912,060.35	Canada
Brown & Brown Inc	35,851,139,205.60	United States of America
Hartford Insurance Group Inc	35,510,032,220.14	United States of America
MS&AD Insurance Group Holdings Inc	35,309,316,663.41	Japan
Cathay Financial Holding Co Ltd	34,964,228,020.77	Taiwan
Great-West Lifeco Inc	34,232,350,524.56	Canada
Arch Capital Group Ltd	33,424,356,084.75	United States of America

Talanx AG	32,907,401,131.40	Germany
Prudential PLC	32,201,105,994.55	United Kingdom
Willis Towers Watson PLC	30,403,291,912.24	United States of America
Swiss Life Holding AG	29,333,339,895.69	Switzerland
Sampo Oyj	29,219,371,100.94	Finland
Japan Post Holdings Co Ltd	28,173,250,270.41	Japan
Dai-ichi Life Holdings Inc	28,164,443,867.20	Japan
Sompo Holdings Inc	27,915,668,523.22	Japan
W R Berkley Corp	27,120,149,073.09	United States of America
Aviva PLC	25,686,553,983.17	United Kingdom
Markel Group Inc	25,395,123,914.61	United States of America
Cincinnati Financial Corp	23,225,153,409.90	United States of America
New China Life Insurance Co Ltd	23,006,838,133.33	China
Power Corporation of Canada	22,682,086,576.03	Canada
QBE Insurance Group Ltd	22,395,853,135.45	Australia
SBI Life Insurance Company Ltd	21,191,968,692.64	India
HDFC Life Insurance Company Ltd	19,771,571,065.33	India
Legal & General Group PLC	19,686,920,659.33	United Kingdom
Corebridge Financial Inc	19,668,438,817.40	United States of America
Loews Corp	19,373,862,221.92	United States of America
Samsung Life Insurance Co Ltd	18,761,892,119.12	Korea; Republic (S. Korea)
Principal Financial Group Inc	18,159,452,694.00	United States of America
Erie Indemnity Co	18,141,446,803.92	United States of America
NN Group NV	17,874,091,552.62	Netherlands
Ryan Specialty Holdings Inc	17,525,024,713.98	United States of America
Fidelity National Financial Inc (Pre-Reincorporation)	15,926,361,886.02	United States of America
Tryg A/S	15,720,142,441.48	Denmark
Samsung Fire & Marine Insurance Co Ltd	15,703,947,696.80	Korea; Republic (S. Korea)
Powszechny Zaklad Ubezpieczen SA	15,195,327,209.30	Poland
Suncorp Group Ltd	14,835,855,607.78	Australia
Everest Group Ltd	14,354,620,005.44	United States of America
Unum Group	14,318,599,474.36	United States of America
ASR Nederland NV	13,967,127,545.49	Netherlands
Admiral Group PLC	13,933,761,493.64	United Kingdom
Unipol Assicurazioni SpA	13,839,891,288.11	Italy
BB Seguridade Participacoes SA	13,494,323,434.78	Brazil

Insurance Australia Group Ltd	13,359,666,597.29	Australia
Ageas SA	13,354,870,780.32	Belgium
Reinsurance Group of America Inc	13,071,144,204.09	United States of America
Helvetia Holding AG	12,862,798,273.78	Switzerland
Mapfre SA	12,796,350,433.58	Spain
Gjensidige Forsikring ASA	12,748,354,249.12	Norway
CNA Financial Corp	12,364,713,011.85	United States of America
Aegon Ltd	12,113,234,600.74	Netherlands
T&D Holdings Inc	12,063,645,855.08	Japan
ICICI Lombard General Insurance Company Ltd	11,797,861,606.32	India
Renaissancere Holdings Ltd	11,719,805,476.50	United States of America
Sanlam Ltd	11,231,226,124.39	South Africa
Baloise Holding AG	11,196,969,314.31	Switzerland
Kinsale Capital Group Inc	11,099,972,889.60	United States of America
ICICI Prudential Life Insurance Company Ltd	10,808,105,548.43	India
American Financial Group Inc	10,642,696,446.26	United States of America
iA Financial Corporation Inc	10,018,245,012.11	Canada
Globe Life Inc	10,004,196,692.40	United States of America
Assurant Inc	9,809,378,624.28	United States of America
Great Eastern Holdings Ltd	9,594,305,452.70	Singapore
Old Republic International Corp	9,384,801,474.33	United States of America
KGI Financial Holding Co Ltd	9,203,745,235.49	Taiwan
Primerica Inc	9,109,853,002.64	United States of America
Medibank Private Ltd	9,010,438,101.72	Australia
Phoenix Group Holdings PLC	8,868,051,969.40	United Kingdom
Discovery Ltd	8,535,973,296.71	South Africa
Japan Post Insurance Co Ltd	8,473,220,016.70	Japan

Source: LSEG

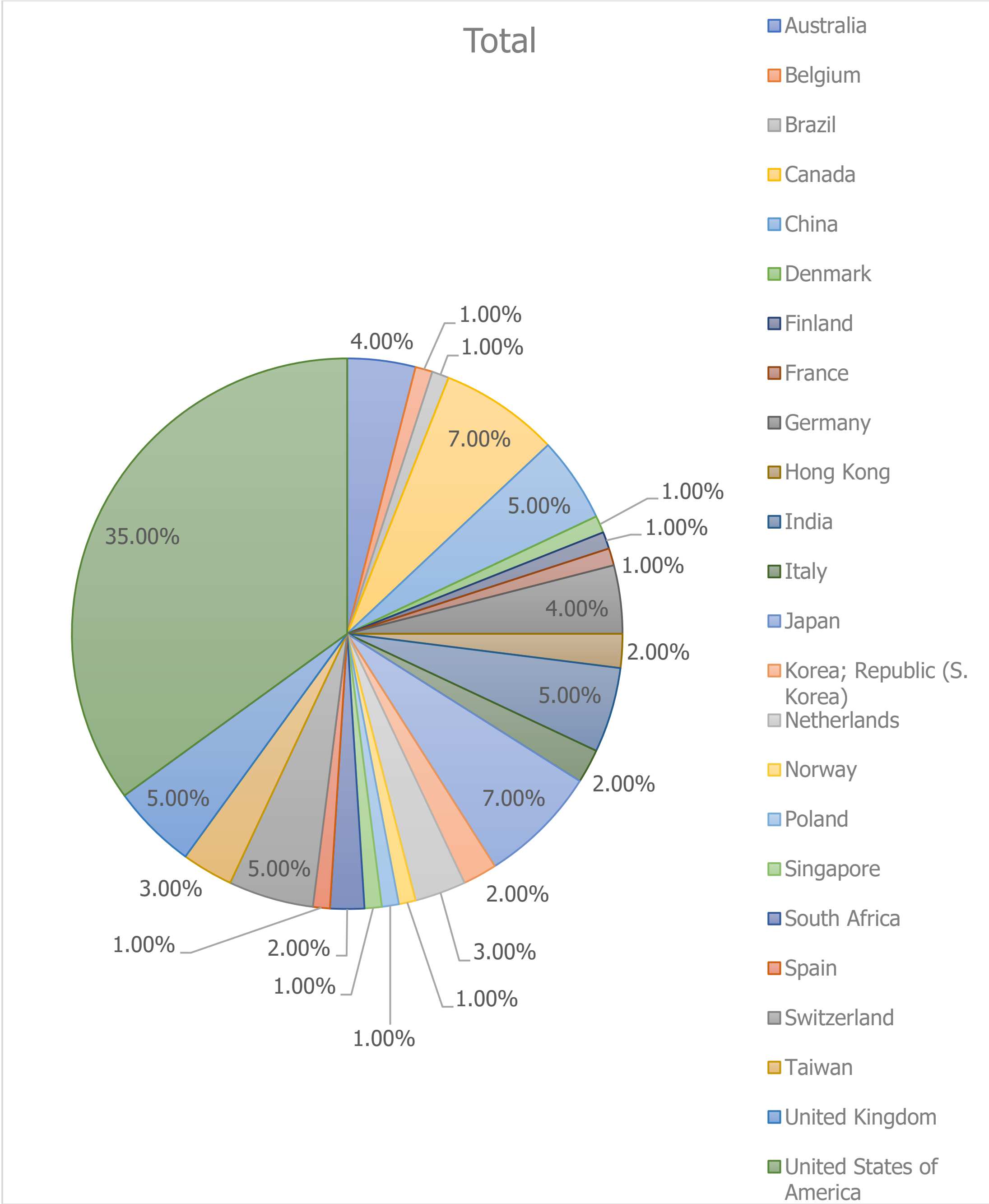
Table 3.2: Percentage of Companies in Each Country

Row Labels	Count of Country of Exchange
United States of America	35.00%
Canada	7.00%
Japan	7.00%
China	5.00%
India	5.00%

Switzerland	5.00%
United Kingdom	5.00%
Australia	4.00%
Germany	4.00%
Netherlands	3.00%
Taiwan	3.00%
Hong Kong	2.00%
Italy	2.00%
Korea; Republic (S. Korea)	2.00%
South Africa	2.00%
Belgium	1.00%
Brazil	1.00%
Denmark	1.00%
Finland	1.00%
France	1.00%
Norway	1.00%
Poland	1.00%
Singapore	1.00%
Spain	1.00%

Source: Developed for the research

Figure 3.3: Percentage of Companies in Each Country



Source: Developed for the research

3.2 Data Pre-Processing

To prepare the data for analysis, we took several steps. First, we found the missing values and removed them by hand. This ensured the dataset worked properly for the next steps. Also, we standardised all the continuous numbers to improve the stability of the models and allow us to compare different firms easily. The standardization process was carried out using the following formula:

$$z = \frac{x - \mu}{\sigma}$$

where x is the original feature value, μ is the mean of x, and σ is the standard deviation of x (GeeksforGeeks, 2025).

3.3 Feature Selection

We used a feature selection process which is common in financial research that uses machine learning. It helps the model perform better and reduces overfitting (Schenkelberg et al., 2020; Wasserbacher & Spindler, 2021). Specifically, we used Least Absolute Shrinkage and Selection Operator (Lasso) regularisation, which applied it in both linear and logistic forms. This helps identify the most important predictors of financial stability and works well with complex financial datasets (Wasserbacher & Spindler, 2021; Pan & Xu, 2021). Lasso L1 penalty on the regression coefficients and srinks less important coefficients towards zero, thereby performing automatic variable selection (Enwere et al., 2023). This makes it very good for handling multicollinearity because Lasso usually keeps only one variable from a similar group and ignores the others. This makes the model easier to interpret (Greenwood et al., 2020).In this study, we applied Lasso in two ways. We used the Lasso regression model for estimating continuous numbers. We used Lasso logistic regression when the target was a category (Zizi et al., 2021; Yang et al., 2022).

To ensure robust estimation, a 10-fold cross-validation process was used to determine the optimal tuning parameter (λ). It balances the complexity of the model with its predictive power (Yan et al., 2020). The main feature included InsurTech adoption.

This is the use of new technologies in insurance (Seyam, 2025). We also included other features for the firm, the industry, and the economy. Together, these explain the financial stability of insurers (Safiullah & Paramati, 2022). The combination of Lasso regression and Lasso logistic regression thus supports both the continuous and categorical modeling frameworks, ensuring that the final model set captures the most informative and stable predictors across analytical contexts (Pabuccu & Barbu, 2024).

The target is financial stability, which reflects an insurer's capacity to meet its obligations, maintain solvency, and adapt to market changes (Safiullah & Paramati, 2022). The feature is InsurTech adoption, defined as the integration of innovative technologies into insurance operations (Seyam, 2025). In addition, the model incorporates the remain feature which are firm-level variables, industry-level variables, and macroeconomic variables that may influence insurers' financial stability.

3.3.1 Target

In this study, target which is financial stability operationalised using the Z-score, a widely recognised measure of insolvency risk and the "distance to default" for financial institutions (Cevik, 2024; Safiullah & Paramati, 2022; Stankevičienė & Kabulova, 2022). While previous studies have also employed composite models such as CAMELS or CARAMELS to assess stability, these require a wider set of financial indicators that are not fully available in the LSEG database. Moreover, the Z-score is extensively adopted in the literature as a parsimonious and robust indicator of insurers' solvency. The Z-score is continuous number which measure of resilience to financial stress. A higher Z-score indicates stronger financial stability, whereas a lower Z-score indicates greater financial instability.

3.3.1.1 Financial Stability

The Z-score is commonly calculated as the sum of profitability and capitalisation divided by the volatility of profitability, expressed as:

$$Z - score_{it} = \frac{ROA_{it} + \frac{Equity}{Asset}_{it}}{\sigma(ROA_{it})}$$

where ROA_{it} denotes the ROA of firm i at time t, $\frac{Equity}{Asset}_{it}$ represents the equity-to-asset ratio, and $\sigma(ROA_{it})$ is the standard deviation of ROA computed over a three-year rolling window (Kramarić et al., 2019).

