International Journal of Innovative Research and Scientific Studies, 8(3) 2025, pages: 3297-3312

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Modeling the determinants of Insurtech Adoption: Evidence from the Saudi Insurance Industry

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Abstract

This research examines the determinants of InsurTech adoption in the insurance sector in Saudi Arabia and their alignment with the Kingdom's Vision 2030 objective of transforming the economy digitally and diversifying it. Employing a previously unutilized, manually created panel dataset of 23 Saudi insurance companies from 2020 to 2022, the research formulates an InsurTech Adoption Index using annual report keyword frequency. The three models of Multiple Linear Regression (MLR), Generalized Additive Models (GAM), and Random Forest (RF) are used to test the impact of firm age, size, profitability, and capital adequacy on the level of InsurTech uptake. The MLR model considers firm age as a linear predictor of increased InsurTech adoption, as a sign of organizational maturity. The GAM model discovers a nonlinear effect of firm size on digital uptake with declining marginal returns at larger sizes. The RF model shows profitability and capital adequacy as prime predictors and demonstrates how interaction terms imply that digitally inclined firms with robust capital buffers are more active in terms of InsurTech uptake. The research concludes that InsurTech uptake is influenced by subtle but multifaceted interactions between structural and financial firm attributes. The linear models might mask vital dynamics and highlight the importance of elastic and machine learning models to comprehend diffusion in insurance. The insights presented are valuable to insurers and policymakers to formulate targeted digitalization plans. Aligning the firm capabilities with the country's goals of digitalization could better foster InsurTech uptake in the Saudi market and contribute to overall financial sector modernization under Vision 2030.

Keywords: Digital transformation, Insurance sector, Insurtech adoption, Machine learning models, Saudi Arabia, Vision 2030.

DOI: 10.53894/ijirss.v8i4.7229
Funding: This study received no specific financial support.
History: Received: 7 April 2025 / **Revised:** 12 May 2025 / **Accepted:** 13 May 2025 / **Published:** 20 May 2025

Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.
Transparency: The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

The worldwide insurance industry is facing an accelerating digital transformation through InsurTech - the use of advanced technologies (AI, blockchain, big data, cloud, etc.) for insurance products and activities. Experts suggest that digitalization obliges insurers to prioritize customer experience improvement, simplification of core activities, enabling innovative products, and readiness to face competition from entrant players in the market. For instanceEling and Lehmann [1] list these four strategic imperatives as the key challenges confronting insurers in a digital age: enhancing service quality, increasing process efficiency, developing novel coverage solutions, and protecting market position from tech-based competitors. Similarly, in line with this, Cosma and Rimo [2] document an increasing body of InsurTech research and emphasize the heavy focus on artificial intelligence and blockchain in insurance. The systematic review of their report indicates that InsurTech is "redefining" traditional insurance by supporting data-driven underwriting and claims automation that is indicative of the industry's move toward completely digital value chains. These observations emphasize that InsurTech is no longer marginal: it is becoming the focal point of change in global insurance, with the potential for efficiency gains and novel business models. Simultaneously, emerging markets provide fertile ground for the adoption of InsurTech due to relatively low insurance penetration as well as extensive use of handheld devices. International industry trends and analyses, as well as individual examples, imply that InsurTech startups are reaching out with coverage to previously unserved segments (i.e., microinsurance through smartphone apps), but scholarly studies on these trends are just starting to materialize. The development of embedded insurance - i.e., when coverage is extended as an integrated feature of other digital goods - is gaining momentum in much of the world. InsurTech is, in short, dramatically reforming the industry, placing pressure on all insurers either to change or fall behind.

1.1. Insurtech and the Saudi Insurance Market

Saudi Arabia's insurance industry is fast becoming the focus of the global digitalization drive. Financial innovation and digitalization have ranked highest in importance for the Kingdom as pillars of diversification in Vision 2030. Policymakers and regulators are actively encouraging fintech innovation (including InsurTech) through measures like sandboxes and innovation centers with the goal of digitizing the financial system and enhancing financial inclusion. These policies make Saudi Arabia an aspiring leader in adopting InsurTech in the Gulf. Indeed, anecdotal evidence suggests increasing interest from local insurers as well as customers: for instance, in a recent survey, an overwhelming majority of Saudi consumers would welcome access through cellular devices [3] anticipating readiness through digital channels.

Nonetheless, the Saudi insurance sector remains traditionally oriented in several ways. The Saudi Arabian penetration levels continue to be low in comparison with other countries, while numerous insurers continue to be equipped with legacy IT systems as well as traditional distribution systems. Previous studies indicate that Saudi insurers face major obstacles to embracing digital transformation, ranging from outdated infrastructure, cybersecurity issues, uncertainty regarding regulation, and skill shortages. Small carriers have an especially tough time with budget constraints when moving their systems or applying new technology. These challenges are also present in other emerging markets but with Saudi-specific conditions (i.e., fast reform in the economy, Islamic finance environment). All in all, whereas the Saudi market features extensive policy support as well as user demand for InsurTech, tangible proof remains ambiguous, as does the limited academic knowledge on how firms behave in such an environment.

Indeed, academic studies of InsurTech in the Middle East - or Saudi Arabia in particular - are relatively rare. Most of the available studies on adoption in the Middle East focus on banks or financial services in general, not directly on insurance companies. Those few policy and industry reports covering Saudi insurance comment on the digital divide but fail to empirically investigate adoption drivers. The gap in the literature indicates that little systematic knowledge exists regarding Saudi insurers' adoption choices of InsurTech solutions. Are larger or more profitable firms going to invest in digital innovations? Does an acquisition cost ratio measure of efficiency explain technology adoption? These issues need to be addressed for practice as well as for regulators seeking to create an innovative, competitive insurance industry in alignment with the 2030 vision. Theoretical Perspectives on Innovation Adoption.

To structure our investigation of InsurTech adoption, we leverage existing innovation-adoption theories. The Technology-Organization-Environment (TOE) framework is of particular relevance at the firm level: it suggests that adoption is jointly dependent on technological context (e.g., perceived value of the innovation, innovation complexity), organizational context (e.g., firm size, management support, resources), and environmental context (e.g., market pressure, regulation)) [4]. For example, Gupta et al. [5] apply the TOE framework in the insurance industry, demonstrating that technological (relative advantage of AI solutions), as well as organizationally and environmentally related variables, considerably contribute to insurers' adoption intentions. For our work, similar TOE variables would encompass the availability of facilitating tech infrastructure, commitment from senior management, as well as the regulatory environment for InsurTech in Saudi Arabia. Complementing TOE, the Resource-Based View (RBV) offers insight into firm-specific capability. RBV advises that distinctive internal resources and capabilities drive a firm's capacity for delivering innovations [6]. Applied in the context of InsurTech, insurers with robust financial resources, technical proficiency, or effective operations should be in a superior position to adopt new technologies. For instance, greater return on equity (ROE) translates into greater financial slack available for funding innovation investments, whereas low policy acquisition costs (PACR) or strong operating cash flow (OCFR) indicate healthy and efficient operations that enable investment in technology. Under an RBV rationale, therefore, we hypothesize that these financial and operational indicators - as surrogates for capability - will correlate with increased adoption of InsurTech. In summary, TOE informs us of external or structural facilitators/boundaries, while RBV draws attention to internal capability; together they help us select predictors in adoption modeling.

1.2. Research Gaps and Study Objectives

Although these models have extensive use in practice, their usage, particularly in the Saudi insurance industry for InsurTech adoption, is novel. There is little empirical research on firm-level drivers of InsurTech adoption within the Saudi market. General overviews (e.g. Cosma and Rimo [2]) emphasize that much about InsurTech has not been investigated in depth, particularly in emerging markets. Our work aims to bridge that gap by developing a quantitative adoption model for InsurTech based on Saudi insurance firm data. The work centers on linking firm performance measures - in particular, ROE, PACR, and OCFR - with adoption probability. Grounding in TOE and RBV is used here to contribute both in practice and in theory.

Particularly, the current investigation aims to respond to the following research Questions.

- To what degree is the adoption of InsurTech solutions affected by firm age?
- How do the likelihood and intensity of adopting InsurTech depend upon firm size?
- How does profitability of firm influence the adoption likelihood of InsurTech?
- How does Policyholder's Capital Adequacy Ratio interact with other organizational features in order to impact adoption of InsurTech?

The results will provide insights for managers as well as regulators in Saudi Arabia on what strengths in the organization to utilize, as well as what barriers to overcome, so that the development of the insurance industry can be harmonized with the country's overall digitization goals of Vision 2030.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on InsurTech adoption, focusing on global trends, technological drivers, barriers, and regional studies, with particular attention to the Middle East and Saudi Arabia. Section 3 presents the methodological framework, including the theoretical foundations (TOE and RBV), data description, and the statistical models applied (MLR, Random Forest, and GAM). Section 4 discusses the empirical results of the models and provides comparative insights into the significance and explanatory power of various financial and organizational predictors. Finally, Section 5 concludes by summarizing the key findings, discussing implications for insurers and policymakers, and proposing directions for future research in the domain of digital insurance transformation.

