Evaluating the Impact of Insurtech-Driven Technology Risks on Insurer Performance Using a Vanilla Neutrosophic Logic Model

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Abstract

This study evaluates the influence of technology risks on insurance company performance through Insurtech innovation, focusing on the roles of Data Privacy (DP), Skill Gaps (SG), and Financial Risks (FR) in predicting Insurance Performance (IP). Employing a questionnaire survey approach, the research extended historical empirical studies, capturing demographic profiles and study variables measured on a 5-point Likert scale. A pilot study refined the questionnaire, achieving an 80% response rate, and minor adjustments were made to enhance clarity. The dataset included 243 responses from employees of Jordanian insurance companies, with 37 excluded due to incomplete data. Validity and reliability were assessed using Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha, confirming the robustness of the measurement model. Multicollinearity was tested using correlation, Tolerance, and Variance Inflation Factor (VIF), with no significant issues detected. ANOVA tests were conducted to examine the impact of experience and technology level on DP, SG, FR, and IP, revealing significant differences across groups. A multiple regression model demonstrated that DP and FR positively affect IP, while SG has a negative effect. To further predict IP, the dataset was split into 80-20% and 60-40% training-test sets, and a Multilayer Perceptron (MLP) model was employed. The MLP neural network model, using the Rprop method, highlights the importance of DP, SG, and FR in predicting IP, achieving an accuracy of up to 72%. These findings highlight the importance of addressing technology risks and leveraging Insurtech innovations to enhance insurance company performance, providing valuable insights for industry stakeholders and policymakers.

Keyword: MLP model; Insurtech; Performance; Financial Risk

1. Introduction

The insurance sector is vital for the economic growth of countries, as it supports all areas of the economy by mitigating financial risks and encouraging investment through compensation for losses [1, 2]. The growth and regulation of Jordan's insurance industry, reflecting its increasing importance in the economy, began in the early 1940s. At the time, the sector had no significant presence due to Jordan's small population (under 400,000) and limited geographical scope. However, as trade and traffic activities expanded, the Ottoman Bank played a key role by insuring imports through London's Eagle Star Insurance. In 1946, the first insurance agency, Al Sharq, was

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established in Amman, focusing on life insurance due to low demand for other types of coverage. This marked the foundation for the sector's development and its growing role in Jordan's economy. As Jordan's economy developed in the 1950s, the insurance sector grew, leading to the establishment of professional bodies, legislative frameworks, and insurance companies. A key milestone was the formation of the Jordan Insurance Association in 1956, initiated by insurance pioneers to meet the demands of economic growth. The Association's preparatory committee, chaired by A.D. Ledger and including figures like Elias Habayeb and Raouf Abu Jaber, laid the foundation for the sector's professionalization. By 1971, the Association was officially licensed under the Societies and Social Bodies Law, marking a significant step in the sector's institutional development [3].

The insurance sector experienced significant growth in the 1960s, with the number of firms rising to 23 by the mid-1980s. However, the economic downturn of the 1980s and heightened competition caused profitability challenges for many companies. To address this, the government introduced Law No. 30 of 1984, which increased capital requirements for insurance firms. This resulted in mergers, closures, and a decline in the number of companies to 17 by 1987 [2]. The number of firms stayed constant until 1994. In 1995, the introduction of Law No. 9 allowed new insurance companies to enter the market, subject to specific capital requirements: $4 million for foreign firms, 20 million for reinsurance companies, and 2 million for existing firms. This regulatory change facilitated the entry of eight new firms in 1995, bringing the total number of operational companies to 25 by the year 2000.