Researchers use the Z-score often because it is a common tool in studies about banking and insurance (Kramarić et al., 2019). In this study, the Z-score has two purposes. For regression models, we use it as a continuous number. It measures financial stability directly and shows how well firms can pay their debts. But for classification models, we change the Z-score into a binary variable to allow us to predict specific categories (Farag et al., 2025).

Firms with a Z-score higher than 3 are "stable". Firms with a score lower than 3 are "unstable". This simple change makes the results easier to understand and lets us compare stable and unstable insurers clearly.

3.3.2 Feature

This study measures InsurTech adoption by analysing text in annual reports which contain details about company strategies and technology. We use the AntConc software to find keywords related to Insurtech. It counts how often these words appear. We use Principal Component Analysis (PCA) to turn these counts into a single score. Past studies simply added up the numbers (Dicuonzo et al., 2023; Seyam, 2025). But PCA is a stronger statistical method because it gives weight to the indicators based on how much they change. This captures the complex nature of InsurTech adoption (Kharrat et al., 2024).

3.3.2.1 InsurTech Adoption

Following the frameworks of Kharrat et al. (2023), the InsurTech Adoption Index (IT) was developed through three main steps:

Step 1: Preprocessing of text information

We made a list of keywords which capture references to digitalisation and InsurTech. We adapted the list from Seyam (2025). The words include *Digital Claims, Digitalization, Digitalizing, Digitalized, Digitally, E-policy, Fintech, Infotech, InsurTech, IoT, Mobile App, Robot, Robotic, Robots, Smart Contracts, Tech, Technological, Technologies, Technology,* and *Telematics*. To ensure accuracy, we removed keywords with negative words like "no" or "none" before them.

Step 2: Keyword frequency extraction and normalization

We used the AntConc software. It counted how often each keyword appeared in the annual reports.We looked only at reports in English. This made the data consistent and made comparisons fair. This process gave us a frequency score and this score lets us compare different firms and years meaningfully.

Step 3: Dimensionality reduction and index construction

We wanted to combine these keyword numbers into one number, so we used Principal Component Analysis (PCA) and factor analysis. This procedure captures the common variance across the keywords, minimises multicollinearity, and prevents overemphasis on any single term. The resulting composite InsurTech Adoption Index reflects the degree of technological integration disclosed in insurers’ annual reports. Higher index values indicate stronger adoption and integration of InsurTech solutions.

This composite index serves as the independent variable in the empirical analysis, enabling the study to examine how InsurTech adoption influences insurers’ financial stability.

3.3.3 Other Features

In line with prior studies on insurers' financial stability, a wide range of firm-level, industry-level, and macroeconomic variables have been considered in the literature. Firm-level determinants include size, reinsurance ratio, premium growth, premium-to-surplus ratio, profitability, ROE, expense ratio, leverage, capital ratio, equity ratio, and investment income. At the industry level, the concentration ratio such as Top 3 concentration ratio or Herfindahl-Hirschman Index (HHI) is including which frequently employed to capture market concentration, while macroeconomic factors are including such as GDP growth and inflation are widely recognised as important external influences.

However, due to the limitations of the LSEG database and World Bank, only a subset of these variables is included in the present study. Specifically, the model employs ROE, firm size, reinsurance ratio, premium growth, premium-to-surplus ratio, profitability, investment income, expense ratio, leverage, capital ratio, and equity ratio at the firm level, top3 concentration ratio at the industry level, and GDP growth and inflation at the macro level. This selection ensures alignment with the existing literature while maintaining data consistency and feasibility within the available dataset. According to table 3.3, there shows the list of other features that will involve in this study.

Table 3.3: List of Other Features

Variable	Measurement	Key References
Firm-Level		
Firm Size	Natural Log of Total Assets	Kramarić et al. (2019); Puławska (2021)
Reinsurance Ratio	Reinsurance to Gross Written Premiums	Kramarić et al. (2019); Altuntas & Rauch (2017)

Premium Growth	% Change in Gross Written Premiums	Kramarić et al. (2019)
Premium-to-Surplus Ratio	Net Premiums Earned to Equity	Kramarić et al. (2019)
Profitability	Natural logarithm of the net income	Puławska (2021)
ROE	Net Income to Equity	Altuntas & Rauch (2017)
Expense Ratio	Operating Expenses to Net Premiums Earned	Altuntas & Rauch (2017)
Leverage	Liabilities to Equity Ratio	Altuntas & Rauch (2017); Puławska (2021)
Capital Ratio	Capital to total assets ratio	Puławska (2021)
Equity Ratio	Equity to total assets ratio	Puławska (2021)
Investment Income	Investment Income to Net Premiums Earned	Altuntas & Rauch (2017)
Industry-Level		
Top 3 Market Concentration Ratio	The sum of premiums earned by the three largest insurers in a country divided by the total premiums earned by the entire insurance industry.	Altuntas & Rauch (2017)
Macro-Level		
GDP Growth	Annual % change	Kramarić et al. (2019); Altuntas & Rauch (2017); Puławska (2021)
Consumer Price Index	Annual % CPI Inflation	Altuntas & Rauch (2017); Puławska (2021)

3.3.3.1 Firm-Level features

At the firm level, company size is a key factor. We measure this using the natural logarithm of total assets to accounts for the effects of scale. Generally, larger insurers benefit from 'economies of scale' because they have lower costs, diverse investments and better access to money. These things usually make them more stable (Kramarić et al., 2019). But becoming too large can have the opposite effect because it leads to 'diseconomies of scale'. Too much bureaucracy and weak control reduce stability (Puławska, 2021).

We also include the reinsurance ratio, which is measured by ceded premiums over gross written premiums. It shows how companies transfer risk. Moderate use of reinsurance is good because it spreads risk and supports safety. But relying on it too much is bad, signals high risk, and exposes firms to problems with partners (Altuntas & Rauch, 2017; Kramarić et al., 2019).

Premium growth is another factor. We calculate this as the percentage change in gross premiums. It reflects business expansion. Controlled growth improves market strength and brings in revenue. But rapid expansion is dangerous without enough capital because increases risk (Kramarić et al., 2019). Similarly, we look at the premium-to-surplus ratio. This divides net premiums by equity. It measures if underwriting is too aggressive compared to capital. Higher ratios mean excessive risk-taking and increase the chance of bankruptcy (Kramarić et al., 2019).

We use Return on Equity (ROE) as a key indicator. This measures a firm's ability to earn money. Stronger ROE supports solvency buffers. It also improves resilience and the ability to innovate (Altuntas & Rauch, 2017; Puławska, 2021). Similarly, profitability which calculated by the natural logarithms of investment income also indicate as the firm's ability to earn money (Puławska, 2021). Finally, the expense ratio reflects efficiency. It compares operating expenses to premiums. Higher numbers mean the company is inefficient. This lowers stability (Altuntas & Rauch, 2017).

Furthermore, the expense ratio, defined as operating expenses relative to premiums, reflects operational efficiency; higher values signal inefficiency and reduced stability (Altuntas & Rauch, 2017). Similarly, leverage (liabilities-to-equity ratio), capital ratio (capital-to-total-assets ratio), and equity ratio (equity-to-total-assets ratio) have also been included. While leverage increases fragility and default risk, higher capital and equity shares enhance solvency and financial strength (Altuntas & Rauch, 2017;

Puławska, 2021). Finally, investment income, expressed as investment returns over premiums, is included since insurers often rely on investment revenues as a stable income stream, thereby reducing dependence on underwriting (Altuntas & Rauch, 2017).

3.3.3.2 Industry-level Features

At the industry level, the Top 3 concentration ratio is used to further capture market concentration which calculates the combined market share of the three biggest insurers in a nation. It is computed as the percentage of the total industry premiums written divided by the total premiums earned by the three biggest insurers. Increased market concentration is indicated by a higher Top 3 ratio. On the one hand, higher concentration could stabilise listed companies by reducing the pressure from competition. However, too much focus could hinder creativity and productivity, which could jeopardise stability in the long run (Altuntas & Rauch, 2017).

3.3.3.3 Macroeconomic-level Features

On the other hand, the Consumer Price Index (CPI) shows price change and it measure by the yearly percentage change. High inflation raises the cost of claims, reduces the real value of profits and wears down capital buffers. This weakens financial stability (Altuntas & Rauch, 2017; Puławska, 2021).

We combine company factors with economic factors to account for both internal and external causes of stability. This approach ensures the results are correct and stops other common factors from confusing the effect of InsurTech and financial stability.

3.4 Model Selection

This study uses many machine learning models, which include both classification and regression algorithms. These models predict financial stability related to InsurTech use. Past studies mostly used only one type of model. They used either classification models or simple linear methods (Sizan et al., 2025; Kramarić et al., 2019). Farag et al. (2025) used regression analysis together with classification and helped them check if their results were strong. This study follows their example and uses both classification and regression methods. This makes the assessment of financial stability complete and reliable.

We measure financial stability with the Z-score. This score is a famous sign of solvency and strength. We follow the rule from Farag et al. (2025). Insurers with a Z-score above 3 are "financially stable". Those with a score below 3 are "financially unstable". So, we use classification models to group the firms by using this threshold. We also use regression models. They predict the exact Z-score number to help us understand small changes in financial health better.

According to table 3.4, there stated the selected machine learning models in this study. By combining both types of models, there makes the results easier to understand and helps the findings apply to more situations. This offers a detailed view of financial stability in the InsurTech field. These models capture all trends in the financial data in both simple straight lines and complex, curved patterns.

Table 3.4: Selected Machine Learning Models

Model	Type	
Linear Regression	Regressor	Kadam (2020); Kinaneva et al. (2021); Choudhary & Gianey (2017); Gupta et al. (2022)
Polynomial Regression	Regressor	Kadam (2020); Kinaneva et al. (2021)
Ridge Regression	Regressor	Jiang et al. (2020); Hoang & Wiegratz (2022)

Elastic Net Regression	Regressor	Jiang et al. (2020); Hoang & Wiegratz (2022)
Support Vector Regression (SVR)	Regressor	Kadam (2020); Kinaneva et al. (2021); Hoang & Wiegratz (2022)
Decision Tree	Both	Kadam (2020); Kinaneva et al. (2021); Choudhary & Gianey (2017); Bao et al. (2019); Bakumenko & Elragal (2022); Osisanwo et al. (2017); Gao et al. (2024); Sobale et al. (2023); Ileri (2025)
Random Forest	Both	Sizan et al. (2025); Farag et al. (2025); Manteigas & António (2024); Kadam (2020); Kinaneva et al. (2021); Jiang et al. (2020); Osisanwo et al. (2017); Bakumenko & Elragal (2022); Bao et al. (2019); Gao et al. (2024); Hoang & Wiegratz (2022); Sobale et al. (2023); Ileri (2025)
K-Nearest Neighbors (KNN)	Both	Kadam (2020); Bao et al. (2019); Bakumenko & Elragal (2022); Sobale et al. (2023); Gao et al. (2024)
Gradient Boosting	Both	Bao et al. (2019); Manteigas & António (2024); Villar & De Andrade (2024); Ileri (2025); Özkurt (2024)
Extreme Gradient Boosting (XGBoost)	Both	Sizan et al. (2025b); Manteigas & António (2024); Sobale et al. (2023); Villar & De Andrade (2024); Ileri (2025); Özkurt (2024); Ali et al. (2023); Rivaldo et al. (2025)
CatBoost	Both	Villar & De Andrade (2024); Ileri (2025); Rivaldo et al. (2025)
LightGBM	Both	Villar & De Andrade (2024); Ileri (2025); Özkurt (2024); Rivaldo et al. (2025)
Support Vector Machine (SVM / SVC)	Classifier	Farag et al. (2025); Bakumenko & Elragal (2022); Bao et al. (2019); Osisanwo et al. (2017); Hoang & Wiegratz (2022); Gao et al. (2024); Sobale et al. (2023); Jiang et al. (2020)
Logistic Regression	Classifier	Sizan et al. (2025); Bakumenko & Elragal (2022); Bao et al. (2019); Choudhary & Gianey (2017); Sobale et al. (2023)
Naïve Bayes	Classifier	Osisanwo et al. (2017); Choudhary & Gianey (2017); Bakumenko & Elragal (2022); Sobale et al. (2023); Kadam (2020); Hoang & Wiegratz (2022); Gupta et al. (2022)
AdaBoost	Classifier	Özkurt (2024); Ali et al. (2023)

3.5 Model Training and Testing

We use the prepared dataset to train the machine learning models and use it to test how well they predict. We follow the framework from Sizan et al. (2025). We divide the dataset into a training set, which gets 80% and a testing set, which gets 20%.The models learn patterns from the training data, and then we test them on new data. We also use 10-fold cross-validation to make the models more reliable. This process splits the training data into ten parts. We train the model ten times. Each time, we use one part for checking and the rest for training, so it can helps reduce overfitting and gives a stable estimate of performance (Bulut & Arslan, 2024; Bhat et al., 2023).