2. Literature Review

The industry is undergoing rapid digital transformation ("InsurTech"), harnessing artificial intelligence, big-data analytics, blockchain, and the Internet of Things to automate processes, improve customer service, and enhance efficiency. A recent systematic review observes an "emergent trend in scientific production on InsurTech" and highlights the priority for research on AI and blockchain implications for insurance [2]. Across the world, insurers are embracing digital solutions to improve efficiency as well as access underinsured segments. For instance, telematics systems based on the Internet of Things enable auto insurers to gather driving conduct data and provide usage-based pricing as well as driving incentives for safety. These innovations can significantly enhance fraud prevention and risk assessment [7]. Indeed, insurers are embracing digitalization through disruptive technologies to enhance operational efficiency, business value, and social wellbeing. In developing markets, InsurTech is viewed as an engine for financial inclusion: low insurance coverage (typically below 10%) prompts leapfrogging to digital solutions [8, 9]. Altogether, the global literature attests that digital innovation is restructuring markets for insurance to provide increased customer-focused and accessible solutions [10].

Drivers of InsurTech Adoption: Technology acceptance studies suggest that some variables promote insurers' as well as customers' adoption of InsurTech. Aligned with the TAM and UTAUT models, perceived usefulness (or performance expectancy) and perceived ease of use (effort expectancy) are key drivers of adoption [11, 12]. On the FinTech front, convenience, as well as cost savings, are key incentives in India [13] also extending their influence on insurance. For example, Velmurugan [14] reports in India that ease of use, usefulness, as well as awareness were found to be significantly and positively associated with InsurTech adoption. For the same, trust also played an indispensable role: a secure platform with reliable performance heightened user confidence in InsurTech services. Similarly, FinTech adoption work emphasizes the mediating role played by trust. Ali et al. [15] demonstrate that the perceived benefits of FinTech increase users' trust, and in turn, increased trust significantly enhances adoption intention, counteracting perceived risks. Simply put, users tend to adopt insurance technology when they find that it functions well, is easy to use, and can be trusted [11, 15].

The insurers are driven by operational benefits: digital solutions can decrease costs and enable insurers to provide personalized products. Telematics platforms provide accurate risk-based pricing and proactive risk management, which is beneficial for insurers as well as customers [16]. AI-based applications are desirable too: TOE framework-based studies indicate that employees in the insurance industry see a relative advantage in AI for underwriting, as well as for claims, although readiness within an organization (for example, in the form of management support and financial resources) is required in order to utilize such systems [5]. InsurTech can generally assist insurers in reducing paperwork, enhancing the speed of delivery of service, as well as accessing new customer segments [7, 17] - all drivers of the adoption choice. Barriers and Risks: While such advantages exist, the adoption of InsurTech is also faced with notable barriers. First is the question of trust and security. Potential users are not keen on exposing personal or financial information on new sites. Consistent with FinTech literature, perceived privacy risk is powerful in deterring usage: according to Gharahkhani and Pourhashemi [18], ease of use and perceived usefulness have positive impacts on the adoption of mobile insurance, while privacy issues negatively impact intent to use. Tian and Liu [16] concur that trust is "crucial" for telematics adoption - in its absence, numerous users resist fitting the car-tracking device. Systematic analysis of FinTech concludes that a lack of trust or security discourages the adoption of the system [19]. For the organization, insurers are clogged with legacy systems and skill shortages: numerous older insurers have no IT capability or capacity within their ranks and do not have the IT systems or talent necessary for applying advanced analytics [20]. Problems of regulation as well as compliance burden adoption as well. InsurTech innovation tends to outrun insurance regulation, generating uncertainty. For instance, Altwijry et al. [21] inform us that Saudi Islamic insurers regard the fragmentation of regulation as an obstacle and cite the need for specialized FinTech regulation in order to aid growth. On the ground, regulators everywhere (including their Saudi central bank counterpart) continue to draft guidelines for digital insurance, with such legal uncertainty hindering adoption. On balance, privacy issues, cultural resistance, as well as compliance uncertainty are major deterrents cited in the literature [15, 21].

Technology Trends: AI and IoT in Insurance: The literature emphasizes particular innovations within InsurTech. IoT/Telematics has already been mentioned; it is an example of how networked devices can revolutionize insurance. Studies characterize telematics as revolutionizing insurer-client relationships through usage-based insurance as well as real-time risk feedback [16]. This generates win-win incentives (safe driving discounts, improved underwriting) as well as causes for concern regarding privacy and trust. Artificial Intelligence is another emerging frontier. Gupta et al. [5] demonstrate that Indian insurers' employees acknowledge AI's relative benefits for tasks such as claims processing. They do, however, comment that technical capability as well as corporate backing are what ensure that AI-based projects succeed. Next-generation blockchain applications (yet not mainstream) also hold out prospects for contracted-upon smoothing as well as fraud prevention, which InsurTech analyses have labeled as areas of particular interest for future research. More broadly, digital services such as smartphone applications, chatbots, and analytics involving large quantities of data are being trialed in areas such as claims handling, underwriting, as well as customer engagement. All of these technologies have common drivers (efficiency, personalization) as well as obstacles (integration cost, data governance) between studies.

Contextual and Regional Studies: Aside from global trends, some recent papers investigate InsurTech in particular regions. For Asia, Velmurugan [14] researched India's fledgling InsurTech market and concluded that TAM variables, awareness, and incentives were important (supporting the role of user perceptions). For Korea, another study finds TAM and social influences are decisive for the adoption of digital insurance, with demographic variables (age, income) having mixed impacts. The Chinese insurance market is also being affected by fintech; [10] reports that Chinese insurers are embracing digital channels and analytics, revolutionizing distribution.

In Africa, the context of InsurTech is set against low insurance penetration. Kiwanuka and Sibindi [8] establish in Uganda that digital literacy is a robust determinant: those with greater technical abilities are more likely to adopt digital insurance, and increased adoption, in turn, facilitates greater insurance inclusion. This indicates that educational and digital infrastructure drivers, usually dismissed in developed economies, play important roles in emerging markets. One associated finding is that both behavioral (trust, literacy) and non-behavioral (cost, documentation) barriers constrain the usage of insurance, and digital platforms help overcome some of these [8, 22].

Empirical work for the Middle East and Saudi Arabia is limited. One such qualitative case study from Altwijry, et al. [21] examines FinTech in Saudi Takaful (Islamic insurance). They document that FinTech tools have entered core activities - for instance, claim handling, sales, and actuarial functions are already embracing digital systems - with efficiency benefits and innovation. The study, however, also highlights that Saudi insurers need strategic assistance (data centralization, regulatory reforms) in order fully to take advantage of FinTech. Another 2019 Saudi insurance market study previously cited also recognized that insurers need to drive a digital culture and upgrade online services in terms of scope and quality in order to fulfill Vision 2030 targets [23]. Combined, these regional contributions establish that Saudi insurers appreciate the importance of InsurTech but struggle with organization and institution.

Synthesis and Gaps: Together, the literature highlights drivers of adoption (perceived usefulness, ease of use, trust, cost savings) as well as barriers (privacy risk, uncertainty of regulation, legacy systems) in insurance technology. Many results mirror universal FinTech adoption models (UTAUT/TAM) supplemented with variables such as awareness and incentives [14, 18]. There are some gaps, though. Most studies either survey end-users (policyholders) or take a narrow focus on a single technology (e.g., telematics or mobile apps). Few take an integrated, firm-level approach including organizational and environmental drivers. As Cosma and Rimo [2] note, InsurTech studies tend to be discipline-specific and fragmented; they recommend interdisciplinarity. Crucially, little peer-reviewed work exists on InsurTech adoption in the Saudi environment. Saudi-based studies existing in the literature [21, 23] are narrow in scope and method. We could not find a quantitative model of drivers of InsurTech adoption for Saudi insurers. That gap is glaring in light of the Kingdom's drive for digital transformation (Saudi Vision 2030) and the distinctive Islamic finance environment.

The purpose of this research is to bridge that knowledge gap through empirical modeling of the drivers of InsurTech adoption in the Saudi Arabian insurance industry. Drawing from international and MENA region-specific evidence, it will test how independent research variable drivers influence insurers' adoption. With that, the study will overcome the drawbacks of existing research (i.e. limited focus or absence of contextual variables) and deliver insights to the Saudi market. Identifying these drivers and inhibitors in situ will enable regulators and industry stakeholders to develop strategies for promoting digital innovation, enhancing insurance take-up, and maintaining the competitive standing of Saudi insurers.

3. Methodology

3.1. Data Description and Preprocessing

This study is based on a manually compiled panel dataset drawn from the annual board reports of all listed insurance companies operating in the Kingdom of Saudi Arabia over a three-year period (2020 to 2022). The data were extracted from publicly available disclosures, including financial statements, management discussions, and operational summaries published by the Saudi Stock Exchange (Tadawul) and official company websites.

A total of 23 insurance firms were analyzed, providing 69 firm-year observations. These firms represent the full scope of the regulated Saudi insurance market, offering a comprehensive view of technological adoption and financial performance across the sector.

The study focuses on examining the relationship between InsurTech adoption and various financial, operational, and structural factors. Variables were selected based on theoretical relevance and data availability, and were cleaned and transformed as needed to ensure consistency across firms and years.