Over the years, the sector experienced fluctuations, with firms exiting or entering the market. By 2008, the number reached 29, but the exit of the firm "DARKOM" reduced it to 28 by 2011. Between 2012 and 2014, three firms closed, bringing the total to 25. By the end of 2022, the number of insurance firms stood at 22, comprising one life insurance firm, 7 composite firms (medical and non-life), and 14 composite firms (medical, non-life, and life). By the beginning of 2025, the Jordan Insurance Federation consists of 19 licensed insurance companies operating in Jordan. Among these, 13 offer life insurance, while 5 focus on general insurance, including medical coverage. Additionally, one foreign branch specializes exclusively in life and health insurance. These companies provide a wide range of services, such as marine, vehicle, fire, earthquake, liability insurance, and life and health insurance contracts. Notably, there are no specialized reinsurers in Jordan; instead, Jordanian companies reinsure amounts with Arab and foreign firms and collaborate on managing large risks [3]. This evolution highlights the sector's resilience and adaptability in response to economic and regulatory changes.

The COVID-19 pandemic accelerated technology adoption in the insurance industry, transforming business models, services, and processes. Companies used technology to address traditional and emerging risks, focusing on product development, sales, and claims management [4]. Jordanian companies also leveraged technology to enhance operations and service quality. Key developments include improved payment channels, electronic insurance platforms, electronic linking of traffic accident reports, and the Hakim platform, which connects medical files with insurance companies, hospitals, and medical entities. Additionally, continuous improvements in internal processes—such as financial management, compliance, human resources, and quality control—have further strengthened the sector. During the pandemic, insurers prioritized digital innovations to address inefficiencies in traditional customer interactions. Technologies like chatbots, telematics, the Internet of Things, artificial intelligence, and predictive analytics became widespread, enabling adaptation to remote work, improved customer service, and enhanced operational efficiency [5, 6].

The insurance companies in Jordan have seen rapid technological advancements over the last five years, driven by two key factors. First, the COVID-19 pandemic challenged business continuity, pushing companies to adopt remote work software, shift to electronic insurance applications, enhance electronic payment processes, and create emergency plans for future crises. Second, government initiatives to develop e-government services required companies to establish plans for regulating insurance operations, adopt advanced technology, and implement sophisticated software to comply with new regulations and guidelines. Interestingly, the impact of technology adoption varies between developed and emerging markets. In developed markets, the COVID-19 pandemic has had significant negative consequences on insurance firms' performance. However, in emerging markets, company size plays a substantial role in performance, with larger insurers experiencing declines during the pandemic [7].

Several models have been used to measure insurance company performance. The dynamic slacks-based measure (DSBM) model revealed that structural capital, including technological systems, positively impacts operating efficiency [8]. The Value Added Intelligent Coefficient Model showed a significant link between intellectual capital and financial performance, with structural capital directly related to return on assets [9]. Porter's (1985) value chain and Berliner's (1982) insurability criteria were used to analyze AI's impact on the insurance sector. The framework showed that AI drives cost efficiencies and new revenue streams but also alters the risk landscape, requiring insurers to redesign products [10]. [2] examined the financial performance of 15 Jordanian insurance firms listed on the Amman Stock Exchange (2008–2020) using the Multi-Layer Perceptron (MLP) model. Inputs included subrogation, market capitalization, shareholders' equity, and claims paid, while total asset turnover

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(TAT) served as the output. The results showed that all inputs had a positive effect on performance, except for shareholders' equity, which had a negative effect. The MLP model demonstrated high efficiency across performance metrics like accuracy, precision, and F-measure. [11] highlighted AI's role in enhancing efficiency, offering benefits like cost reduction and fraud detection, while noting challenges such as data privacy and high costs. Companies adopting digitalization gain competitive advantages, while those resisting face operational hurdles. There several studies on financial technology such as [12-14].

The problem in this study arises from the significant technological advancements in the Jordanian insurance sector, which have introduced several new risks. Cybersecurity is a major concern, as many companies lack effective protection systems against cyberattacks due to high costs and a shortage of expertise, despite being required to back up their data daily. Data privacy remains a priority, with studies showing that improved data handling enhances performance. Additionally, the high costs of implementing new systems, such as artificial intelligence, pose barriers for smaller companies, while larger firms with foreign branches often have the resources to invest in software development. Financial risks also emerge as rapid technological advancements may outpace regulatory frameworks, complicating compliance and potentially harming reputations. Lastly, the market faces skill gaps in technology, with a significant disparity between available competencies and the requirements of insurance companies. This study aims to achieve two main objectives: (1) identifying the factors that influence the performance of insurance companies in Jordan, and (2) classifying their financial performance using MLP model. The study tests five hypotheses:

H01: There is no significant effect of DP factor on IP;

H02: There is no significant effect of SG factor on IP;

H03: There is no significant effect of FR factor on IP.