Hyperparameters are settings we choose before training. We tune these settings to improve ability of classification. We use techniques like Random Search. Alibrahim and Ludwig (2021) support this method as they found that Random Search works better than Grid Search because it finds better models when using the same amount of computer power and explores a larger range of options effectively.

3.6 Model Evaluation

We use specific metrics to evaluate the models. For regression models, we use MAE, MSE, RMSE, and R-squared (R^2). These measure how accurate the predictions are. They also show how much variance the model explains (Farag et al., 2025). Using both types of evaluation gives us a complete picture of performance.

For classification models, we use Accuracy, Precision, Recall, and F1-score. We also use ROC-AUC. Gao & Liu (2021) have stated that Accuracy, Precision, Recall, and F1-score check correctness during training. The ROC curve and AUC value measure the ability to distinguish between categories. Together, these measure the quality of predictions (Naved et al., 2024; Farag et al., 2025).

We present a confusion matrix to show the number of correct and incorrect prediction (Naved et al., 2024; Farag et al., 2025). GeeksforGeeks (2025) explains the elements. True Positive (TP) means the model correctly predicted a positive result. True Negative (TN) means the model correctly predicted a negative result. False Positive (FP) happens when the model predicts positive, but the real result is negative. False Negative (FN) happens when the model predicts negative, but the real result is positive.

We will choose the best regression model based on the highest R-squared value. We will select the best classification model based on several performance metrics combined. This model will forecast financial stability outcomes. We also use feature importance measures to make the results easier to understand. Specifically, we use SHAP values. These values show the contribution of InsurTech adoption to the results. They also show the effect of other variables (Farag et al., 2025).

3.7 Summary of the Chapter

Chapter 3 outlines the quantitative method for this study. It investigates the link between InsurTech adoption and financial stability. The study uses a conceptual framework. It comes from key theories like RBT, Disruptive Innovation Theory and the TOE framework. This framework suggests that InsurTech adoption drives financial stability and other factors like firm characteristics, industry-level and macroeconomic factors also influence it. We choose the top 100 global insurers and collected data from 2017 to 2024 in the LSEG database. This period captures the fast growth in technology investment. We performed 'pre-processing' steps to prepare the data. We manually removed incomplete records. We also standardised the numbers using 'z-scores'. This ensures fair comparisons between different firms.

We used Lasso regularisation to select the important features. This technique manages complex data by shrinking the influence of small factors to zero. This prevents errors from similar variables. The target variable is financial stability. We measure this using the Z-score. Regression models treat this as a continuous number. Classification models convert it into a binary category. A score above 3 means the firm is 'stable'. The main independent variable is the InsurTech Adoption Index. We built this using AntConc software. It extracted technology keywords from annual reports. Then, we used PCA to calculate the weight of each indicator.

This framework uses different machine learning algorithms to ensure strong results. We use regression models for predicting numbers. We also use classification model methods to categorize firms. We split the data into two parts. The training set is 80%. The testing set is 20%. We used 10-fold cross-validation and RandomSearch to find the best settings to prevent overfitting. We used MAE, MSE, RMSE, and R-squared for number predictions. We used Accuracy, Precision, Recall, F1-score and ROC-AUC value for classification. We used SHAP values to visualise the results. They show which factors had the largest impact on financial stability and help to make the result besome easy to understand. Finally, we did all analyses using Python and its libraries like scikit-learn, pandas, NumPy, and matplotlib.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter shows the results about factors of financial stability and the impact of InsurTech in this study. The analysis has three main parts. Section 4.1 provides a descriptive statistical overview. Section 4.2 explains pre-estimation diagnostics. These checks include correlation analysis and multicollinearity checks. We also used LASSO for selecting features. Finally, Section 4.3 evaluates the predictive model performance. It discusses the results based on our hypotheses and past research.

4.1 Descriptive Statistics

Table 4.1 shows the statistics for 319 observations. The Z-score shows high variability in financial stability. It has the largest standard deviation in the dataset. The mean is 8.1410. The range is very large, which suggests that few businesses are unstable but others are very stable. The distribution is positively skewed, which means there are some highly stable outliers in the group. Firm_Size is the log of total assets. It has an average value of 11.4990. The standard deviation is low at 1.3594. The skewness is also low. This indicates that company size is usually stable. It is also evenly distributed.

On the other hand, some variables which are Leverage, Expense Ratio, and Premium Growth show extreme volatility and high kurtosis values. This implies the distributions have heavy tails and significant deviations from the mean. Profitability and ROE show a wide spread which reflects different performance levels among insurers. The Top_3_Concentration_Ratio shows a normal distribution based on its skewness. This implies a standard level of market competition during the period and no significant bias.

GDP growth reflects extreme economic volatility. This was likely caused by the COVID-19 pandemic, as the rate swings from a low of -10.94% to a high of 9.69%. The CPI also showed a lot of volatility. It ranged from -0.73 to a peak of 8.00 and the average was 2.42. The distribution leans toward high inflation, as shown by the positive skewness. It indicates that insurers faced rising cost expenses during this time.

Table 4.1: Descriptive Table

	Count	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
Zscore	319	8.1410	9.1834	0.1521	72.9455	3.4022	16.1044
InsurTech Index	319	-0.1797	1.4717	-2.8144	5.6084	1.2642	1.5721
Firm Size	319	11.4990	1.3594	6.9944	14.1941	-0.2679	-0.0321
Reinsurance Ratio	319	0.8815	0.1623	0.3101	1.4425	-0.8734	2.3643
Premium Growth	319	0.0898	0.3263	-0.9420	4.1649	7.0192	85.9372
Premium to Surplus Ratio	319	1.2923	0.7750	0.2037	4.4823	1.6782	3.1617
Profitability	319	7.1405	1.1427	3.6217	10.0777	-0.3476	0.0923
ROE	319	12.8565	7.8497	0.0300	56.2700	2.1385	7.8751
Expense Ratio	319	1.2505	0.6648	-3.4335	8.1775	3.9707	50.0895
Leverage	319	6.1264	6.2586	0.0600	50.9300	4.7514	30.1357
Capital Ratio	319	0.2178	0.1170	0.0321	0.6062	0.5900	-0.1408
Equity Ratio	319	0.1476	0.0885	0.0149	0.4175	0.6982	-0.1946
Investment Income	319	0.2175	0.2415	0.0110	1.6663	3.2252	12.8374
Top 3 Concentration Ratio	319	0.5886	0.3005	0.2451	1.0000	-0.0053	-1.7145
GDP Growth	319	1.8361	3.4949	-10.9401	9.6896	-1.1340	2.5212
Consumer Price Index	319	2.4167	1.7745	-0.7259	8.0028	1.3954	2.0920

Source: Developed for the research

4.2 Pre-Estimation Tests

Before running the main models, we conducted a series of pre-estimation tests to ensure the data was good and the statistics were strong. First, we performed a Correlation Analysis to identify the initial links between variables. Then, we used the Variance Inflation Factor (VIF) test to detect and fix potential multicollinearity. Finally, we applied LASSO Regression and Classification techniques. These methods select the most important predictors of financial stability.

4.2.1 Correlation Test

Figure 4.1 displays the correlation heatmap. Table 4.2 shows the correlation coefficients and their p-values. The goal of this analysis is to check the connection between financial stability and InsurTech adoption. Relationships with ***, which means $p < 0.01$, are highly significantly connected. Relationships with **, which means $p < 0.05$, are significant. Relationships with *, which means $p < 0.10$, are marginally significant.

The matrix shows strong links between several internal financial numbers. For example, the Capital Ratio and Equity Ratio have a very high positive correlation. They both measure a firm's strength and equity position, which matches the findings of Tsvetkova (2019). The author noted that capital adequacy and equity-based indicators often move together because they depend on the same balance sheet items. However, the correlation is higher than 0.8 which signal a problem called multicollinearity. This problem could bias the results. We will conduct a VIF test in the next section to confirm this.

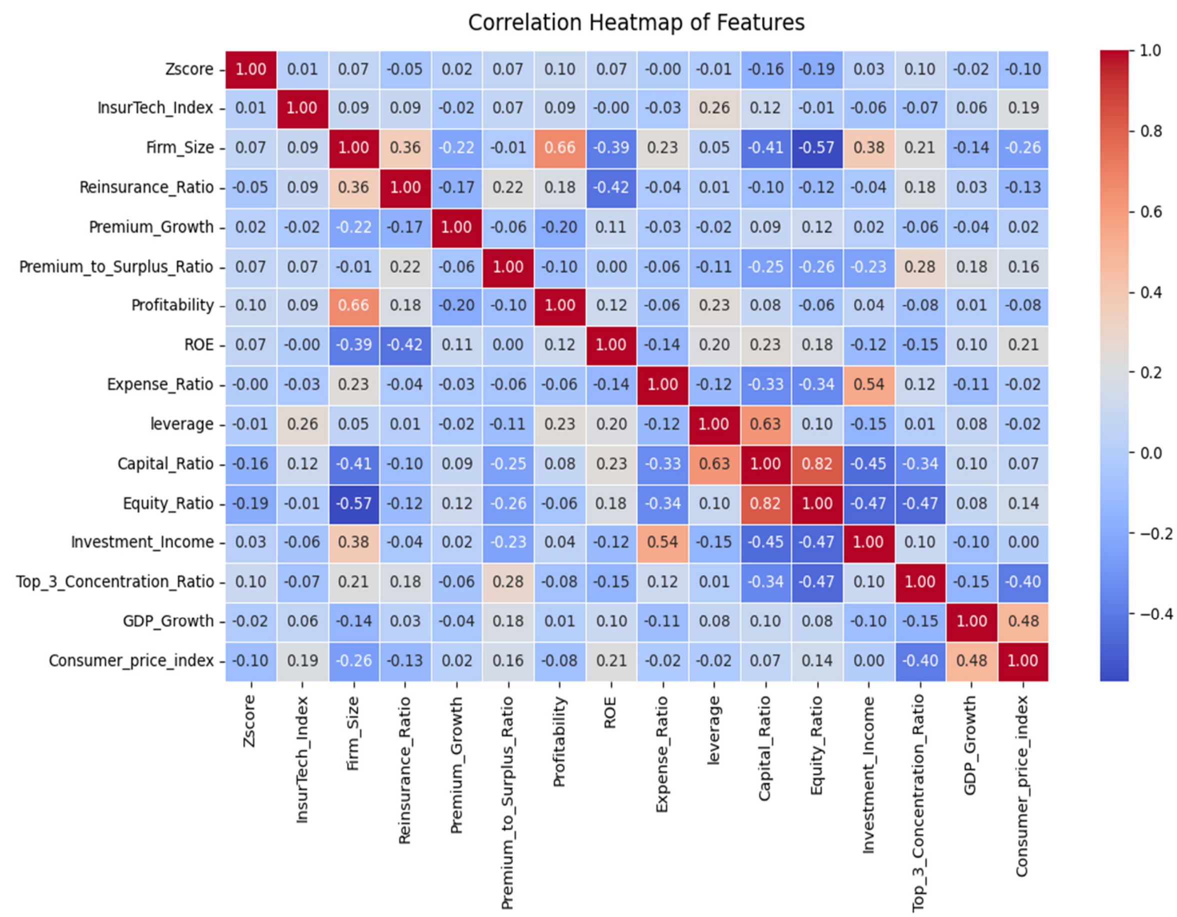
The Leverage Ratio and Capital Ratio also show a strong positive relationship. This means that insurers with more debt also keep higher capital buffers which supports the work of Pfeifer and Pikhart (2019). They observed that both measures are interrelated through regulatory design and their shared sensitivity to exposure levels and asset qualities. We also found a strong positive correlation between Profitability and Firm Size ($r = 0.6625$, $p < 0.01$). This indicates that larger insurers are generally more profitable, which matches Zainudin et al. (2018), as they found that big life insurance firms benefit from scale efficiencies.

However, we found negative correlations between the Z-score and both the Capital and Equity Ratios. This is because the high equity levels might pressure managers to take riskier strategies to please shareholders (Kusi et al., 2017). Also, too much capital can reduce efficiency, which aligns with Hersugondo et al. (2021). Thus, high capital does not always guarantee better stability when companies face pressure to take risks and operational constraints.

The Consumer Price Index (CPI) has a negative link with financial stability (Z-Score, r = –0.0996). This suggests that high inflation weakens insurer stability, which aligns with the finding from Ritho (2024). Additionally, concentrating on specific lines of business helps resilience, and profitability also shows a strong positive correlation with financial stability (Lee, 2023; Pułska, 2021).