Table 1.
Variable Descriptions and Formulas.

Abbreviation	Description	Formula
IT	InsurTech Adoption Index per 1,000 Words	(Ratio of keywords frequency / total word count in the annual board report)*1000
AGE	Number of years since establishment	-
log(ASSE)	Natural log of total assets	log(Total Assets)
log (NCC)	Natural log of Net Change in Cash and Cash Equivalents	log(Cash_{end} - $\text{Cash}_{\text{begin}}$)
OCFR	Operating Cash Flow Ratio	Net cash flows from operating activities / Total shareholders' liabilities
IAR	Investment Activity Ratio	Net cash flows from investing activities / Total shareholders' assets
FAR	Financing Activity Ratio	Net cash flows from financing activities / Total shareholders' liabilities and equity
PGR	Premium Growth Rate	(Net premiums $_{t}$ - Net premiums $_{t-1}$) / Net premiums $_{t-1}$
PACR	Policy Acquisition Cost Ratio	Policy acquisition costs / Gross premiums written
NPRR	Net Premium Retention Ratio	Net premiums earned / Gross premiums written
PM	Profit Margin (Pre-Zakat)	Net profit before zakat / Net premiums earned
ROA	Return on Assets	Net profit before zakat / Total shareholders' assets
ROE	Return on Equity	Net profit before zakat / Total shareholders' equity

The dependent variable, InsurTech adoption (IT), was derived through text analysis of the annual board reports of each insurance firm. Specifically, the IT index was computed by quantifying the relative frequency of key digital and technological terms indicative of InsurTech initiatives. These terms included: Digital Claims, Digitalization, Digitalizing, Digitalization, Digitalized, Digitally, E-policy, Fintech, Infotech, InsurTech, IoT, Mobile App, Robot, Robotic, Robots, Smart Contracts, Tech, Technological, Technologies, Technology, and Telematics.

For each report, the number of occurrences of these terms was summed and then divided by the total word count of the report, resulting in a normalized score representing the firm's emphasis on technology adoption. This approach allows the measure to reflect not only the presence but also the intensity of InsurTech-related discourse in official disclosures, thereby serving as a consistent proxy for digital engagement across firms and years.

Additionally, selected financial variables such as total assets (ASSE) and net change in cash (NCC) were log-transformed to mitigate the effects of skewness and ensure homoscedasticity in the regression models. All continuous and ratio-based independent variables were standardized prior to model estimation to facilitate interpretation and comparability.

3.2. Model Descriptions

3.2.1. A Multiple Linear Regression (MLR)

A Multiple Linear Regression (MLR) is a parametric model with the assumption that the response variable Y is linearly dependent on multiple predictors. Mathematically, for observations $i = 1, \dots, n$ Extending

where $\beta_0, \beta_1, \dots, \beta_p$ are unknown coefficients and ε_i is a random error term. In vector form one often writes $Y = X\beta + \varepsilon$, where X is the design matrix of covariates. The classical assumptions for MLR (sometimes called the Gauss-Markov conditions) are that the model is correctly specified (linearity in parameters), the errors ε_i have zero mean and are uncorrelated, and have constant variance (homoscedasticity) across all i [24]. In practice this also implies that the predictor values x_{ij} are measured without error and that there is no perfect multicollinearity among the columns of X. Under these conditions the ordinary leastsquares (OLS) estimator $\hat{\beta} = (X^\top X)^{-1} X^\top Y$ is unbiased and achieves the smallest variance among all linear unbiased estimators. If the errors are further assumed Gaussian, one can perform standard hypothesis tests and confidence intervals on the β_j coefficients [24]. In predictive modeling, the linearity assumption means MLR can only capture additive linear effects of the predictors on the outcome. Violations of assumptions can degrade performance: for example, heteroscedasticity or correlated errors invalidate inference, and high intercorrelations among predictors (multicollinearity) can inflate coefficient variances and make individual effects unstable Shrestha [25]. Shrestha [25] notes that when predictors are highly collinear, the standard errors of the estimated coefficients increase and apparent significance may be lost, rendering the model difficult to interpret [25]. MLR is widely used because of its simplicity and interpretability: each coefficient β_j represents the average change in Y per unit change in predictor X_j, holding other variables constant. This makes MLR transparent and easy to implement. The model can be fit efficiently even for large n and p using closed-form OLS or iterative solvers. However, MLR has well-known limitations in predictive accuracy if its assumptions are violated. In particular, if the true relationship between the predictors and the response is nonlinear, a purely linear model will be misspecified and yield biased predictions. Also, MLR is sensitive to outliers and influential observations, and it cannot automatically capture interactions or complex effects unless they are explicitly included. In high-dimensional settings, OLS can overfit or fail if p is large relative to n, and inference breaks down in the presence of perfect collinearity or near-collinearity [25]. In summary, MLR provides a baseline linear predictor that is easy to interpret and analyze, but its assumptions (linearity, independence, homoscedasticity, and no multicollinearity) must be met, and it may be limited when modeling complex or highly nonlinear data.

3.2.2. Random Forest (RF)

Random Forest (RF) is a nonparametric ensemble learning approach brought forth by Breiman [26] for regression and classification [26]. RF creates numerous decision trees by repeatedly resampling the training set and choosing bootstrap sets of features to use in each split. For regression, tree t makes prediction $f_t(x)$ for input x, and the forest's overall prediction is the average of the tree outputs:

Here, T is the number of trees, with each tree constructed from a bootstrap sample of the training set, with some random subset of predictors used in each split. Randomness (bagging and feature subsampling) makes the trees decorrelated. Biau and Scornet [27] characterize RF as "averaging several randomized decision trees that make predictions and combining them" [27]. RF makes little or no parametric assumptions other than assuming that the training cases are i.i.d and the covariates are informative. RF can represent complex, high-dimensional, and non-linear relationships as with each tree being able to partition the space in an arbitrary way. Random forests are known to converge when $T \to \infty$ and not overfit in virtue of averaging citebreiman2001random.

The key strength of RF in prediction is its flexibility and robustness. It can pick up on nonlinearities and interactions between predictors non-parametrically. RF is relatively insensitive to outliers as well as the scaling of the input features, and mixed data types can be accommodated. It offers an implicit variable importance measure as well as in-built cross-validation through out-of-bag samples. The advantage of RF being applicable in complex structures with large numbers of predictors and few tuning parameters is pointed out by Biau and Scornet [27]. RF is non-parametric in its assumptions, so issues of heteroscedasticity or multicollinearity of predictors do not discredit the method (albeit highly correlated predictors may make the trees correlate with decreased performance slightly). RF is not devoid of its weaknesses: it is basically a "black box" with low interpretability in comparison with linear models. The model outputs no simple coefficient, with predictions being piecewise constants, which can make its extrapolation outside training ranges poor. Moreover, RF can overfit unless suitably tuned, and its applicability needs large enough data for the purpose. The cost of computation is greater than that of MLR, as multiple trees are constructed, with RF not offering prediction intervals other than through heuristics.

3.2.3. Generalized Additive Models (GAM)

Generalized Additive Models (GAM) provide an interpolation between completely linear and completely nonparametric models in that they allow for nonlinear additive effects. The formulation of a GAM is that the expected response is expressed as the sum of smooth functions of the predictors, usually through the use of some link function. Precisely, one can express for observation i : and

where g is a known link function, α is an intercept, and each $s_j(\cdot)$ is an unknown smooth function that is estimated from the data. For the simplest instance of continuous response with identity link, $E[Y_i] = \alpha + \sum_j s_j(x_{ij})$. Hastie and Tibshirani [28] presented GAMs as an extension of generalized linear models, in which the linear predictor $\sum \beta_j x_j$ is replaced with additive smooth terms Hastie and Tibshirani [28]. Wood [29] also describes that GAMs are GLMs with the linear predictor being the sum of functions of covariates that are smooth, and the smooth functions are typically represented as spline bases (or other smoothers) with penalization for control of wiggliness, with their smoothness parameters being chosen through methods such as cross-validation or marginal likelihood [29]. The fundamental assumption of GAM is that the impact of every predictor on the response is a smooth (continuous) function, and that the effects are added (no unmodeled interactions). Similar to GLMs, the errors in GAM have some distribution in the exponential family (i.e., Gaussian for the continuous outcome) and observations are independent. Since every s_j is nonparametrically estimated, smoothness assumptions (each s_j having a finite number of derivatives or penalization) are necessary for GAM. The implication of the added assumption is that unless interactions are added in specifically, GAM misses them, but estimation and interpretation are much easier.

GAMs share the strengths of both parametric and nonparametric approaches. They can accommodate flexible nonlinearity: unlike MLR, they can accommodate curved or thresholded relationships without manual transformations. However, they are still interpretable, as individual smooth terms can be plotted and used to determine how that predictor influences Y. GAMs also include formal statistical inference on smooth terms with the conceptual elegance of regression. For predictive modeling, GAM performs as well as or better than MLR for moderately nonlinear relationships, without the full complexity of tree-based methods. There are, however, limitations with GAMs: when smoothing penalties are not optimally selected, they can overfit. They are also less accommodating of complexly interacting or jumpily changing relationships than RF. Computationally, estimating multiple smooth terms is sometimes slower than estimating a simple linear model. Lastly, GAMs do not intrinsically accommodate large numbers of predictors as well as RF, as every term must be included in the model.