H04: There is no statistically significant difference in the mean responses for DP, SG, and FR on IP based on Experience.

H05: There is no statistically significant difference in the mean responses for DP, SG, and FR on IP based on Technology Level.

The study is organized as follows: Section 2 provides a comprehensive literature review, discussing relevant research studies and theoretical foundations. Section 3 outlines the methodology, including a detailed description of the MLP model, its learning process, the Rprop algorithm, and evaluation measures, along with a flowchart illustrating the data processing stages. Section 4 presents the experimental results, covering data description, demographic information, exploratory factor analysis, multiple regression model, ANOVA test, and MLP results. Section 5 discusses the empirical findings and provides actionable recommendations for stakeholders. Finally, Section 6 concludes the study by summarizing the key insights and their implications for the insurance sector and proposes future research directions.. This structured approach ensures a thorough exploration of the topic, from theoretical underpinnings to practical applications and future opportunities.

2. Related Work

Data privacy concerns have become increasingly important in the insurance industry, particularly with the rise of big data and IoT technologies. The discovery of potential privacy data risks, such as data leakage and security vulnerabilities, is crucial for insurance companies [15]. Interestingly, while privacy concerns are generally seen as a barrier, they can also drive the adoption of new technologies. For instance, RFID systems in medical settings can effectively address privacy issues by ensuring secure authentication and data exchange. This technology could potentially be applied to insurance processes to enhance data protection [16].

The impact of data privacy on company performance is multifaceted, influenced by compliance structures like the General Data Protection Regulation (GDPR) and consumer perceptions. Research shows that the GDPR has led to an average profit decline of 8% for firms targeting European consumers, with smaller technology companies facing even greater losses due to increased compliance costs and operational adjustments [17, 18]. These costs have reduced profitability without significantly affecting sales. Additionally, customer perceptions of data vulnerability play a critical role; firms that fail to manage data transparently risk negative performance outcomes, as consumer trust erodes [19].

Investments in data privacy and security, however, can mitigate risks and enhance firm value. For instance, such investments reduce systematic risk, particularly for firms not heavily reliant on big data analytics, and help maintain stakeholder trust in a digitized environment [20]. While stringent privacy regulations impose initial costs, they can foster long-term consumer trust and loyalty, potentially offsetting early negative impacts. This duality underscores the need for companies to strategically balance compliance, transparency, and investment in data privacy to optimize performance outcomes. Data breaches not only harm the affected firm but can also benefit competitors, further complicating market dynamics.

Furthermore, the skill gap in technology among employees significantly influences company performance by reducing productivity, operational efficiency, and competitiveness. Research shows a negative relationship between Information and Communication Technology (ICT) skill gaps and sales performance, with companies experiencing larger gaps often seeing lower sales figures [21]. Technological proficiency is critical for employee performance, which directly influences overall company productivity and competitiveness [22, 23]. Addressing these gaps through targeted training and development programs can enhance employee competencies, particularly in digital skills, leading to improved operational efficiency [21]. Management plays a vital role in identifying skill gaps, aligning employee development with organizational goals, and fostering a culture of continuous learning to keep pace with technological advancements [23, 24].

In addition, investing in new technologies involves financial risks such as cost overruns, budget constraints, and uncertain returns, which can significantly hinder company growth and profitability. [25] explore the use of RFID systems and big data analytics to enhance financial risk detection and assessment. By analyzing transaction patterns and user behaviors with deep learning models, their study demonstrates that these technologies improve risk management strategies and protect sensitive information, enabling businesses to navigate dynamic financial environments more effectively. However, limited access to financial resources often restricts the development of new technology-based firms (NTBFs), leading to long-term losses and challenges in optimizing internal processes and human resource management, both of which are critical for performance improvement [26].