Finally, the InsurTech Index did not show a significant direct relationship with the Z-Score. This suggests that InsurTech adoption alone does not directly predict financial stability in this linear model. Its impact might be indirect instead, as technologies like big data improve efficiency and reserve accuracy; hence, it reduces risks and enhances stability in other ways (Braun & Jia, 2025).

Figure 4.1: Correlation Heatmap



Source: Developed for the research

Table 4.2: Pearson Correlation Matrix

	Zscore	**InsurTech_ Index**	**Firm_Size**	**Reinsurance _Ratio**	**Premium_ Growth**
Zscore	1.0000	0.0138	0.0703	-0.0510	0.0240
InsurTech_ Index	0.0138	1.0000	0.0873	0.0887	-0.0192
Firm_Size	0.0703	0.0873	1.0000	0.3618***	-0.2237***
Reinsurance _Ratio	-0.0510	0.0887	0.3618***	1.0000	-0.1702***
Premium_ Growth	0.0240	-0.0192	-0.2237***	-0.1702 ***	1.0000***
Premium_to _Surplus_ Ratio	0.0687	0.0741	-0.0146	0.2214***	-0.0572

Profitability	0.0958*	0.0900	0.6625***	0.1826***	-0.1973***
ROE	0.0664	-0.0017	-0.3901***	-0.4247***	0.1076*
Expense_ Ratio	-0.0018	-0.0333	0.2302***	-0.0351	-0.0287
Leverage	-0.0076	0.2575***	0.0513	0.0134	-0.0242
Capital_ Ratio	-0.1599***	0.1153**	-0.4104***	-0.1009*	0.0858
Equity_ Ratio	-0.1920***	-0.0072	-0.5695***	-0.1168**	0.1166**
Investment_ Income	0.0272	-0.0633	0.3796***	-0.0399	0.0231
Top_3_ Concentration_Ratio	0.1042*	-0.0727	0.2060***	0.1840***	-0.0622
GDP_ Growth	-0.0169	0.0621	-0.1378**	0.0334	-0.0387
Consumer_ price_index	-0.0996*	0.1931***	-0.2561***	-0.1334**	0.0234

	Premium_to _Surplus_ Ratio	**Profitability**	**ROE**	**Expense_ Ratio**	**Leverage**
Zscore	0.0687	0.0958*	0.0664	-0.0018	-0.0076
InsurTech_ Index	0.0741	0.0900	-0.0017	-0.0333	0.2575***
Firm_Size	-0.0146	0.6625***	-0.3901***	0.2302***	0.0513
Reinsurance _Ratio	0.2214***	0.1826***	-0.4247***	-0.0351	0.0134
Premium_ Growth	-0.0572	-0.1973***	0.1076*	-0.0287	-0.0242
Premium_to _Surplus_ Ratio	1.0000	-0.1035*	0.0022	-0.0553	-0.1050*
Profitability	-0.1035*	1.0000	0.1186**	-0.0607	0.2329***
ROE	0.0022	0.1186**	1.0000	-0.1382**	0.1973***
Expense_	-0.0553	-0.0607	-0.1382**	1.0000	-0.1249**

Ratio					
	0.3246	0.2794	0.0135	0.0000	0.0257
Leverage	-0.1050**	0.2329***	0.1973***	-0.1249**	1.0000
Capital_ Ratio	-0.2483***	0.0820	0.2337***	-0.3309***	0.6257***
Equity_Ratio	-0.2620***	-0.0595	0.1848***	-0.3409***	0.0954*
Investment_ Income	-0.2330***	0.0449	-0.1184**	0.5408***	-0.1466***
Top_3_ Concentration_Ratio	0.2830***	-0.0787	-0.1482***	0.1155**	0.0093
GDP_ Growth	0.1818***	0.0099	0.1011*	-0.1070*	0.0791
Consumer_ price_index	0.1577***	-0.0839	0.2057***	-0.0186	-0.0220

	Capital_ Ratio	**Equity_ Ratio**	**Investment_ Income**	**Top_3_ Concentration_Ratio**	**GDP_ Growth**	**Consumer _price_ index**
Zscore	-0.1599***	-0.1920***	0.0272	0.1042*	-0.0169	-0.0996*
InsurTech_ Index	0.1153**	-0.0072	-0.0633	-0.0727	0.0621	0.1931***
Firm_Size	-0.4104***	-0.5695***	0.3796***	0.2060***	-0.1378**	-0.2561***
Reinsurance_Ratio	-0.1009*	-0.1168**	-0.0399	0.1840***	0.0334	-0.1334**
Premium_ Growth	0.0858	0.1166**	0.0231	-0.0622	-0.0387	0.0234
Premium_ to_Surplus_ Ratio	-0.2483***	-0.2620***	-0.2330***	0.2830***	0.1818***	0.1577***
Profitability	0.0820	-0.0595	0.0449	-0.0787	0.0099	-0.0839
ROE	0.2337***	0.1848***	-0.1184**	-0.1482***	0.1011*	0.2057***
Expense_ Ratio	-0.3309***	-0.3409***	0.5408***	0.1155**	-0.1070*	-0.0186
Leverage	0.6257***	0.0954*	-0.1466***	0.0093	0.0791	-0.0220
Capital_	1.0000	0.8190***	-0.4530***	-0.3435***	0.0986*	0.0738

Ratio						
Equity_ Ratio	0.8190***	1.0000	-0.4674***	-0.4651***	0.0829	0.1403**
Investment _Income	-0.4530***	-0.4674***	1.0000	0.1048*	-0.0992*	0.0033
Top_3_Con centration_ Ratio	-0.3435***	-0.4651***	0.1048***	1.0000	-0.1520***	-0.3959***
GDP_ Growth	0.0986*	0.0829	-0.0992*	-0.1520***	1.0000	0.4790***
Consumer_ price_index	0.0738	0.1403**	0.0033	-0.3959***	0.4790***	1.0000

Source: Developed for the research

4.2.2 Multicollinearity Test

After the correlation analysis, we performed a VIF test to check the multicollinearity issues. Table 4.3 shows the VIF test results. Usually, a value higher than 10 means there is severe multicollinearity (Dahiyat et al., 2021).

The results show that Capital Ratio, Equity Ratio, and Leverage go over the limit. This confirms a high level of multicollinearity among them and the result matches the earlier correlation matrix. That matrix showed a strong link between Leverage and Capital Ratio. It also showed a strong link between Capital Ratio and Equity Ratio. Moussa and Yahiyaoui (2025) noted strong correlations between equity and leverage indicators. They suggested removing extra ratios to prevent this problem. The high VIF values suggest these variables share the same information about a firm's solvency and capital structure. Bateni et al. (2014) found similar results. They discovered that capital and equity indicators move together because they rely on the same balance sheet numbers.

But other variables show acceptable VIF values, which are below or near the recommended thresholds. We identified significant multicollinearity in some capital structure variables. So, we use the LASSO regression method in the next step. The LASSO technique is one of the techniques that not only mitigates multicollinearity by applying penalization to correlated predictors but also performs variable selection, enhancing model stability and interpretability (Greenwood et al., 2020).

Table 4.3: Multicollinearity Test Result

Features	Centered VIF
InsurTech_Index	1.1871
Firm_Size	8.6652
Reinsurance_Ratio	1.5715
Premium_Growth	1.0962
Premium_to_Surplus_Ratio	1.6870
Profitability	4.9652
ROE	2.5973
Expense_Ratio	1.4796
leverage	14.7666
Capital_Ratio	42.5017
Equity_Ratio	27.3736
Investment_Income	1.1871
Top_3_Concentration_Ratio	8.6652
GDP_Growth	1.5715
Consumer_price_index	1.0962

Source: Developed for the research

4.2.3 Lasso Regression Test

Table 4.4 presents the LASSO regression used for feature selection. This approach identifies the most relevant predictors of insurers' financial stability while addressing multicollinearity. Unlike traditional diagnostics such as VIF, LASSO automatically penalises redundant variables through an L1 penalty, shrinking unimportant coefficients to zero (Enwere et al., 2023). This shrinkage process is shown in the Figure 4.2 which is Lasso Regressioncoefficient path diagram where all predictors are active at low regularization but some converge to zero as the penalty increases. The crossvalidated model that strikes a balance between parsimony and prediction accuracy is reflected in the ideal penalty (shown by the red dashed line).

Profitability is the largest positive predictor of financial stability which shown in Table 4.4, suggesting that more successful insurers typically have higher Z-scores. This result is consistent with Pułska's (2021) findings, which showed a strong positive correlation between European insurers' financial stability and profitability during the COVID-19 epidemic. Similarly, InsurTech adoption contributes positively, suggesting that digitalization enhances operational efficiency and risk control which consistent with Braun and Jia (2025), who emphasised the stabilizing effects of data analytics and digital transformation on insurers’ reserve accuracy and solvency.

Furthermore, Premium Growth and GDP Growth show a positive link with financial stability. These results match the findings of Pramusinta and Aryani (2023). They found that premium growth improves financial performance. Lagnai et al. (2025) also highlight this importance. They showed that economic growth makes the insurance sector stronger. Finally, the Premium-to-Surplus Ratio contributes positively too. This aligns with Bressan (2025). He noted that this ratio supports financial soundness.

On the other hand, several predictors have negative effects on financial stability. Firm Size and Equity Ratio suggest that larger or more equity-funded insurers may face reduced efficiency or higher operational risk, consistent with Rahel (2025), who found that firm size negatively correlates with insurer profitability. The negative equity ratio coefficient can be explained through the pecking order theory framework which is higher equity capital attracts high cost of financing and consequently pressures management to perform to meet equity-holders' required return potentially undermining stability (Kusi et al., 2017). In line with Kaufmann et al. (2024), investment income shows a negative correlation with financial stability. This result implies that a move towards riskier stocks and smaller cash buffers are what drive higher returns; however, a higher liquidity risk will be taken.

Similarly, the Capital Ratio and Reinsurance Ratio show that having too much capital or relying too much on reinsurance can hurt financial performance. Ekanayake & Jayasundara (2024) support the negative finding for the reinsurance ratio. They found a negative link between this ratio and financial performance in their study. This aligns with Hersugondo et al. (2021). They reported that high capital adequacy negatively affects performance and shows the inefficiency of keeping idle capital buffers. Finally, the negative result for CPI highlights the bad impact of inflation. It hurts insurers' real profitability and solvency, which supports Binder et al. (2024). They showed that uncertainty about inflation lowers both economic output and company performance.

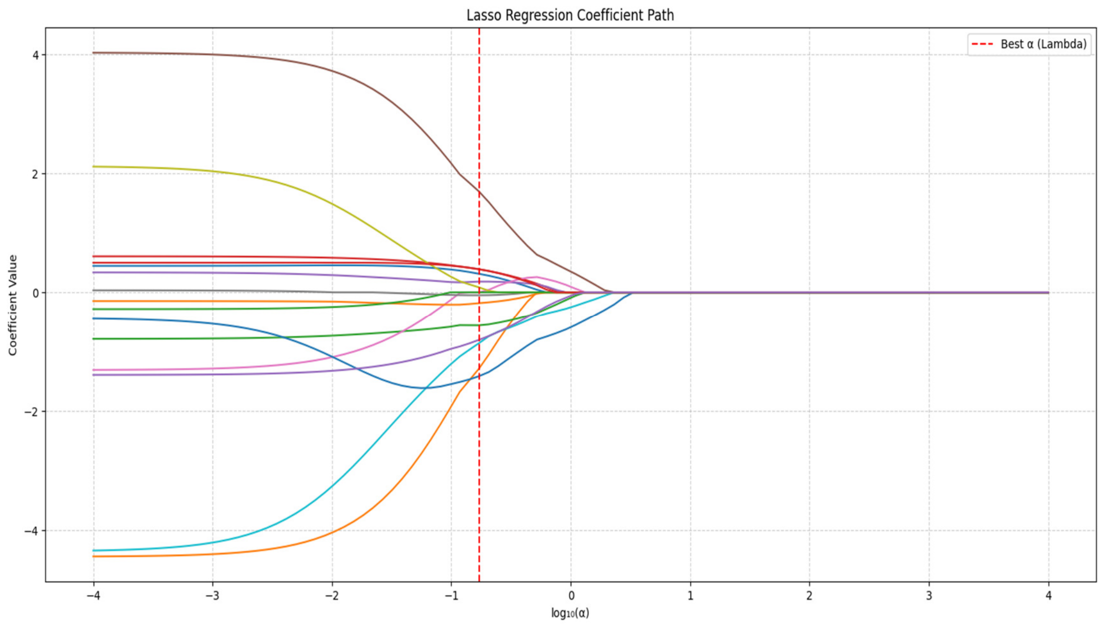
ROE, Expense Ratio, Leverage, and the Top 3 Concentration Ratio were shrunk to zero in the LASSO regression, indicating limited additional explanatory value once core predictors are included. ROE and Expense Ratio appear redundant, consistent with prior findings (Alarussi & Alhaderi, 2018; Altuntas & Rauch, 2017). Leverage shows weak relevance to Z-score–based stability (Puławska, 2021). The correlation table demonstrates several significant associations with variables like the capital and equity ratios, and the Top 3 Concentration Ratio was reduced to zero, indicating that its effect is absorbed by these related predictors.