In short, MLR, RF, and GAM all have different statistical underpinnings and assumptions. MLR is an easy linear parametric model that makes strong assumptions (linearity, normality, homoscedasticity, independence) in exchange for interpretability. Random Forest is an adaptive ensemble technique with weak assumptions on data structure, instead bootstrapping and tree averaging for variance reduction [26, 27]. GAM is a semiparametric model assuming additivity and smoothness of predictors, linear models extended to non-linear contexts [28, 29]. The decision between them will depend on the true underlying structure and the bias-variance balance: linear models have low variance but high bias when misspecified, forests have low bias but potentially higher variance and complexity, and GAM has an in-between solution with interpretable non-linear fits. For predictive applications such as estimating an InsurTech adoption index, these methods provide complementary strengths: for simple inference of MLR, for robust structure capture of RF, and for smooth adaptive modeling under additive assumptions of GAM.

3.2.4. Comparison of the Models

The selection among MLR, RF, and GAM hinges on various factors, such as the type of data, modeling purposes (interpretation versus prediction), and data generation process. Table 2 provides a summary of the main differences.

Table 2.
Comparison of MLR, RF, and GAM.

Feature	MLR	RF	GAM
Model type	Parametric	Nonparametric	Semiparametric
Assumptions	Strong	Minimal	Moderate
Handles Nonlinearity	No	Yes	Yes
Captures Interactions	Only explicitly	Automatically	Limited
Interpretability	High	Low	Moderate
Sensitivity to Outliers	High	Low	Moderate
Computational Cost	Low	High	Moderate
Inference	Full	Limited	Full (on smooth terms)

For modeling InsurTech adoption in this study, the three methods have complementary strengths. MLR provides transparency and simplicity in exploring linear relationships. RF is worth using where relationships are complex, nonlinear, and include high-order interactions. GAM is an interpretable, flexible substitute that reconciles the complexity of RF with the transparency provided by MLR.

All of the methods have trade-offs in flexibility, interpretability, and computational cost. MLR is most appropriate for hypothesis-driven inference under linear conditions. RF is ideal for predictive modeling with intricate structures but is not interpretable. GAM provides a principled method to include nonlinearity without losing statistical inference and partial interpretability. An overall appraisal of the methods gives us insight into the InsurTech adoption's underlying structure and guides the choice of appropriate modeling approaches to employ in upcoming studies.

4. Results and Discussion

4.1. Descriptive Statistics

This section reports and discusses the empirical results of the investigation. First, we summarize the main descriptive measures of the variables included in the analysis in order to present an overall depiction of sample characteristics and distributions. Knowing the central tendencies and patterns of dispersion is a prerequisite for an assessment of the types of data as well as for guiding the right selection of the models. The summary measures of central tendency, spread, as well as the shape of the distribution (skewness and kurtosis) are presented in Table 3.

Table 3.
Descriptive Statistics of Main Variables.

Variable	Mean	SD	Min	Max	Median	Skewness	Kurtosis
IT	0.50	0.89	0.03	3.56	0.14	2.48	4.92
AGE	17.68	5.26	12.00	39.00	17.00	3.26	10.80
log_ASSE	15.11	3.14	11.35	20.78	13.72	0.78	-1.12
log_NCC	12.65	3.11	6.86	19.15	12.15	0.44	-0.83
OCFR	1.39	1.89	0.01	10.05	0.75	2.91	9.68
IAR	0.15	0.14	0.00	0.52	0.10	1.03	0.21
FAR	0.11	0.21	0.00	0.88	0.01	2.26	4.51
PGR	0.09	0.22	-0.48	0.75	0.09	0.23	1.04
PACR	0.07	0.03	0.03	0.21	0.06	1.72	4.92
NPRR	0.75	0.19	0.31	1.05	0.78	-0.68	-0.29
PM	0.13	0.11	0.01	0.49	0.09	1.47	1.60
ROA	0.15	0.21	0.00	1.22	0.09	3.53	13.78
ROE	0.14	0.80	-4.93	3.10	0.09	-3.40	27.62

Table 3 shows the descriptive statistics for the key variables of analysis. The InsurTech Adoption Index (IT) is found to have a heavy right tail (skewness = 2.48) with excess kurtosis (4.92), representing a right-skewed, leptokurtic distribution. The Firm Age (AGE) also depicts comparably large values of skewness and kurtosis, which indicates enormous variations in firm maturity within the sample. Financial measures like return on equity (ROE) and return on assets (ROA) depict extreme values as well as fat tails, with ROE having its largest value of kurtosis (27.62) with an indication of strong left skew (-3.40), representing an occasional large negative outlier in the distribution. On the other hand, variables like the Net Premium Retention Ratio (NPRR) as well as the log of the Net Change in Cash (log_NCC) demonstrate nearly normality with low values of both skewness and kurtosis. The overall data suggest enormous heterogeneity in firm characteristics as well as financial performance, with emphasis on the necessity of applying strong models capable of fitting non-normality as well as skewed distributions.

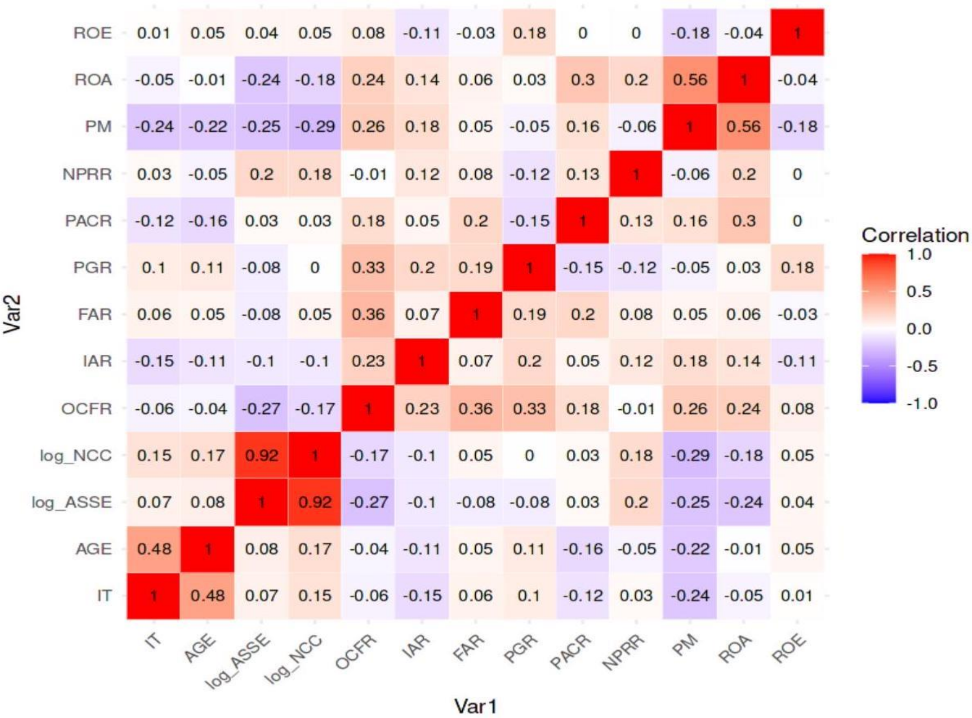

Figure 1.
Pearson Correlation Matrix of Key Variables.

Figure 1 displays the Pearson correlation coefficients between the major variables of the study. The matrix highlights the possibility of multicollinearity as well as bivariate correlation, which are both of key importance in determining the specification of the model. As anticipated, log_ASSE is strongly correlated with log_NCC ($r = 0.92$), suggesting that the size of the firm and liquid assets could be measuring overlapping aspects of the firm's finances. Moderate correlations are also found between PM and ROA ($r = 0.56$), which can be interpreted as profitability being consistent between measures. However, the InsurTech Adoption Index (IT) is weakly related to other variables, with the highest being with the age of the firm ($r = 0.48$), suggesting that older firms are mildly associated with adopting InsurTech innovations. Most other correlations are weak and within reasonable ranges, reducing the likelihood of multicollinearity issues in regression. This makes their presence as variables in subsequent multivariate models justifiable.