The study by [27] investigates the impact of digitalization on the firm value of 41 publicly-traded European insurance companies over a period from 2007 to 2017. The objective is to analyze how digital agendas, reflected in annual reports, influence business performance, with key variables including counts of digital-related terms, their relative frequency, and binary indicators of digital engagement. The findings reveal a significant increase in the mention of digitalization in annual reports, from approximately 20% in 2007 to around 90% in 2017, and indicate that companies with comprehensive digital agendas exhibit a firm value (measured by Tobin's Q) over 8% higher than those with less engagement, with the positive impact being statistically significant at the 1% level. The study emphasizes the importance of a holistic approach to digital transformation in enhancing competitive advantages within the insurance industry. In addition, there are several studies on finance with technology such as [28-31]

The study by [32] aims to investigate the impact of various risks associated with the adoption of financial technology (FinTech) on bank performance, utilizing a sample of 263 bank managers in Yemen. The study employs a Structural Equation Modeling (SEM) approach, specifically utilizing a disjoint two-stage technique for its structural model assessment. The research focuses on four key variables: systemic risks, operational risks, outsourcing risks, and cyber risks. The findings reveal that technology risks, particularly cyber risks, significantly negatively affect bank performance across multiple perspectives, including financial and operational metrics. Additionally, operational risks also demonstrate a negative impact on performance, while outsourcing risks are found to have a positive effect. The study underscores the critical importance of managing cyber risks in the context of FinTech adoption to enhance overall bank performance. This suggests that insurance companies may face similar challenges as they increasingly adopt digital technologies. However, it also indicates that, despite the risks, technological innovation can lead to improved performance outcomes.

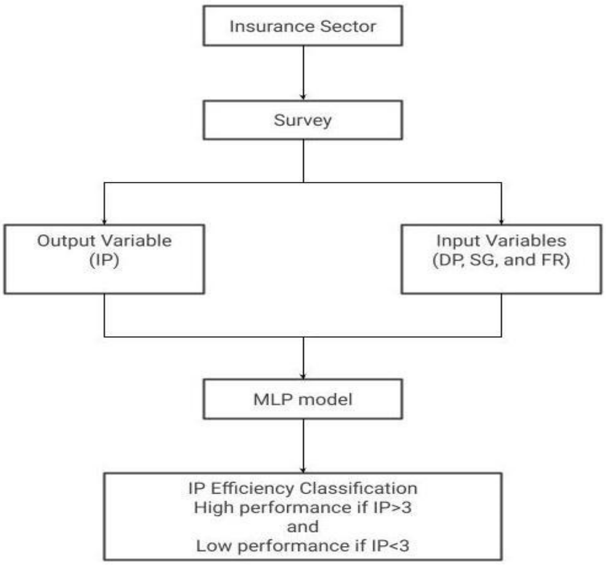

Figure 1. Conceptual Framework of the Research Process

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3. Computational Models and Methodology

The methodology is divided into two steps. In the first step, IP is calculated using data collected from employees in insurance companies through surveys. Given that most IP values fall below a threshold, a value of 3 is used to classify IP into high efficiency (IP > 3) and low efficiency (IP < 3) performance categories. In the second step, the MLP model is employed with the input factors DP, SG, and FR to analyze their impact on IP. The two steps are presented in the flowchart (Figure 1).