Table 4.4: LASSO Regression Result

Features	Coefficient Value
Profitability	1.9697
Premium_Growth	0.3352
GDP_Growth	0.2954
InsurTech_Index	0.2518
Premium_to_Surplus_Ratio	0.0623
Investment_Income	-0.1308
Reinsurance_Ratio	-0.4075
Capital_Ratio	-0.5829
Consumer_price_index	-0.7364
Firm_Size	-1.7206
Equity_Ratio	-1.8683

Source: Developed for the research

Figure 4.2: Lasso Regression Coefficient Path



Source: Developed for the research

According to Table 4.5 which is the multicollinearity test result after feature selection, this table provides clear evidence that the LASSO regression successfully resolved the severe multicollinearity. With all VIFs well below the problematic threshold of 10, the final model is stable and free of significant multicollinearity.

Table 4.5: Multicollinearity Test Result After Feature Selection

Features	Centered VIF
InsurTech_Index	1.1443
Firm_Size	4.9915
Reinsurance_Ratio	1.3789
Premium_Growth	1.0854
Premium_to_Surplus_Ratio	1.5395
Profitability	2.8112
Capital_Ratio	3.5391
Equity_Ratio	4.5354
Investment_Income	1.7605
GDP_Growth	1.3722

Consumer_price_index	1.5808

Source: Developed for the research

To complement the earlier analysis, a separate L1-regularised logistic (LASSO Classification) model was employed specifically for feature selection and prediction in the financial-stability classification task that shown in Table 4.6. Unlike the LASSO regression, which estimates continuous Z-score outcomes, this classification model is designed to identify the most influential predictors for distinguishing stable versus unstable firms. The coefficient path diagram in Figure 4.3 illustrates how variables enter or drop from the model as regularization increases, with the optimal penalty level (red dashed line) selected through cross-validation. The LASSO classification kept all variables, although the regression model removed a number of predictors (Table 7). This suggests that each feature has some discriminatory strength for predicting stability results.

The main defenses against insolvency are profitability and ROE, demonstrating the importance of consistent earnings and capital efficiency. These results match the findings of Puławska (2021) and Altuntas and Rauch (2017). They confirmed that Profitability and ROE significantly improve financial stability in both European and international insurance markets. The InsurTech Index shows a clear negative link with instability as digital adoption improves operational stability. It suggests that integrating technology protects financial stability. This aligns with Braun and Jia (2025), who emphasize the stabilizing effect of the digital revolution.

The model suggests a preference for active money management over being too conservative. Leverage and the Premium-to-Surplus Ratio act as protective factors. They support financial stability. In contrast, the Capital Ratio and Equity Ratio are linked to higher instability risk. This implies that firms that use debt and capital actively are healthier than those that hoard excessive reserves, as the result matches with the finding from Hersugondo et al. (2021). They reported that high capital adequacy can negatively affect performance. It reflects the inefficiency of idle capital. However, the result for leverage differs from Ritho (2024). Ritho (2024) found a negative link between leverage and stability in Kenya, as it depends on the market context.

Firm Size acts as a dominant risk factor, as larger insurers face a higher chance of instability. This is likely due to operational rigidities compared to smaller peers, which aligns with Rahel's (2025) finding, who observed that firm size negatively correlates with profitability. Operational inefficiency, which is measured by the Expense Ratio also increases risk. Heavy reliance on risk transfer, shown by the Reinsurance Ratio, does the same. This aligns with Altuntas and Rauch (2017). They observed that higher expenses lead to more instability. Additionally, Ekanayake and Jayasundara (2024) found a negative link between reinsurance and performance, as they suggest that relying too much on risk transfer reduces net profit.

CPI highlights the destabilising effect of inflation which aligns with Ritho's (2024) finding. Ritho (2024) observed that inflation undermines insurer stability. On the other hand, GDP Growth improves economic conditions. It has a slight stabilising effect, which aligns with Lagnai et al. (2025). They emphasised the importance of economic growth for resilience. Furthermore, the model gives the Top 3 Concentration Ratio a negative coefficient. This suggests that companies in concentrated markets are slightly less likely to be unstable. This matches Akintoye et al. (2024). They found a positive relationship between performance and market concentration.

Finally, the LASSO algorithm excluded Investment Income and Premium Growth. It assigned them zero coefficients. This attributes their predictive power to other variables. This aligns with Ritho (2024). Ritho noted that inflation dictates investment performance. So, the model captures this through the CPI metric. Similarly, the exclusion of Premium Growth indicates it is not a decisive predictor here. This matches Kramarić et al. (2019). They found that premium growth has an insignificant relationship with financial stability.

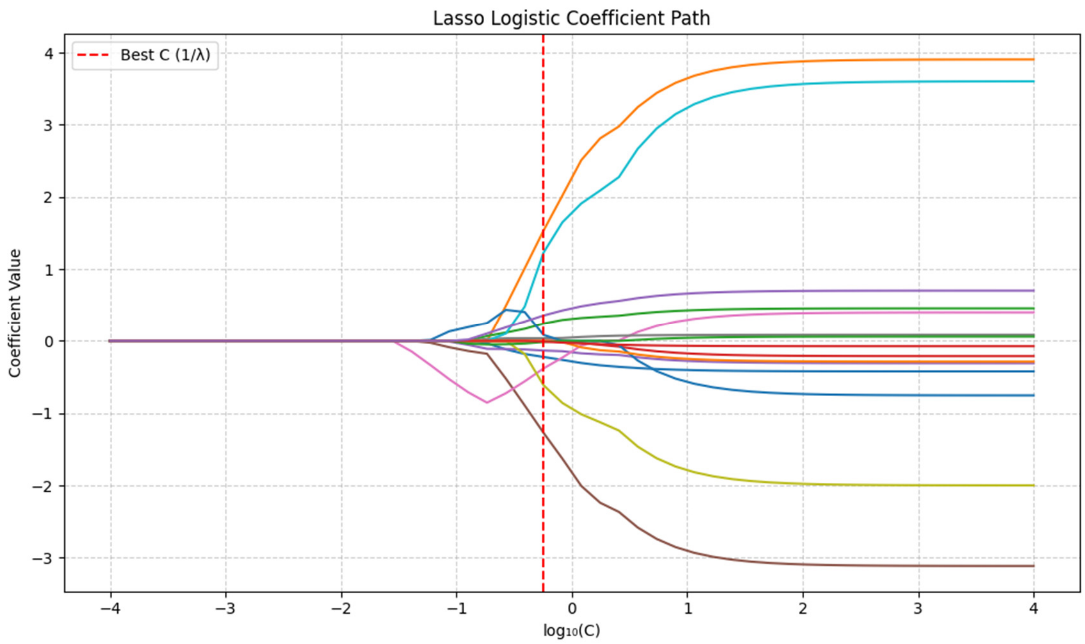
Table 4.6: LASSO Classification Result

Features	**Coefficient**

	Value
Firm_Size	1.53589
Capital_Ratio	1.230328
Consumer_price_index	0.356615
Reinsurance_Ratio	0.242868
Equity_Ratio	0.083467
Expense_Ratio	0.036101
GDP_Growth	-0.00998
Top_3_Concentration_Ratio	-0.01508
Premium_to_Surplus_Ratio	-0.13367
InsurTech_Index	-0.22259
ROE	-0.38118
L**everage**	-0.61341
Profitability	-1.27219

Source: Developed for the research

Figure 4.3: Lasso Logistic Coefficient Path



Source: Developed for the research

4.3 Results and Discussions

This section presents the empirical findings and analysis of the predictive models developed to forecast financial stability and instability. To ensure a robust analysis, the modelling process began with feature selection via LASSO. This technique was used to isolate the most significant predictors and reduce data dimensionality. Subsequently, the dataset was partitioned into training and testing subsets to evaluate model generalization. To maximize predictive accuracy and control overfitting, hyperparameter tuning was executed using Random Search CV. The following sections detail the performance metrics of the optimised models and provide a critical discussion of the key determinants driving financial stability outcomes.

4.3.1 Machine Learning Model Result

4.3.1.1 Regression Model Performance Comparison

To assess the predictive capability of various regression algorithms, we implemented a series of machine learning models. The goal was to estimate the financial stability (Z-score) of global insurance firms. We evaluated these models using key performance metrics. These metrics include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) collectively to evaluate both the accuracy and the explanatory power of each model.

R^2 is the main evaluation metric used in this study to choose the top-performing algorithm. We exclude MAE, MSE, RMSE and MAPE from the selection of the best performing regression rate. These statistics range in the [0, +∞) interval, with 0 meaning perfect regression, and their values alone therefore fail to communicate the quality of the regression performance, both on good cases and in bad cases. Chicco et al. (2021) point out that because metrics like MSE and RMSE are not standardised and range from 0 to +∞, their values by themselves are insufficient to convey a model's performance quality. On the other hand, R^2 offers a more consistent and informative way to measure model fit. A model that performs no better than a basic baseline is represented by a value of 0.0, a model that performs even worse than that baseline is represented by a negative value, and a perfect prediction is represented by a value of 1.0.

The regression machine learning result as shown in Table 4.7, The XGBoost model achieved the highest R^2 and the lowest MSE and RMSE, outperforming all other methods. This aligns with Lao et al. (2021), who demonstrated that XGBoost offers superior accuracy and stability compared to SVR and neural networks when they predicting complex financial risks. Besides that, the CatBoost model produced comparable performance, with an R^2 value of 0.1923 which aligns with prior studies (Ahn et al., 2023; Sahin, 2020). They recognise these gradient boosting variants as effective implementations of the boosting framework.

Gradient Boosting and Random Forest demonstrated consistent performance, with R^2 values of 0.1784 and 0.1673, respectively. This result is align with previous study result which stated the Gradient Boosting typically outperforms single decision trees or other ensemble techniques like Random Forest in prediction performance (Sahin, 2020; Yadav et al., 2024). Overall, this result is consistent with those authors' statement. While their relative accuracy may differ based on data structure, bagging and boosting algorithms frequently show comparable predictive strength (Huang et al., 2020; Didavi et al., 2021).

In contrast, traditional linear models such as Linear Regression, Ridge, Elastic Net, and Polynomial Regression demonstrated noticeably weaker performance as the R^2 values ranged between 0.1453 and 0.1182. This suggests that linear structures struggle to capture the non-linear interactions present in insurers' financial stability data. This observation aligns with comparative studies in other applied domains where ensemble tree-based models clearly outperform linear approaches (Yadav et al., 2024).

LightGBM underperformed compared with other boosting models, which is expected in smaller financial datasets because its leaf-wise splitting strategy tends to overfit when data are limited or noisy (Sathiyamoorthy & Subramanian, 2025; Hartanto et al., 2023). SVR, Decision Tree, and KNN were the weakest models, with low R squared values ranging from 0.0684 to 0.0448. Decision Trees commonly overfit due to uncontrolled tree growth, while KNN showed sensitivity to high-dimensional data (Garcia Leiva et al., 2019; Hartanto et al., 2023).

However, it is worth noting that while SVR delivered the lower explanatory power, but it achieved the best MAE. This suggests the model minimises average error by predicting close to the central tendency but fails to capture the overall variance of the data which aligns with Winch (2025), who similarly observed that SVR consistently minimises MAE even when predictive accuracy regarding variance which is the R-squared, is low, thereby limiting its applicability for tasks where capturing volatility is essential.

Overall, the results reveal that ensemble-based algorithms, particularly XGBoost, CatBoost, and Gradient Boosting, provide the most accurate and reliable predictions of financial stability. These models outperform linear and non-ensemble methods because of their capacity to manage nonlinear dependencies and complex feature interactions inherent in financial datasets.

Table 4.7: Regression Models Performance Comparison

Model	MSE	RMSE	MAE	R^2
XGBoost	41.99951	6.480703	4.497515	0.221661
CatBoost	43.58185	6.601655	4.658101	0.192337
Gradient Boosting	44.33426	6.658398	4.786439	0.178393
Random Forest	44.93375	6.703264	4.902448	0.167283
Polynomial Regression	46.11885	6.791086	4.882797	0.145321
Linear Regression	46.11885	6.791086	4.882797	0.145321
Elastic Net	46.92995	6.850544	4.965791	0.130289
Ridge Regression	47.5804	6.897854	4.998556	0.118235
LightGBM	48.30071	6.949872	4.941651	0.104886
SVR	49.75459	7.053694	4.030049	0.077943
Decision Tree	50.26741	7.089951	4.777986	0.068439
KNN	51.54147	7.179239	5.31887	0.044828

Source: Developed for the research

4.3.1.2 Classification Machine Learning Model Performance Comparison

To further evaluate the predictive capability of InsurTech adoption and other firm-level factors on the categorical dimension of financial stability, a series of classification algorithms were developed using the key predictors identified through the LASSO classification process. The performance of these models was assessed based on Accuracy, Precision, Recall, F1 Score, and ROC-AUC, as summarised in Table X. Consistent with prior empirical work, using ROC-AUC as the primary parameter for model optimization, the evaluation results reveal important insights into the predictive performance of various models in forecasting financial stability within insurance companies (Isangediok & Gajamannage, 2022).