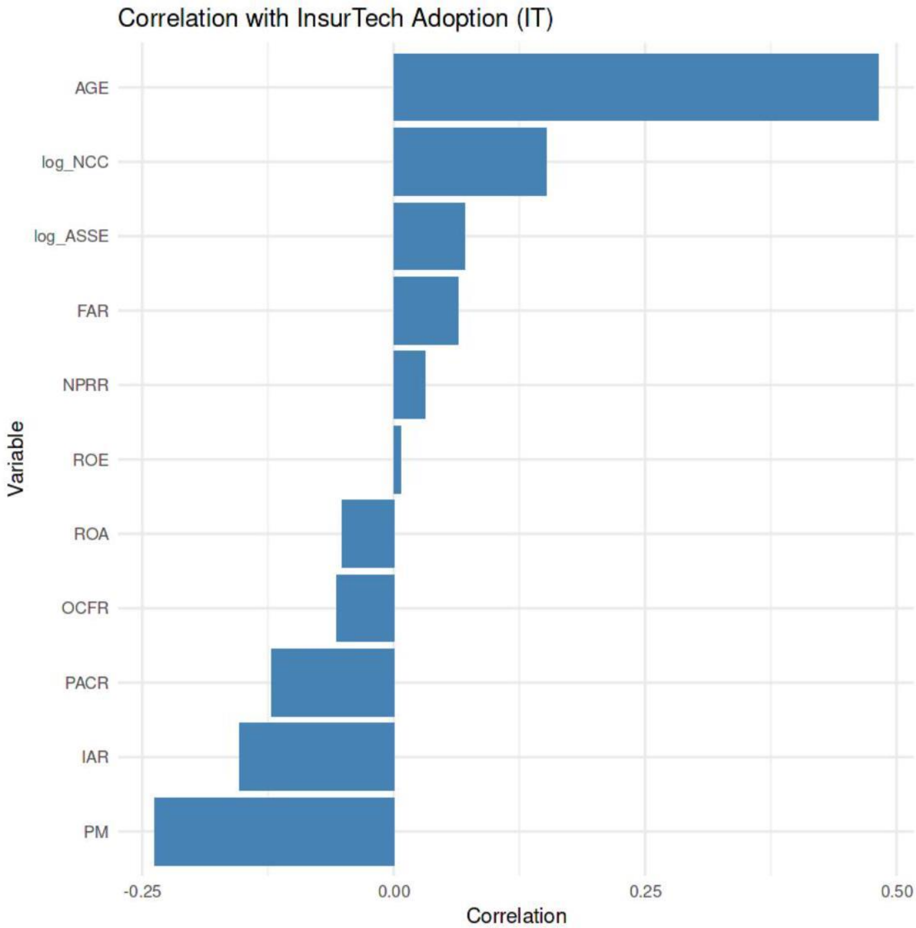

Figure 2.
Bivariate Correlation Between InsurTech Adoption (IT) and Independent Variables.

Figure 2 outlines Pearson correlation coefficients for the InsurTech Adoption Index (IT) with the chosen independent measures. Firm age (AGE) correlates the highest with IT ($r \approx 0.48$), with older firms presumably being more likely candidates for InsurTech adoption-possibly thanks to increased capacity or resources within the firm. Financial size measures like log_NCC and log_ASSE also have moderate positive associations, suggesting assets' size could facilitate or be associated with technological adoption. On the other hand, profitability measures like profit margin (PM) and investment activity ratio (IAR) demonstrate weak negative correlations, possibly an indication of short-term shortcoming in monetary returns from investment in technology. The rest of the measures have weak or negligible correlations with IT, suggesting little immediate bivariate impact. These findings will provide preliminary direction for model selection and multivariate analysis.

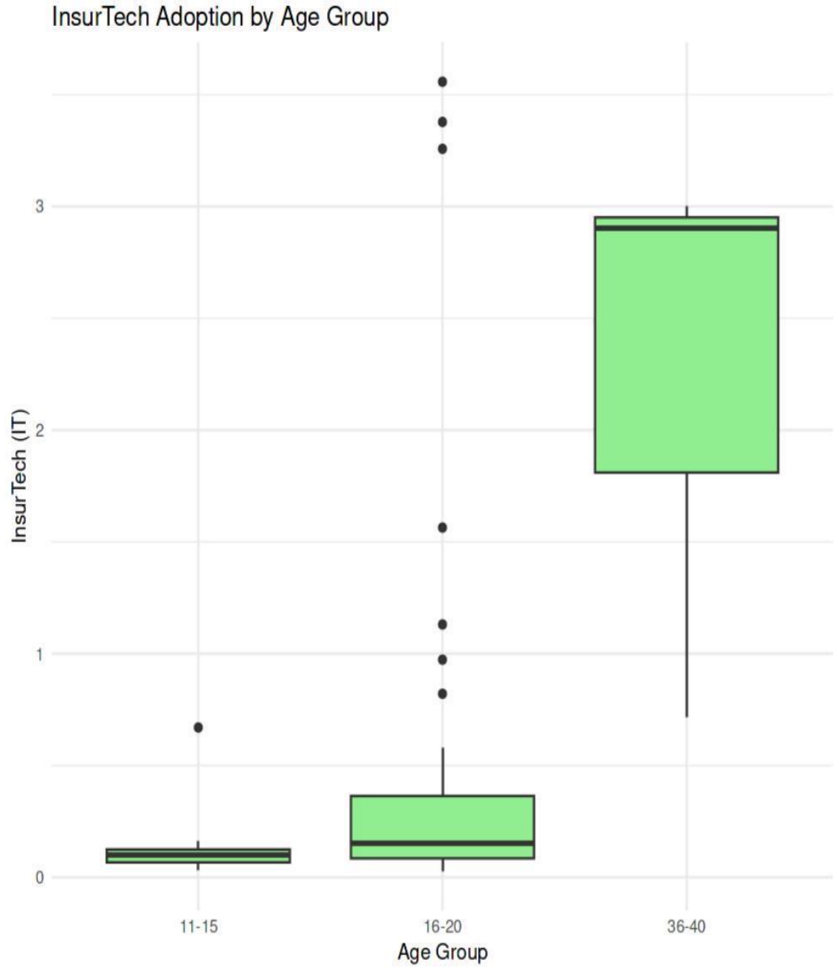

Figure 3.
InsurTech Adoption Across Firm Age Groups.

Figure 3 is a boxplot of InsurTech Adoption (IT) over three firm age ranges. The results show an unambiguous positive correlation between firm age and the extent of InsurTech adoption. The 36-40-year age group has much greater IT adoption with both greater spread in the interquartile range as well as greater median when compared with the other age ranges ($11-15$ and $16-20$ years). The $11-15$ years age group has the lowest median with low variation, indicating least digital activity. The implications are that older firms may have greater technological preparedness, infrastructure, or strategic inclination for adopting InsurTech solutions. The fact that all age groups do have outliers also proves heterogeneity in the adoption rate within each group. This is in line with the working hypothesis that the maturity of the organization is an important force driving technological advancement in the field of insurance.

4.2. Empirical Analysis

We used a Random Forest model with variable importance for refining the set of explanatory variables and eliminating the threat of multicollinearity with the aid of the randomForest package in R. The InsurTech Adoption (IT) was used as the dependent variable while fitting the model with all predictors standardized. The variable importance was evaluated through both the percentage increase in mean squared error (IncMSE) as well as the node purity increase (IncNodePurity). On the results of the analysis, variables like PM, AGE, and log_ASSE ranked highest in terms of predictive importance while variables like FAR, PGR, and NPRR had little or negative importance. As such, for the purpose of increasing parsimony of the model as well as eliminating the threat of multicollinearity, we included only the highest predictors of relevance for use in subsequent regression as well as machine learning models, namely, AGE, ROA, PM, PACR, as well as log

Table 4.
Linear Regression Results: Predicting InsurTech Adoption (IT).

Variable	Estimate	Std. Error	t-value	P-value
Intercept	-0.6345	0.7209	-0.880	0.3827
AGE	0.0736	0.0211	3.487	0.0010^{***}
ROA	0.2585	0.6440	0.401	0.6898
PM	-1.3180	1.1984	-1.100	0.2764
PACR	-1.2110	3.5394	-0.342	0.7336
log_ASSE	0.0026	0.0352	0.073	0.9422

Model Summary: Residual SE $= 0.8018$; DF $= 53$ $R^2 = 0.2525$; Adjusted $R^2 = 0.1820$; F-statistic $= 3.581$ ($p = 0.0073$)
Model Performance: RMSE $= 0.7599$; MAE $= 0.4668$

Table 4 presents the results of the linear regression model that regresses InsurTech Adoption (IT) as a function of five chosen predictors. Firm age (AGE) is the only statistically significant factor ($\beta = 0.074$, $p < 0.01$), with the implication that older firms use InsurTech solutions on a larger scale. The other variables, such as profitability measures (ROA and PM), capital adequacy (PACR), and firm size (log_ASSE), have no statistically significant influences. The model as a whole account for about 25% of the variation in IT adoption ($R^2 = 0.2525$), having an adjusted R^2 of 0.1820, and is statistically significant at the 1% level ($p = 0.0073$). The diagnostics for the model provide an RMSE of 0.7599 and an MAE of 0.4668, with no indication of low predictive accuracy. The results confirm the primacy of organizational maturity as the key driver of digital adoption in the insurance industry.

Table 5.
Variable Importance in Random Forest Model Predicting InsurTech Adoption (IT).