3.1 MLP model

The MLP, a class of feedforward artificial neural networks (ANNs), has been pivotal in advancing machine learning and deep learning. It also called vanilla deep neural network model and Neutrosophic Logic. Its origins trace back to the [33], the first mathematical model of a neural network, capable of binary logical operations. [34] introduced a single-layer network (Perceptron) for binary classification, though it was limited to linearly separable problems. [35] introduced the perceptron, a simple binary classification model that serves as the building block of deep learning. The perceptron, an artificial neuron, processes multiple weighted inputs to produce a binary output ("0" or "1"). When interconnected with many perceptrons, it forms an artificial neural network capable of solving complex, previously intractable problems in a manner akin to human reasoning. With adequate training data and computational power, these networks can tackle a wide array of challenges, making them a cornerstone of modern machine learning.

[36] exposed these limitations, particularly the inability to solve non-linear problems like XOR, leading to the AI winter. The field revived with the development of backpropagation by [37], enabling efficient training of MLPs with multiple layers to solve non-linear problems. [38] demonstrated MLPs' universal approximation capability, though challenges like vanishing gradients persisted. Advances in hardware (GPUs) and techniques like ReLU activation [39], dropout [40], and batch normalization [41] later made MLPs more efficient and scalable, solidifying their role as a cornerstone of modern deep learning architectures. MLPs are better suited for complex, non-linear relationships where their ability to learn hierarchical features and non-linear patterns shines, making them indispensable for tasks requiring sophisticated modeling of intricate data structures.

In Figure 2, the flowchart represents a Multilayer Perceptron (MLP) model with three input features (DP, SG, FR), three hidden neurons (H_1, H_2, H_3), and one output (IP). Each perceptron in the first layer (the input layer) sends its output to all perceptrons in the second layer (the hidden layer), and all perceptrons in the hidden layer forward their outputs to the final layer (the output layer). Each perceptron uses different weights for each signal it sends to the next layer. The diagram illustrates a three-layer MLP, which is considered a shallow neural network, while an MLP with four or more layers is termed a deep neural network. Unlike the traditional perceptron, which uses a step function for binary outputs, MLPs employ various activation functions to produce real-valued outputs, typically between 0 and 1 or -1 and 1. This allows MLPs to make probability-based predictions or classify objects into multiple categories. This structure enables the MLP to model complex, non-linear relationships between the inputs and the output, making it a powerful tool for tasks like regression or classification. The model learns by adjusting weights and biases during training to minimize prediction errors.

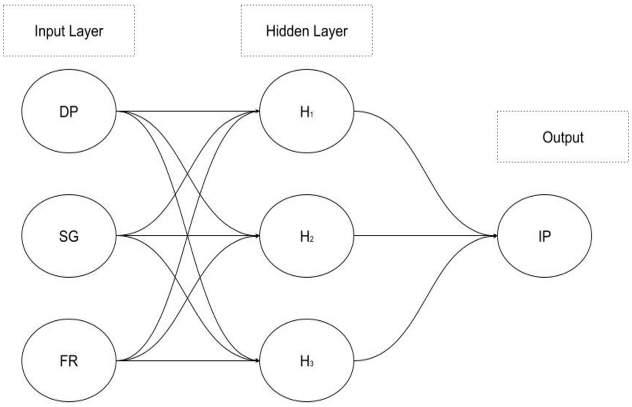

Figure 2. Flowchart of MLP model

The perceptron calculates a weighted sum by taking input features (DP, SG, and FR), each assigned a distinct weight on the connections leading to the hidden layers. These input features must be numeric and are used to calculate the weighted sum as follows:

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$$k_j = \omega_{j1}.DP + \omega_{j2}.SG + \omega_{j3}.FR + b_j \tag{1}$$

$$k_{Out} = \omega_1.a_1 + \omega_2.a_2 + \omega_3.a_3 + b_{out} \tag{2}$$

$$Output = \begin{cases} 1, & if\ k_j > \theta \\ 0, & otherwise \end{cases} \tag{3}$$

where θ is a threshold parameter

From input to hidden neuron in Equation 1, k_j represents the weighted sum of inputs (also called the pre-activation value) for neuron j (where j=*1,2,3*) in a given layer. Here, ω_{ji} represents the weight from input i to hidden neuron j, and b_j represnts the bias for hidden neuron j. The activation function ($a_j = f(k_j)$) is applied to k_j to produce the output of the hidden neuron. From hidden layer to output in Equation 2, ω_j represents the weight from hidden neuron j to the output, and b_{out} represnts the bias for output neuron. The activation function ($IP = g(k_{Out})$) is applied to the weighted sum to generate the final output. The origional perceptron represnts in Equation 3.