Acoording to Table 4.8, which shown the classification model performance. The highest ROC-AUC was obtained by Random Forest (0.8762), closely followed by SVM (0.8694) and AdaBoost (0.8687). As a result, Random Forest proved to be the best model, confirming the findings of Dong et al. (2024) about its better performance and ability to withstand overfitting in datasets that are unbalanced. SVM and Logistic regression exhibited lower accuracy compared to the tree-based ensembles. This divergence parallels findings by Zhao and Bai (2022), who observed that Logistic Regression and SVM can achieve higher AUC scores but lower accuracy rate, indicating that the models effectively classify risk probabilities but less capable of capturing correctly.

Meanwhile, tree-based ensemble models such as random forest and Adaboost recorded the quite higher overall Accuracy and Precision which all above 0.7. However, their relatively low Recall scores suggest a tendency to prioritise the prediction of stable firms, thereby missing a substantial portion of instabilityed cases. Naïve Bayes also have a similar situation with those tree-based ensemble models. This observation aligns with Gu et al. (2019), who caution that models trained on imbalanced datasets often favor the majority class, producing inflated accuracy scores but limited effectiveness in identifying minority cases.

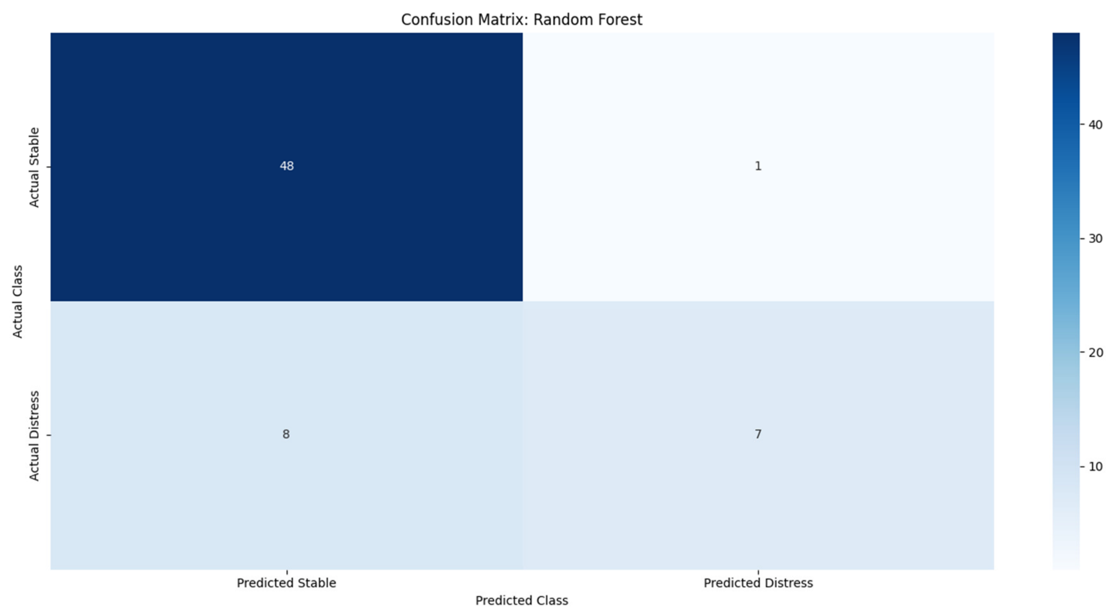
Figure 4.4 displays the Random Forest model's confusion matrix. According to the matrix, the model accurately identified seven unstable firms (True Positives) and 48 stable enterprises (True Negatives). Besides that, it misclassified one stable company as unstable (False Positives) and eight unstable companies as stable (False Negatives). The recall is 0.4667 when there are eight false negatives. Although the Random Forest model has better accuracy and ROC-AUC, this relatively low false negative shows that about half of the at-risk companies are not identified by this particular model.

Table 4.8: Classification Model Results

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
Random Forest	0.8594	0.8750	0.4667	0.6087	0.8762
SVM	0.7969	0.5556	0.6667	0.6061	0.8694
AdaBoost	0.8438	0.7273	0.5333	0.6154	0.8687
CatBoost	0.8281	0.7000	0.4667	0.5600	0.8476
XGBoost	0.8438	0.7778	0.4667	0.5833	0.8354
LightGBM	0.8594	0.7500	0.6000	0.6667	0.8136
Logistic Regression	0.7656	0.5000	0.8000	0.6154	0.8054
Gradient Boosting	0.8281	0.7500	0.4000	0.5217	0.7864
Decision Tree	0.7656	0.5000	0.7333	0.5946	0.7830
Naive Bayes	0.8438	1.0000	0.3333	0.5000	0.7510
KNN	0.8125	0.6667	0.4000	0.5000	0.7197

Source: Developed for the research

Figure 4.4: Random Forest's Confusion Matrix



Source: Developed for the research

4.3.1.3 Classification Machine Learning Model Performance After SMOTE

According to table 4.9, there is shown the class distribution statistics before Synthetic

Minority Oversampling Technique (SMOTE) and after SMOTE. By applying SMOTE to address class imbalance, SMOTE improved the models' sensitivity toward financially unstable firms by generating synthetic samples for the minority class, ensuring that the classifiers learned more effectively from both stable and instable cases. According the model result without SMOTE, there result been affected by data imbalanced; hence, relying solely on accuracy is insufficient due to the class imbalance between stable and instable firms.

According to Hassanzadeh et al. (2023) and Li (2024), classifiers may obtain high scores by only predicting the majority class while failing to catch the minority events of interest, therefore accuracy is frequently not a reliable metric for imbalanced datasets. Therefore, rather than merely maximizing overall correct classifications, the ROC-AUC result was given priority to ensure that the models successfully indicated financial instability.

The classification model result following SMOTE is displayed in the table 4.10. After comparing to the imbalanced dataset's model result, the SMOTE implementation produced better model results in the ROC-AUC score. This enhancement is consistent with the findings of Zhao and Bai (2022), who emphasized the important contribution of SMOTE to improving AUC performance. With the greatest ROC-AUC of 0.8721, following with slightly higher F1-score of 0.6250, and an accuracy of 0.8125, the XGBoost Classification model proved to be the most reliable and well-balanced classifier in this investigation.

Figure 4.5 displays the confusion matrix for the XGBoost model after applying SMOTE. It shows that XGBoost model correctly identified 10 cases of financial instability (True Positives) and 42 financially stable firms (True Negatives). Besides that, the model missed five distress cases, labeling them stable. It also incorrectly flagged seven stable firms as distressed. This shows the model effectively finds the minority class while keeping accuracy high. These results match Qi's (2025) findings. That study showed enhanced regularisation improves AUC scores in distress prediction.

Other model such as Adaboost also produced the best overall accuracy and F1 score. However, it had a marginally lower ROC-AUC compared to XGBoost, so the model was less successful at class separation. SVM also attained a ROC-AUC of 0.8408. However, it is less practical due to its lower precision and F1-score. Overall, the outcome demonstrates that ensemble approaches outperform conventional single classifiers. This is consistent with the research conducted by Kitova et al. (2025) and Liu et al. (2025). They discovered that models like SVM and Logistic Regression were consistently outperformed by tools like XGBoost.

Besides that, the XGBoost also achieved the highest R^2 value in the regression analysis. This proves its superior stability and power in predicting financial performance. Its result is consistent outperformance across both classification and regression frameworks, highlighting its reliability. Therefore, XGBoost is the most dependable model for predicting financial stability in insurance firms.

Table 4.9: Class Distribution Statistics

	Count	**Percentage (%)**	**Stage**
0	193	75.69	Before SMOTE
1	62	24.31	Before SMOTE
0	193	50	After SMOTE
1	193	50	After SMOTE

Source: Developed for the research

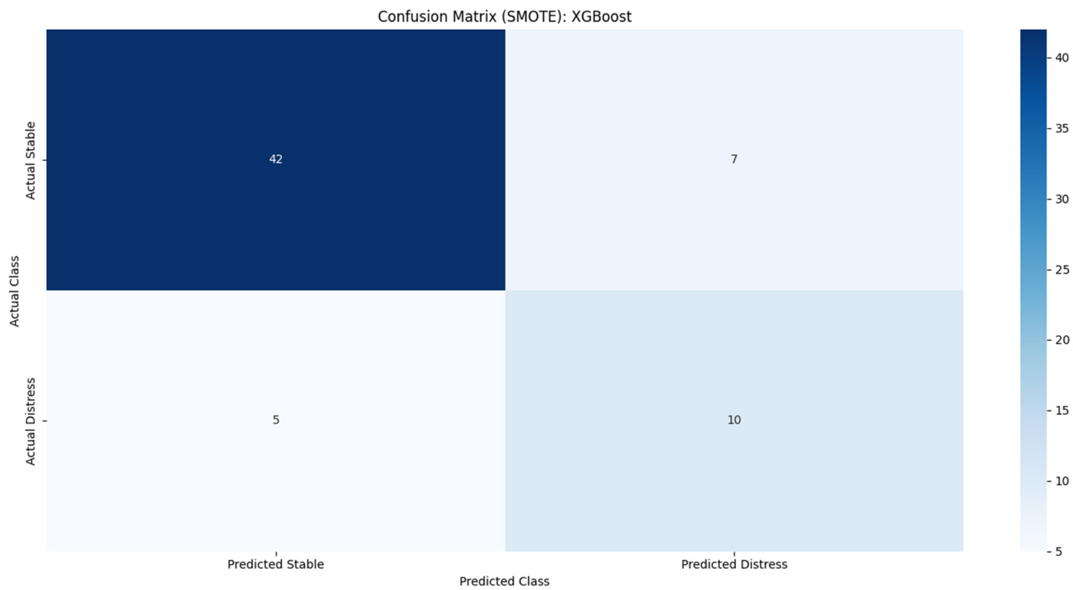
Table 4.10: Classification Model Result After SMOTE

Model	Accuracy	Precision	Recall	F1 Score	ROC-AUC
XGBoost	0.8125	0.5882	0.6667	0.6250	0.8721
AdaBoost	0.8594	0.6875	0.7333	0.7097	0.8653
CatBoost	0.8125	0.5882	0.6667	0.6250	0.8599
Gradient Boosting	0.8125	0.5789	0.7333	0.6471	0.8531
Random Forest	0.8281	0.6250	0.6667	0.6452	0.8476
SVM	0.7813	0.5294	0.6000	0.5625	0.8408
Logistic Regression	0.8125	0.5789	0.7333	0.6471	0.8367

LightGBM	0.8438	0.6667	0.6667	0.6667	0.8313
KNN	0.7969	0.5500	0.7333	0.6286	0.7469
Naive Bayes	0.6094	0.3333	0.6667	0.4444	0.7306
Decision Tree	0.7344	0.4583	0.7333	0.5641	0.7272

Source: Developed for the research

Figure 4.5: XGboost's Confusion Matrix



Source: Developed for the research

4.3.2 SHAP Analysis

To gain deeper, SHAP analysis was employed to get more transparent insights into the factors driving the predictive outcomes of the best-performing models. The summary plots show the direction and strength of a feature's influence. The feature's value for that specific instance is represented by the colour, which goes from low (blue) to high (red).