Variable	IncMSE	IncNodePurity
PM	11.0879	8.8267
ROA	8.8028	6.8132
PACR	7.9820	8.6471
AGE	7.6241	5.5909
log_ASSE	6.2739	8.4790

Model Performance: RMSE $= 0.3921$; MAE $= 0.2296$; $R^2 = 0.877$

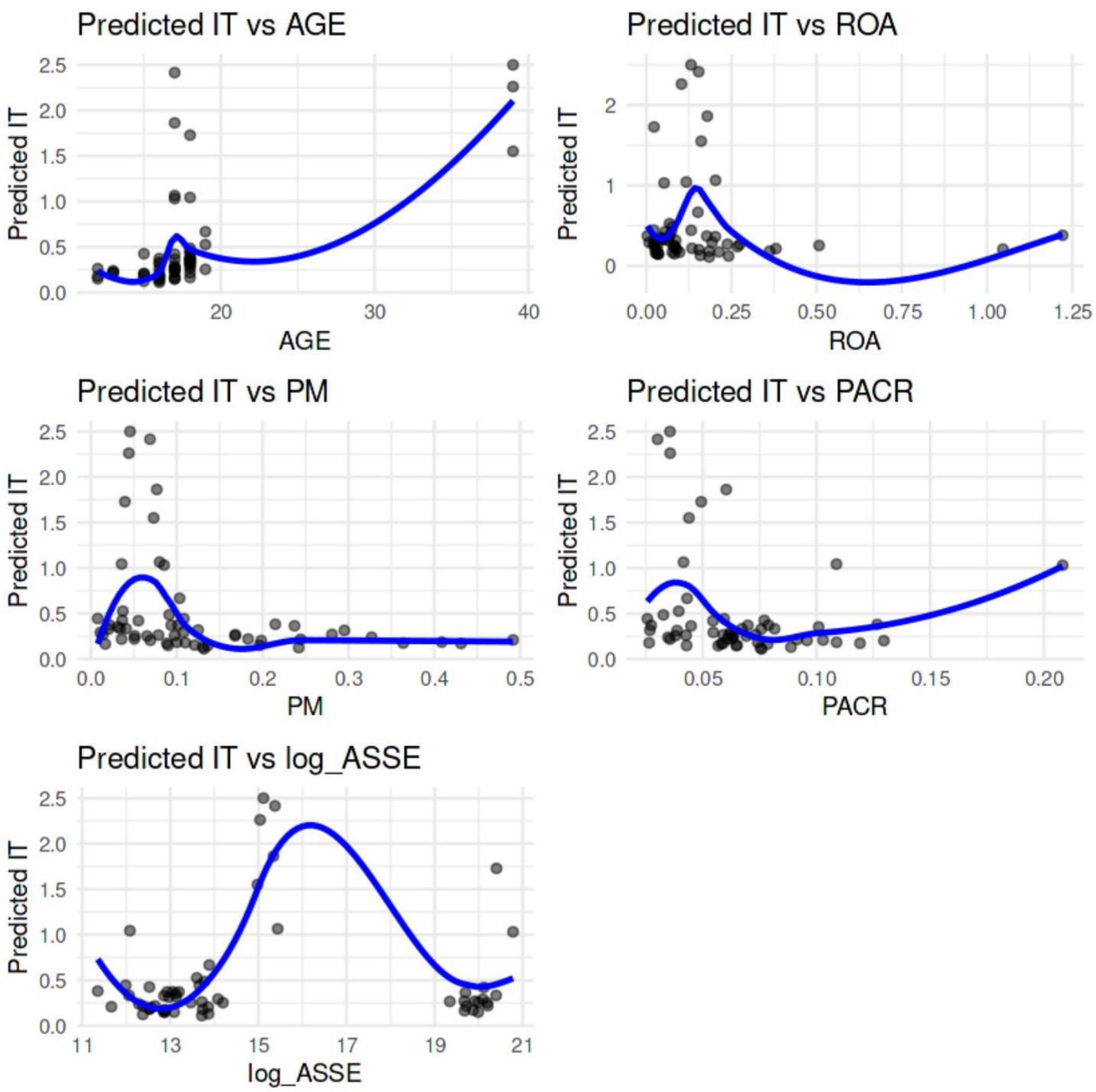

Figure 4.
Partial Dependence Plots for Predicted InsurTech Adoption (IT) by Independent Variables.

Table 5 indicates the relative importance of predictors in the Random Forest model of estimating InsurTech Adoption (IT), whereas Figure 4 shows the corresponding partial dependence plots (PDPs) which show the marginal impact of every variable on the predicted value. Among the five variables considered, PM (profit margin) is found with the highest importance, then comes ROA followed by PACR, which indicates the leading role played by profitability and capital adequacy in determining digital adoption. The Random Forest model performs outstandingly with respect to predicting performance, with an R^2 of 0.877 and low error in prediction (RMSE $= 0.3921$; MAE $= 0.2296$), far superior to the linear model.

The PDPs (Partial Dependence Plots) provide useful insights into the non-linear impacts captured through the model. For example, AGE exhibits an increasing relationship with IT, especially for older establishments, in line with previous results. The impact of ROA and PM is also non-linear, with peaks in low-to-moderate ranges and declining or flat responses, indicating threshold impacts. Both PACR and log_ASSE also demonstrate non-monotonic relationships with IT, further supporting the necessity of non-linear modeling techniques like Random Forests. Together, these results emphasize heterogeneous and non-linear drivers of technology adoption for the insurance industry.

Table 6.
GAM Results: Smooth Effects on InsurTech Adoption (IT).

Term	Estimate / EDF	Ref.df	F-Statistic	p-value
Intercept	0.5002	-	5.917	<0.001***
Smooth Terms s(AGE)	1.160	1.296	0.917	0.2925
s(ROA)	1.000	1.000	2.482	0.1215
s(PM)	1.000	1.000	0.137	0.7126
s(PACR)	1.000	1.000	0.009	0.9266
s(log_ASSE)	3.803	3.979	6.794	< 0.001***

Model Summary: Adjusted $R^2 = 0.463$; Deviance Explained $= 53.7\%$ REML $= 69.366$; Scale Estimate $= 0.4217$; Observations $= 59$ Model Performance: RMSE $= 0.598$; MAE $= 0.39$; $R^2 = 0.5387$

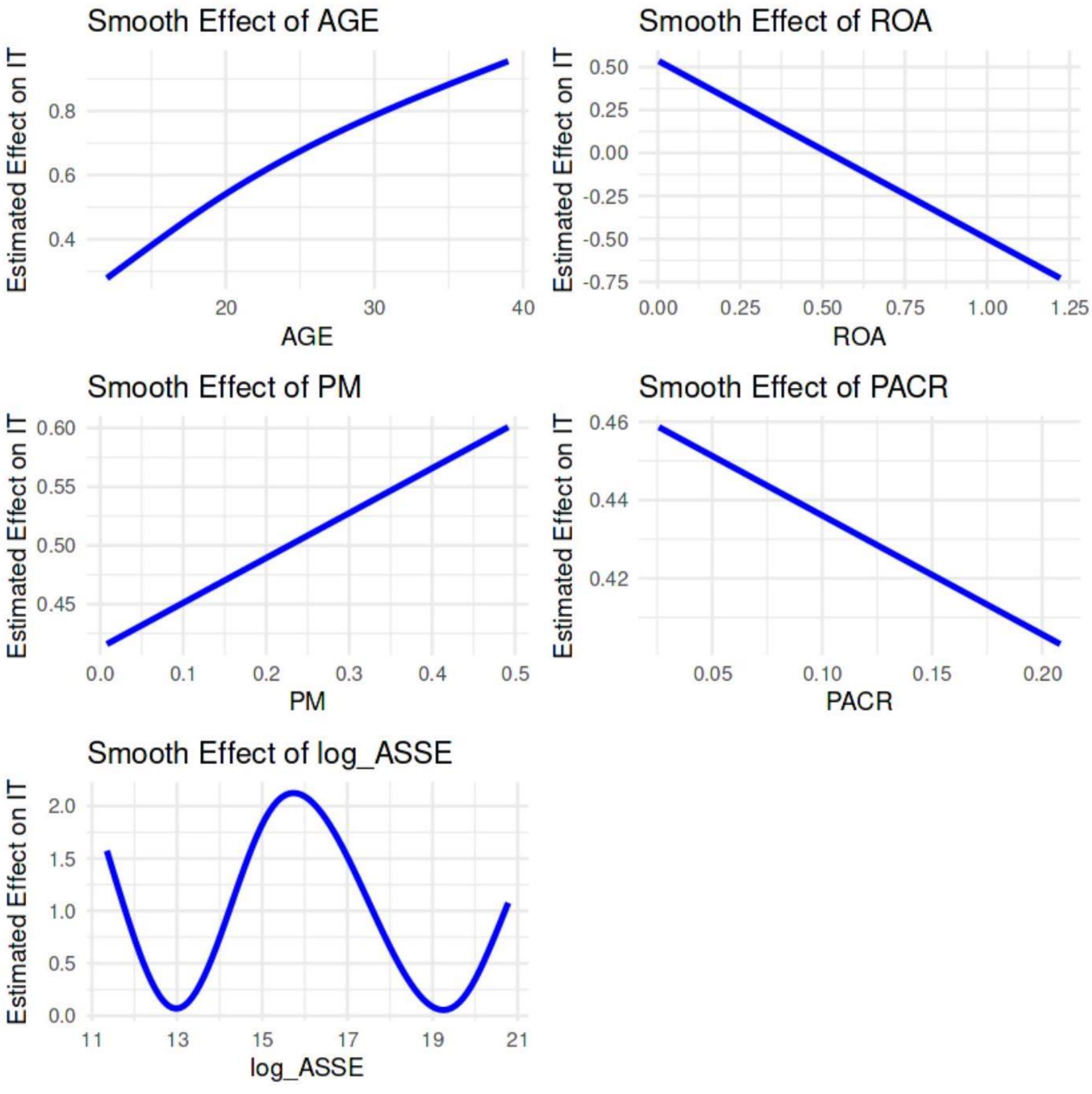

Figure 5.
Smooth Effects of Predictors on InsurTech Adoption (IT) from GAM Model.