4.3.2.1 Regression Model SHAP Analysis

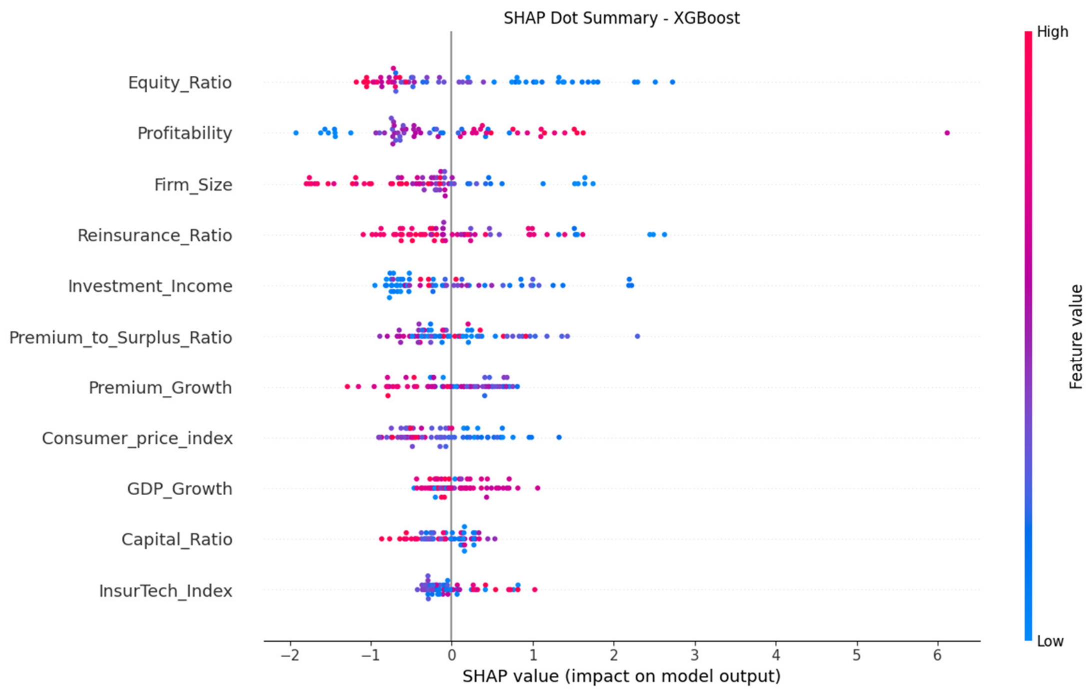
According to Figure 4.6, The SHAP summary plot for the XGBoost regressor reveals the key drivers of predicted financial performance among insurance firms. The plot shows how each feature influences the model's continuous output which is Z-score or financial stability, with colours indicating the magnitude of feature values. The red colours for high and blue for low. Then, the Figure 4.7 which is the SHAP bar summary, there shown the SHAP value and rank start from most significant. The SHAP analysis largely supports the LASSO regression findings and validates the key determinants of financial stability.

Consistent with the LASSO model, Firm Size and Equity Ratio show a negative relationship with the Z-score. High feature values (shown in red) result in negative SHAP values. This trend aligns with Rahel (2025). It highlights operational inefficiencies in larger firms. It also supports the pecking order theory (Kusi et al., 2017). This theory suggests that too much equity financing puts pressure on management, so it will undermine stability. Conversely, Profitability stands out as the main positive driver. Higher margins push the model toward greater stability, which aligns with Puławska's (2021) findings on European insurers. Furthermore, the positive impact of InsurTech adoption confirms Braun and Jia's (2025) claim. They stated that digital transformation improves solvency through better risk control and efficiency.

However, the SHAP analysis gives better insight into variables with non-linear relationships, especially for Premium Growth and the Premium-to-Surplus Ratio. LASSO assigns a positive coefficient to Premium Growth which suggests a linear benefit to expansion, but the SHAP summary plot reveals a different story. High growth rates often have a negative impact on the model's output. This indicates that the non-linear model captures the risks of rapid expansion. The linear model overlooks this.

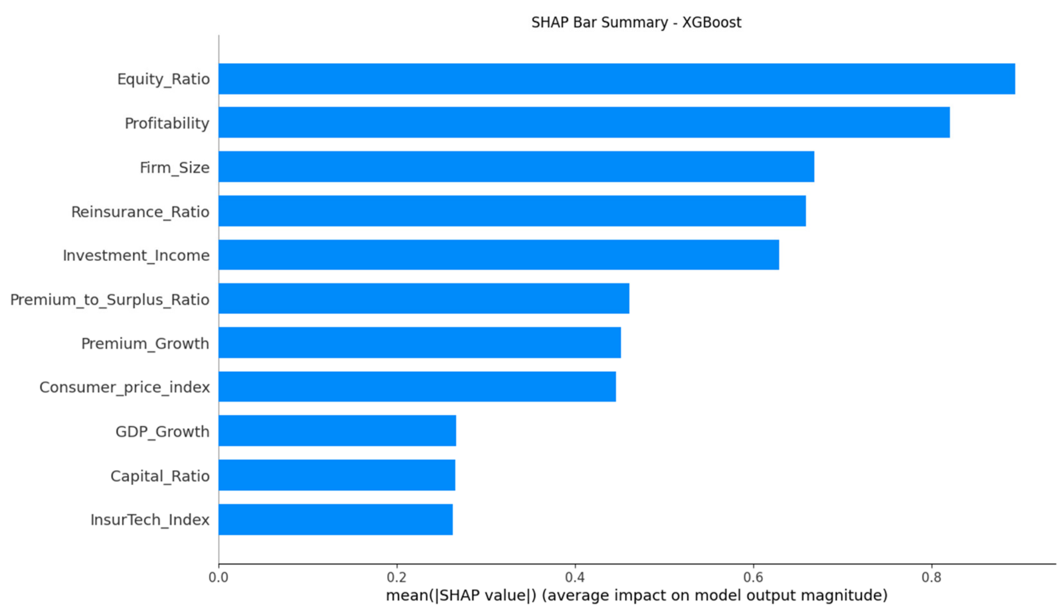
Similarly, LASSO suggests a small positive effect for the Premium-to-Surplus Ratio. But SHAP values align more closely with economic theory. They indicate that high ratios negatively impact stability. This suggests that the XGBoost model detects the risks of over-leverage successfully. Lee (2023) supports this interpretation. He observed that higher premium growth without more surplus harms financial stability. This confirms the inverse relationship between insurance leverage and solvency.

Figure 4.6: SHAP Summary Plot in Regression Model



Source: Developed for the research

Figure 4.7: SHAP Bar Chart in Regression Model



Source: Developed for the research

4.3.2.2 Classification Model SHAP Analysis

The Figure 4.8, which is the SHAP summary plot for the XGBoost classifier provides valuable insight into the drivers of financial instability among insurance firms, where the binary target variable indicates instability (1) if the firm's Z-score is below 3, and stability (0) otherwise. Each dot represents the SHAP value for a single observation, showing both the magnitude and direction of each feature's contribution to the model's output, while color represents whether the feature value is high (pink/red) or low (blue). Surprisingly, the summary plot shown the same directional findings with the LASSO classification. Moreover, Figure 4.9 which is the SHAP bar summary hierarchy in feature importance. While both models agree on the protective nature of efficiency metrics and the risk posed by inflation, the XGBoost model reorders the priority of these drivers based on their non-linear contribution to predicting financial instability.

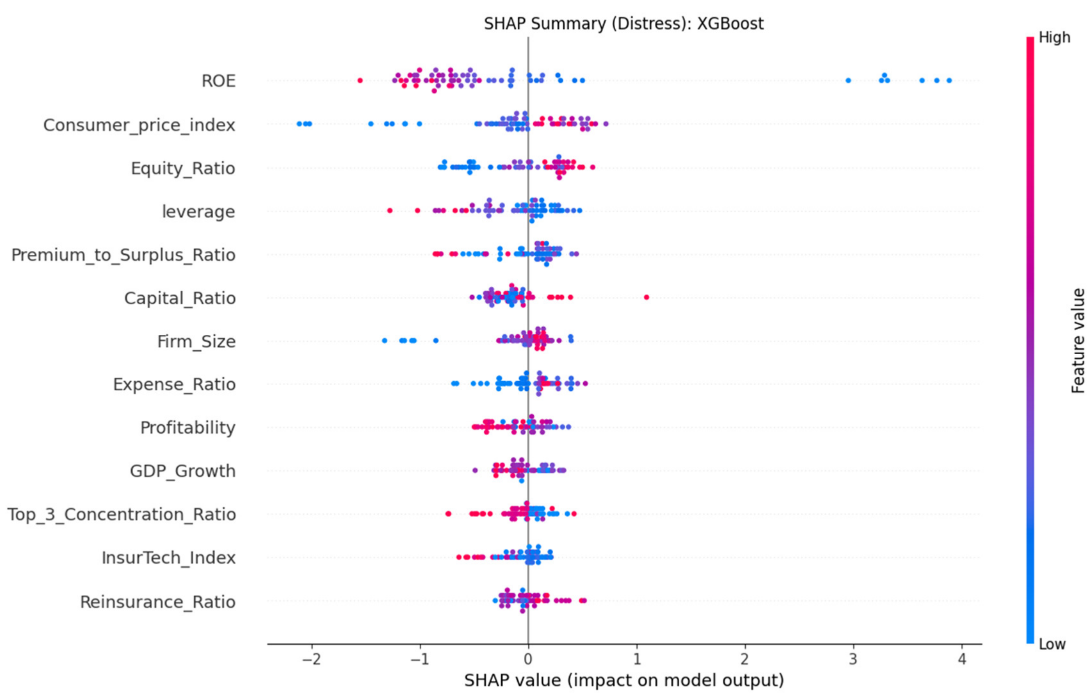
At the top of the chart, ROE stands out as the most influential predictor. Higher ROE values (shown in red) correspond to lower SHAP values. This indicates a negative relationship with financial instability. Basically, firms with strong profitability and shareholder returns are less likely to become unstable. This finding aligns with Altuntas and Rauch (2017). They validated the significant positive impact of ROE on financial stability across global insurance markets. Conversely, the Consumer Price Index (CPI) also shows a strong influence. Higher CPI values tend to increase SHAP values. This suggests that inflationary pressures raise financial risk by eroding real profitability. This positive link with instability matches Ritho (2024), who observed that inflation tends to undermine insurer stability.

The Equity Ratio follows as a key explanatory variable. The SHAP summary plot shows mostly positive SHAP contributions for high values. This means a higher equity ratio tends to increase the predicted probability of financial instability. In contrast, the

SHAP summary plot shows that Leverage has negative SHAP contributions. This means higher leverage tends to increase financial stability. This suggests that holding too much capital might be inefficient compared to using debt. This aligns with the findings of Hersugondo et al. (2021).

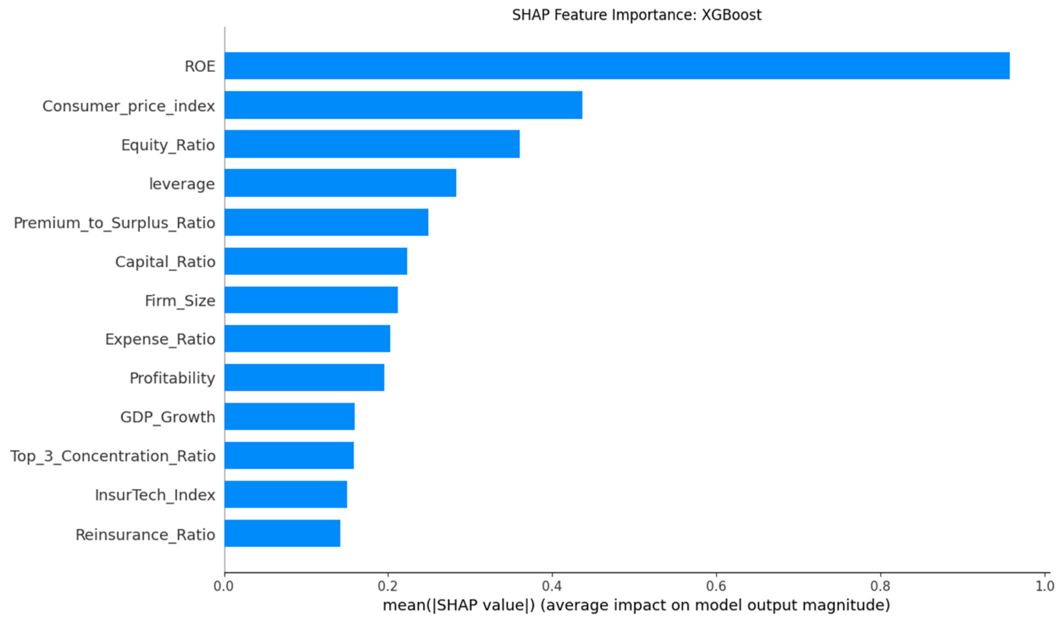
Finally, the InsurTech Index remains a relevant protective factor in the non-linear analysis. Its importance ranking is lower than dominant financial ratios like ROE. However, the SHAP summary plot reveals a consistent pattern. High adoption levels (represented by red dots) contribute to a lower probability of instability (negative SHAP values). This confirms that financial resilience is actively supported by technological modernity. This data supports Braun and Jia (2025). They highlighted the stabilizing effect of digital transformation. They proposed that insurers using cutting-edge technologies are better able to reduce operational risks and preserve solvency.

Figure 4.8: SHAP Summary Plot in Classification Model



Source: Developed for the research

Figure 4.9: SHAP Bar Chart in Classification Model



Source: Developed for the research

4.4 Summary of Empirical Results

This chapter presented a complete empirical analysis. It looked at what determines financial stability and instability in the global insurance sector. We built the analytical framework using strict pre-estimation checks. We fixed multicollinearity issues using VIF tests. We also optimized feature selection using LASSO regression. This two-stage process ensured the machine learning models used a strong, clean set of features. This made the predictive results more reliable.