Table 6 reports the generalized additive model (GAM) results for InsurTech Adoption (IT) as the function of five smoothed predictors. Only the nonparametric effect of log_ASSE is statistically significant at 1%, with an estimated 3.803 effective degrees of freedom (EDF), implying a richly structured nonlinearity with IT. The model performs moderately well in terms of explanation with an adjusted R^2 of 0.463 as well as deviance explained of 53.7%, reflecting a significant advancement over linear specifications.

Figure 5 plots the smooth effects of individual predictors. AGE depicts an increasing effect on IT, consistent with existing results that organizational maturity facilitates digital adoption. Conversely, ROA, PM, and PACR have flat or near-linear trends with large confidence bands, suggesting weak or irregular relationships. Interestingly, log_ASSE presents an intense non-linear trend with peaks and troughs indicating cyclical behavior, which is in agreement with the statistical significance found in the GAM table. The non-linearity means that firm size does not always positively contribute towards digital adoption and can involve threshold or saturation phenomena. These results demonstrate the benefit of employing versatile models such as GAM in discovering subtle, data-based associations in InsurTech behavior.

Table 7.
Performance Metrics for Competing Models Predicting InsurTech Adoption (IT).

Model	RMSE	MAE	R^2
Linear Regression	0.7599	0.4668	0.2525
Random Forest	0.3921	0.2296	0.877
GAM	0.598	0.39	0.5387

Table 7 highlights the predictive performance of three statistical learning models employed in estimating InsurTech Adoption (IT): Linear Regression, Generalized Additive Model (GAM), and Random Forest. The Random Forest model provides the highest predictive accuracy with the widest margin, having lowest RMSE (0.3921), lowest MAE (0.2296), as well as highest explanatory power ($R^2 = 0.8770$), which indicates its superior capacity in handling nonlinearities and intricate interactions. The GAM model provides substantial improvement over linear regression through its use of flexible functional forms with an R^2 of 0.5387. The linear model fares comparatively, with an ability of just 25% variance in IT with increased residual errors.

Surprisingly, the statistically significant variables vary from model to model. For the linear model, only AGE is significant; for the GAM model, only log_ASSE has a statistically significant smooth effect; for the Random Forest model, the highest-ranking predictors are PM, ROA, and PACR. These results mirror the methodological variability of the models. Linear regression makes rigid linearity and additivity assumptions, which can hide weaker or non-linear effects. GAMs make smooth non-linear effects possible while continuing to treat variables additively. Random Forests, on the other hand, are very versatile and can capture nonlinearities as well as interactions automatically.

The patterns of varying significance imply that firm characteristics may have an intricate, non-additive relationship with InsurTech adoption. For that reason, exclusively using parametric models risks inducing misleading inferences. Flexible, data-driven approaches such as Random Forests are thus preferable for capturing the underlying structure of such relationships in applied contexts.

4.3. Discussion

Our results indicate that firm age has a strong effect on the propensity to adopt InsurTech, but the influence is multifaceted. In the linear model, AGE is found to be an important determinant of the InsurTech Adoption Index, meaning that old and young firms develop InsurTech capabilities at different rates. This is consistent with previous findings that firm maturity determines digital adoption: e.g., [30] found that the age of the firm is an important determinant of e-insurance performance [31]. Analogously, Bromideh [32] determined that elevated age decreases the readiness of customers to insure online, which implies that mature organizations are presumably slower to implement new technologies. In our case, the positive sign for the AGE coefficient implies that older insurers exhibit greater InsurTech adoption, which is indicative of accumulated resources or legacy hindrance. This result is corroborated by recent analytical works, which emphasize that traditional insurers need to upgrade to stay competitive [33]. Overall, the role of AGE in the linear model - in combination with the existing literature findings - indicates that the age of the organization provides systematic differences in adoption likelihood.

The size of the firm also plays an important role, but nonlinearly. The GAM model shows that log assets (log_ASSE) are an important predictor, albeit nonlinear in shape: InsurTech intensity of adoption rises very strongly at first with firm size, but then the marginal benefit falls off at the very largest firms. This nonlinearity indicates threshold effects: mid-sized and large insurers quickly scale digital take-up, but mega-firms are subject to bureaucratic drag or regulatory restrictions. The result is in line with Lee and Cata [30] finding that firm size is an e-insurance success factor. Big insurers normally possess greater resources and the scope to benefit from economies of scale in technology, which can account for the steep rise. Smaller insurers are selective in adopting or collaborating with insurtechs. Contrary to the linear model (which identified no material effect of size), the GAM unearths these curvilinear dynamics. This highlights that size does matter, but in no straightforward linear fashion. On the whole, the evidence is that scale is important to InsurTech: bigger is better is the tendency towards greater likelihood and intensity of take-up to a point of saturation.

Financial performance is another significant determinant. For the Random Forest model, the profitability indicators - return on assets (ROA) and profit margin (PM) - are among the most influential variables. This indicates that insurers with higher profitability have a greater tendency to invest in InsurTech. The reasoning is straightforward: profitable companies have higher financial slack to invest in innovation. In fact, technology uptake and the profitability of companies are positively correlated in the theory of economics, and existing empirical literature documents profit gains for the adopters. For example, Puelz [34] established that insurers utilizing online channels achieve material improvements in revenue. We surmise that well-capitalized insurers invest in InsurTech to benefit from these gains as well as to fuel growth. Importantly, both ROA and PM were not significant in the less flexible linear or GAM models. This difference is presumably because the linear model cannot pick up nonlinearities or interactions: profitability may increase uptake only beyond very specific thresholds, which the Random Forest is able to do but the linear model is not. Briefly, our models suggest that profitability is a cause of uptake, albeit with an intricate effect.

Policyholder's Capital Adequacy Ratio (PACR) is also particularly notable in the Random Forest, reflecting that well-capitalized insurers are more likely to be InsurTech adopters. A higher PACR implies the presence of a greater capital buffer, which may encourage firms to take the risks associated with new technology. Furthermore, PACR seems to interact with other features: for example, a large, profitable firm with a high PACR is most likely to be an early adopter, but a similar firm with low capital metrics is held back. In effect, PACR has the potential to strengthen the impact of size and profitability. Although interaction terms were not explicitly included in the estimation, the feature importance from the Random Forest indicates that these synergies matter. While there is little specific literature on PACR and innovation, the finding is consistent with the broader philosophy that financial solidity (equity and earnings) facilitates strategic investment. Insurers' capital adequacy is therefore influencing how other organizational drivers translate to InsurTech adoption.

The divergent trends in our three models demonstrate the significance of methodology. The linear regression identified only AGE, measuring the simple linear effect of firm maturity. By contrast, the GAM found the strong nonlinear relationship between firm size (log_ASSE) and InsurTech adoption, which linear regression did not detect. Lastly, the Random Forest identified profitability (PM, ROA) and PACR as the leading predictors, despite the absence of these as significant in the parametric models. These discrepancies are to be expected: linear regression can only find additive linear effects; GAM is able to fit smooth nonlinear effects (and so identified the size effect); and the flexible nature of the Random Forest allows it to detect intricate patterns and interaction effects. For instance, AGE can have an approximately linear trend (identified by OLS), but the effects of size follow the stepwise distribution (detected by the GAM). Profitability and capital adequacy might influence the adoption only together or beyond certain thresholds, which are identified through splits using tree-based techniques. Briefly, each model shows a piece of the complete picture: the linear model offers parsimony, the GAM shows the functional form, and the Random Forest indicates the relative importance of the variables without the need for parametric assumptions. They collectively provide an enriched insight into which organizational variables drive InsurTech uptake.

Our results have several implications for academics. First, future studies should employ multi-method methodologies. The varied findings across linear, semi-parametric, and machine-learning models imply that using one technique risks missing important effects. For example, academics might pair regression with GAMs or ensembles to cross-check results. Second, there is work to be done to disentangle interactions. The results imply that PACR moderates the impact of profitability and size; tests of interaction terms or segmentations (e.g., high- vs low-PACR firms) would resolve these associations. Third, longitudinal data can shed light on causality: do large, profitable, well-capitalized insurers actively seek InsurTech, or do digital innovations drive improvements in financial performance in the long term? Researchers can employ panel models or case studies to shed light on these questions. Fourth, contextual factors are worthy of investigation. For example, the regulatory regime or market competition may influence how these firm characteristics translate into take-up - something identified by industry experts [33]. Lastly, academics should incorporate theory from innovation diffusion or technology acceptance to account for why certain insurers take up InsurTech. For instance, adding concepts such as risk aversion or culture to models may facilitate interpretation. In short, by capitalizing on varied methodologies and richer data, future studies can build on ours to establish an integrated theory of InsurTech take-up.