XGBoost was the best performer in both regression (predicting Z-score) and classification (forecasting instability) tasks. Its success over linear models highlights the complexity of financial data. SHAP analysis clearly found hidden risks or non-linear relationships related to Premium Growth and the Premium-to-Surplus Ratio. Linear LASSO models either overestimated or underestimated these risks.

Combining SHAP and LASSO results gives important economic insights. First, ROE and Equity Ratio consistently stood out as the main features affecting stability. Most features showed the same type of relationship in both SHAP and LASSO. Second, the analysis reveals a clear preference for efficiency over caution. The models indicate that active leverage acts as a protective shield. In contrast, holding excessive capital reserves actually increases the risk of instability. This suggests that solvency is better maintained by putting capital to work rather than letting it sit idle. Finally, the study proves the stabilizing role of technology. The InsurTech Index consistently showed a protective influence across both model types.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter builds on the empirical results and discussions from Chapter 4, which identified the key drivers of financial stability using LASSO and XGBoost analysis. Now, this chapter synthesises the overall conclusions of the study. The main goal is to turn the statistical findings into practical insights. This addresses the research objectives regarding how InsurTech adoption and specific firm characteristics impact insurer solvency.

Section 5.1 will summarise the statistical studies and highlight the key empirical findings. Section 5.2 covers the theoretical and managerial implications. It explains how the results benefit stakeholders in the insurance sector. Section 5.3 acknowledges the limitations of the study's methods and data. Section 5.4 suggests directions for future research to address these gaps. Finally, Section 5.5 offers closing thoughts.

5.1 Summary of Statistical Analyses and Major Findings

The statistical analyses in this study combined regression, classification, and model interpretability frameworks. This provided a thorough assessment of the features influencing financial stability in the insurance industry. The dataset included 319 firm-year observations. It showed significant variation in financial performance, especially in the Z-score. While strong multicollinearity among Capital Ratio, Equity Ratio, and Leverage (VIF values exceeding 10) required the use of LASSO regression for variable selection, high volatility was seen in variables like Leverage and Premium Growth. In order to ensure model parsimony and robustness in capturing the most significant firm-level and macroeconomic factors, this technique successfully penalised redundant predictors.

Financial stability was examined from both continuous and categorical perspectives using a dual-modeling framework. While the classification models predicted binary stability outcomes, the regression models predicted the continuous Z-score. The SMOTE was used to improve the model's sensitivity to financial instability by addressing the data imbalance between stable and instable firms.

For every algorithm, Random Search CV optimised model configurations are used for hyperparameter tuning. In both tasks, the XGboost algorithm consistently proved to be the most dependable predictor among all tested models. XGBoost outperformed conventional linear models in the regression analysis and confirmed the non-linear nature of relationships within financial data with the highest explanatory power. It demonstrated strong discrimination ability and reliability in identifying at-risk firms, with the highest ROC-AUC.

The results provide additional support for the proposed connections across all study goals. According to our hypothesis 1 (H1), we stated that financial stability was demonstrated to be positively impacted by InsurTech adoption, and both regression and classification analyses revealed the InsurTech Index to be a significant determinant. In line with earlier research by Braun and Jia (2025), this suggests that technological modernisation, including the incorporation of data analytics and automation, improves solvency and operational resilience.

The results of the model align with Hypothesis 2 (H2). They confirm that firm-specific characteristics play a major role in predicting financial stability. Equity Ratio and ROE were identified as the main stabilizing factors. They safeguard insurers from instability. The capital structure analysis revealed an interesting dynamic. Excessive capitalization, reflected in high Equity and Capital Ratios, was linked to inefficiency. It actually increased the risk of instability. On the other hand, optimal leverage and a balanced premium-to-surplus ratio enhanced stability.

These results support Arhinful and Radmehr (2023). They argued that using leverage effectively strengthens ROE through productive capital deployment. This suggests that solvency is better maintained by using capital efficiently rather than holding it idle. Profitability also stands out as a key factor that safeguards firm stability. However, Firm Size showed a mixed effect, as larger insurers often exhibited lower stability. This indicates possible inefficiencies related to scale. This finding aligns with Rahel (2025). He reported that firm size negatively correlates with insurer profitability, increasing financial vulnerability.

The results for Hypothesis 3 (H3) show a partial divergence from expectations. Industry-level characteristics do influence financial stability, but not in the expected direction. The Top 3 Concentration Ratio exhibited a small but stabilising effect. Insurers in more concentrated markets tend to face a lower likelihood of instability. This reject the hypothesised negative relationship. This finding likely reflects the dataset's composition, as approximately 35% of the top 100 firms are US-based. In mature economies like this, high concentration often characterises stable environments dominated by strong incumbents. This result is consistent with Akintoye et al. (2024). They discovered that increased market concentration boosts profitability and operational efficiency. Therefore, under some market settings, concentration can increase stability rather than diminish it, even if the effect is small.

The model also supports the importance of macroeconomic variables, addressing Hypothesis 4 (H4). Ritho (2024) noted that the CPI frequently had a detrimental effect on financial stability as inflationary pressures threaten insurer solvency. Besides that, there was a marginally positive link between GDP Growth and financial stability which align with the finding of Lagnai et al. (2025). They noted that economic expansion boosts the resilience of the insurance sector.

The SHAP analysis further enhanced these results. It revealed interaction and non-linear effects that linear models missed. Equity Ratio, ROE, Profitability, and Firm Size were the strongest contributors to financial performance in the model. However, excessive Premium Growth and high Premium-to-Surplus Ratios negatively influenced stability. This signals the risks of over-expansion without sufficient capital support. Interestingly, smaller insurers exhibited slightly higher predicted stability which indicates potential efficiency advantages relative to larger firms.

5.2 Implications of the Study

The study's findings have significant ramifications for legislators and business professionals. In an increasingly digitalised insurance environment, they emphasise the necessity of updating regulatory frameworks and bolstering firm-level strategic resilience. The effective application of modern machine learning models, particularly the XGBoost classifier and regressor, highlights the growing need for data-driven decision-making in insurance supervision and corporate strategy. Moreover, SHAP analysis's interpretability reveals intricate, non-linear relationships that conventional econometric methods typically ignore. This helps us understand what changes financial stability as InsurTech grows (Braun & Jia, 2025).

The results emphasise how important it is for regulators to update solvency laws in order to keep up with technological developments. Risk-Based Capital (RBC) and Solvency II might not adequately cover the additional risks connected with digital innovation. This is primarily due to the fact that these regulations were created prior to the widespread adoption of InsurTech (Firouzi et al., 2025). Regulators could identify risk more quickly and accurately and gives supervisors the ability to dynamically improve solvency regulations by incorporating machine learning and predictive analytics into regulatory oversight.

From a managerial perspective, the findings provide clear guidance on strengthening financial stability. Monitoring macroeconomic risk becomes a priority. Inflation weakens real profitability and solvency, which was repeatedly identified as a destabilising factor. Strong earnings are the cornerstone of sustainability, as is demonstrated by the consistent identification of Profitability and Return on Equity (ROE). Executives must manage expenditure ratios and use InsurTech to automate processes, enhance claims processing, and boost underwriting precision.

The empirical validation of the InsurTech Index as a protective factor adds to the strategic significance of digital transformation. By using modern technologies, businesses can significantly improve their operational agility and risk assessment capabilities. Smaller insurers also can be benefited from collaborative partnerships with InsurTech startups. This allows them to overcome scale disadvantages and boost competitiveness.

Regarding capital management, the study contends that the efficiency of capital use determines financial stability, rather than just the size of reserves. Excessive capitalisation often indicates inefficiency and increases vulnerability. In contrast, active capital deployment promotes solvency and growth through optimal leverage and balanced premium-to-surplus ratios. Lastly, risk managers can find early warning indicators of instability by using advanced predictive analytics, such as XGBoost with SHAP interpretability. These models are particularly good at identifying hidden risks that linear models might miss, such as the destabilising effects of rapid premium growth or excessive leverage.

5.3 Limitations of the Study

This study, while offering valuable insights into the determinants of financial stability and the predictive role of InsurTech adoption, is subject to several limitations that should be acknowledged.

First, the limited availability of financial indicators and control variables in the LSEG dataset restricted the scope of the analysis. Some potentially important metrics, such as technical reserve growth and specific solvency or efficiency ratios, were excluded from the predictive modeling framework due to their unavailability. The models' capacity to accurately represent every element influencing the financial stability of insurers may have been hampered by the absence of these factors.

The second restriction concerns the creation of the InsurTech Adoption Index. Although the index was constructed using a strict text-mining and normalisation procedure that included Principal Component Analysis (PCA) and AntConc keyword extraction, it remains a keyword-based measurement. As a result, it might oversimplify the intricate nature of InsurTech adoption. It may fail to adequately convey the strategic context or the qualitative depth of technological integration within each insurer.

5.4 Recommendations for Future Research

Based on the findings and limitations of this study, several directions for future research are suggested to further investigate our understanding of InsurTech's influence on financial stability.

First, the main goal should be to improve measuring techniques and overcome restrictions on data availability. Future research is encouraged to combine numerous data sources rather than relying only on databases like LSEG. This would help capture a larger range of financial indicators, such as technical reserve growth and granular efficiency ratios.

At the same time, InsurTech adoption should be measured in a way that goes beyond simple keyword counting. Researchers should employ modern Natural Language Processing (NLP) and sophisticated text-mining tools to capture the quality and strategic depth of technology integration rather than merely concentrating on its frequency.

Additionally, although this study confirmed the effectiveness of ensemble models, further research should investigate Deep Learning architectures. Models such as Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) could better capture intricate non-linear patterns and temporal dependencies in financial time series data.

To improve the industry's comprehension of digital transformation, thematic expansion is essential. Future research should go beyond composite indices. It should disaggregate InsurTech adoption by looking at the distinct effects of specific technologies, such as blockchain in operations versus AI in underwriting. Comparative studies should also be carried out to distinguish the risk profiles and InsurTech effects between Life and Non-Life (P&C) insurers. Comparisons between developed and emerging markets are also needed, as there are notable differences in market dynamics and regulatory maturity.

Lastly, future research should investigate the creation of updated regulatory frameworks. This could include a "Pillar IV" extension to Solvency II or RBC models. These updates should specifically address the systemic implications of the digital insurance ecosystem, where technological integration introduces new risks like algorithmic bias and cybersecurity threats.

5.5 Conclusion

This study successfully navigated the intricate relationship between InsurTech adoption and the financial stability of international insurers. Using sophisticated machine learning techniques, it provided a solid empirical validation of how digital modernization protects stability. The analysis was grounded in Resource-Based Theory (RBT), Disruptive Innovation Theory, and the TOE framework, covering 319 firm-year observations.The results provide strong evidence regarding the primary research objective: InsurTech adoption serves as a crucial protective shield. The analysis consistently showed that technological integration increases operational resilience across both regression and classification models, validating Hypothesis 1 (H1). The LASSO coefficients highlight a positive connection. This proves that technological modernization is a quantifiable driver of risk management and financial health, rather than just a passing trend.

The study supports Hypothesis 2 (H2), revealing a clear preference for efficiency over sheer scale. ROE, and Equity Ratio were unquestionably the pillars of stability. Crucially, the models challenged conventional wisdom on capital structure. They demonstrated that while managing excessive capital and equity ratios was associated with increased instability risk, active leverage acted as a protective factor. This suggests that the best strategy to preserve solvency in the modern market is to use capital efficiently rather than letting it sit idle. Furthermore, identifying Firm Size as a risk factor challenges the "too big to fail" notion by highlighting the operational limitations that often impede larger businesses.

Regarding the external environment, the analysis confirmed Hypothesis 3 (H3) and Hypothesis 4 (H4). Insurers are highly susceptible to macroeconomic pressures.1 Real profitability and solvency were severely undermined by Inflation (CPI), which proved to be a powerful destabilizing force. Conversely, GDP Growth provided a resilience buffer, and increased Market Concentration offered a marginal stabilizing effect.

Methodologically, this paper advances the field by demonstrating the value of non-linear machine learning algorithms. The XGBoost algorithm outperformed traditional methods. It achieved the highest prediction accuracy with a ROC-AUC of 0.8721 in classification and an R^2 of 0.2217 in regression. Additionally, the application of SHAP analysis provided essential transparency. It identified subtle, non-linear risks, such as the destabilising impacts of rapid premium growth, that traditional linear models were unable to detect.

In summary, this study depicts a changing industry. In the modern global insurance market, operational effectiveness, robust profitability, inflation resistance, and the strategic integration of InsurTech are the decisive factors for financial stability. These matter more than defensive capital conservatism. The practical suggestions and future research directions covered in the dissertation's concluding sections have a strong empirical basis thanks to these findings.

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