5. Conclusion

The organizational determinants of InsurTech uptake in this study were analyzed using three complementary modeling approaches: linear regression, generalized additive model (GAM), and random forests. With access to broad data at the firm level to refer to, we examined the effect on the uptake probability and intensity of firm age, firm size, profitability, and capital adequacy. According to the research, the drivers have varying influences depending on the methodology of the study, which is reflective of the complexity of digitalization in insurance.

Instead, firm age emerged as the most predictive variable in the linear model, corroborating the hypothesis that organizational maturity influences digital preparedness. The GAM analysis similarly obtained a nonlinear firm-size impact with threshold effects at which additional firm size has diminishing returns to technology adoption. Finally, the random forest model identified profitability measures (PM and ROA) and measures of capital adequacy (PACR) as the most significant attributes, which have interactive and conditionality not observable using linear models.

Our findings provide valuable theoretical and empirical insights into the determinants of the uptake of technologies in insurance firms. Methodologically, they illustrate the promise of employing flexible regressions to uncover nonlinearities and complex patterns often underplayed within the usual regression framework. Substantively, the paper shows that one cannot refer to any single firm-level determinant to explain InsurTech uptake; rather, it is the interplay among age, financial health, and size that collectively defines digital behavior.

Future research can build upon the work in some key areas. First, longitudinal research is needed to test causality—whether companies invest in InsurTech due to being financially strong or if the embracing of technology itself results in better financial performance in the long term. Second, future studies should have interaction terms and moderation analysis by design, specifically to unpack the relationship between PACR and the effect of size and profitability. Third, qualitative studies should examine how organizational culture, leadership, and risk appetite come to mediate the adoption decisions and supplement the quantitative findings. Finally, comparative cross-country studies will uncover how market maturity and the regulatory environment at the country level affect the adoption environment. By expanding the base of knowledge about the drivers of InsurTech adoption, the research is making contributions to both technology diffusion and digital innovation management within financial services.

References

[1] M. Eling and M. Lehmann, "The impact of digitalization on the insurance value chain and the insurability of risks," *The Geneva papers on risk and insurance-issues and practice,* vol. 43, pp. 359-396, 2018.

[2] S. Cosma and G. Rimo, "Redefining insurance through technology: Achievements and perspectives in Insurtech," *Research in International Business and Finance,* p. 102301, 2024. https://doi.org/10.1016/j.ribaf.2024.102301

[3] U. Noreen, "Mapping of FinTech ecosystem to sustainable development goals (SDGs): Saudi Arabia's Landscape," *Sustainability,* vol. 16, no. 21, p. 9362, 2024. https://doi.org/10.3390/su16219362

[4] L. G. Tornatzky and M. Fleischer, *The processes of technological innovation* United States: Lexington Books, 1990.

[5] S. Gupta, W. Ghardallou, D. K. Pandey, and G. P. Sahu, "Artificial intelligence adoption in the insurance industry: Evidence using the technology–organization–environment framework," *Research in International Business and Finance,* vol. 63, p. 101757, 2022. https://doi.org/10.1016/j.ribaf.2022.101757

[6] J. Barney, "Firm resources and sustained competitive advantage," *Journal of Management,* vol. 17, no. 1, pp. 99-120, 1991.

[7] S. La Barbera, "Insurtech revolution in the insurance sector: A comprehensive review of the transformational impact and the lemonade case study," *International Journal of Management Research and Economics,* vol. 3, no. 2, pp. 57-64, 2023.

[8] A. Kiwanuka and A. B. Sibindi, "Digital literacy, insurtech adoption and insurance inclusion in Uganda," *Journal of Risk and Financial Management,* vol. 17, no. 3, p. 119, 2024. https://doi.org/10.3390/jrfm17030119

[9] S. Chauhan, "Fintech: The new DNA of financial services," *Journal of Financial Perspectives,* vol. 3, no. 3, 2015. 1-10

[10] W. Bian, T. Ge, Y. Ji, and X. Wang, "How is Fintech reshaping the traditional financial markets? New evidence from InsurTech and insurance sectors in China," *China Economic Review,* vol. 80, p. 102004, 2023. https://doi.org/10.1016/j.chieco.2023.102004

[11] T. H. Nguyen and T. L. D. Huynh, "Trust and the adoption of FinTech services: A study in emerging markets," *Journal of Financial Innovation,* vol. 10, no. 2, pp. 45-62, 2023.

[12] K. Bajunaied, N. Hussin, and S. Kamarudin, "Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 9, no. 1, p. 100010, 2023. https://doi.org/10.1016/j.joitmc.2023.100010

[13] A. A. Shaikh, R. Glavee-Geo, and H. Karjaluoto, "Exploring customer adoption of mobile payment services in the pandemic: A hybrid SEM-ANN approach," *Journal of Retailing and Consumer Services,* vol. 70, p. 103129, 2023.

[14] J. M. Velmurugan, "Exploring key drivers of InsurTech adoption: Insights from India's digital insurance revolution," *Smart Journal of Business Management Studies,* vol. 21, no. 1, pp. 106-113, 2025.

[15] M. Ali, S. A. Raza, B. Khamis, C. H. Puah, and H. Amin, "How perceived risk, benefit and trust determine user Fintech adoption: A new dimension for Islamic finance," *Foresight,* vol. 23, no. 4, pp. 403-420, 2021.

[16] X. Tian and X. Liu, "The role of trust and data sharing willingness in users' acceptance of insurance telematics," *Journal of Knowledge Management Practice,* vol. 24, no. 2, pp. 28-47, 2024. https://doi.org/10.62477/jkmp.v24i2.399

[17] M. Mustafina, A. Idris, and N. Omar, "Digitalization and performance of Takaful companies: Evidence from Malaysia," *Journal of Islamic Marketing,* vol. 12, no. 3, pp. 536–550, 2020.

[18] M. Gharahkhani and S. O. Pourhashemi, "Adoption of mobile insurance technology using TAM: A case study," *International Journal of Industrial Engineering and Management Science,* vol. 7, no. 2, pp. 45-54, 2020.

[19] J. A. Jafri, S. I. M. Amin, A. A. Rahman, and S. M. Nor, "A systematic literature review of the role of trust and security on Fintech adoption in banking," *Heliyon,* vol. 10, no. 1, p. e22980, 2024. https://doi.org/10.1016/j.heliyon.2023.e22980

[20] L. M. Johnson and R. Davis, "Legacy systems in insurance: Challenges and pathways to modernization," *Journal of Insurance Technology,* vol. 18, no. 3, pp. 210–225, 2024.

[21] O. Altwijry, M. O. Mohammed, and A. A. Alshammari, "Financial technology and Islamic insurance: The Saudi context," *Scientific Journal of King Faisal University, Humanities & Management Sciences,* vol. 24, no. 2, pp. 1-7, 2023.

[22] C. Van der Cruijsen, L. Hernandez, and N. Jonker, "In love with the blockchain: A usability study of Dutch retail investors," De Nederlandsche Bank Working Paper No. 713, 2021.

[23] M. A. Zayed, "Digital insurance: A case study of the Saudi insurance sector," *International Journal of Electronic Commerce Studies,* vol. 10, no. 3, pp. 337-354, 2019.

[24] A. F. Schmidt and C. Finan, "Linear regression and the normality assumption," *Journal of Clinical Epidemiology,* vol. 98, pp. 146-151, 2018. https://doi.org/10.1016/j.jclinepi.2017.12.006

[25] N. Shrestha, "Detecting multicollinearity in regression analysis," *American Journal of Applied Mathematics and Statistics,* vol. 8, no. 2, pp. 39-42, 2020. https://doi.org/10.12691/ajams-8-2-1

[26] L. Breiman, "Random forests," *Machine learning,* vol. 45, pp. 5-32, 2001.

[27] G. Biau and E. Scornet, "A random forest guided tour," *Test,* vol. 25, no. 2, pp. 197-227, 2016. https://doi.org/10.1007/s11749-016-0481-7

[28] T. Hastie and R. Tibshirani, "Generalized additive models," *Statistical Science,* vol. 1, no. 3, pp. 297-310, 1986. https://doi.org/10.1214/ss/1177013604

[29] S. N. Wood, "Generalized additive models," *Annual Review of Statistics and Its Application,* vol. 12, pp. 497-526, 2025.

[30] S. M. Lee and T. Cata, "Critical success factors of Web-based e-service: The case of e-insurance," *International Journal of E-Business Research,* vol. 1, no. 3, pp. 21-40, 2005. https://doi.org/10.4018/jebr.2005070102

[31] M. F. Nsour, S. A. AL-Rjoub, M. Tayeh, and H. Kokash, "Factors and issues affecting electronic insurance adoption in an emerging market," *Insurance Markets and Companies,* vol. 14, no. 1, pp. 46-58, 2023.

[32] A. A. Bromideh, "Factors affecting customer e-readiness to embrace auto e-insurance in Iran," *Journal of Internet Banking and Commerce,* vol. 17, no. 1, pp. 1-12, 2012.

[33] McKinsey & Company, *Insurance trends private-equity investors should understand in 2021*. United States: McKinsey Insights, 2021.

[34] R. Puelz, "Technology's effect on property–casualty insurance operations," *Risk Management and Insurance Review,* vol. 13, no. 1, pp. 85-109, 2010. https://doi.org/10.1111/j.1540-6296.2009.01175.x