3.2 Learning process

The network consists of multiple weights ω_{ji} linking input nodes to hidden neurons and subsequently to the output node. During the learning process, these weights are adjusted using the backpropagation algorithm, which relies on the output error E between the predicted and actual outputs. Over several epochs (or iterations), the network works to reduce the discrepancy between the actual responses and the predicted output IP, as defined by Equation 4.

$$\omega_{ji}(t+1) = \omega_{ji}(t) - \eta \frac{\partial E}{\partial \omega_{ji}}(t) \tag{4}$$

The equation represents the weight update rule in a neural network's learning process using gradient descent. Here, $\omega_{ji}(t)$ is the weight between neuron i and neuron j at time step t, and $\omega_{ji}(t+1)$is the updated weight at the next time step. The term E represnts the error (or loss) function, which quantifies the discrepancy between the predicted and actual values. The gradient $\frac{\partial E}{\partial \omega_{ji}}$ is the derivative of the error function with respect to the weight, indicating how much and in which direction the weight should be adjusted to minimize the error. The parameter η, also known as the learning rate, controls the step size of the weight update.

The learning rate η controls the speed at which the backpropagation algorithm processes a batch of samples in each iteration. A smaller learning rate value increases the training time per epoch, enabling the model to converge more gradually while potentially achieving higher accuracy. Conversely, a larger learning rate may cause the model to update weights too aggressively, preventing it from reaching the minimum error and leading to instability or divergence. The gradient descent method, which updates the weights based on the derivative of the error function, relies on the learning rate to regulate the magnitude of these updates. Thus, the selection of the learning rate plays a crucial role in determining the effectiveness of the backpropagation algorithm in minimizing errors and reaching optimal results. To address oscillations that may arise with a higher learning rate, [42] introduced the inclusion of a momentum term M, as outlined in Equation 5.

$$\Delta\omega_{ji}(t) = \eta \frac{\partial E}{\partial \omega_{ji}}(t) + \mu\, \Delta\omega_{ji}(t-1) \tag{5}$$

However, while this parameter stabilizes the learning process, its optimal choice is problem-dependent, much like the learning rate. Most neural network software provides default values for learning rate and momentum that generally perform well. Initial learning rates in the literature vary widely, typically ranging from 0.1 to 0.9.

3.2 Rprop algorithm

To address oscillations caused by large learning rates, [42] introduced the Resilient propagation (Rprop) algorithm, which incorporates a momentum term μ as shown in Equation 6. The Rprop method updates each weight individually using a local adaptation rule. According to this rule, each update value Δ_{ji} is either increased or decreased at every iteration by multiplying it with an asymmetric factor α (for increase) or β (for decrease). This approach ensures more stable and efficient weight updates compared to traditional gradient-based methods in Equation 6.

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$$\Delta_{ji}^{(t)} = \begin{cases} \alpha * \Delta_{ji}^{(t-1)}, if \ \dfrac{\partial E^{(t-1)}}{\partial \omega_{ji}} * \dfrac{\partial E^{(t)}}{\partial \omega_{ji}} > 0 \\ \beta * \Delta_{ji}^{(t-1)}, if \ \dfrac{\partial E^{(t-1)}}{\partial \omega_{ji}} * \dfrac{\partial E^{(t)}}{\partial \omega_{ji}} < 0 \\ \Delta_{ji}^{(t-1)}, \quad otherwise \end{cases} \tag{6}$$

where $0 < \beta < 1 < \alpha$, ω_{ji} is the weight from neuron i to neuron j, and t is degree of partial derivatives of the error E with respect to the weight ω_{ji}.

3.4 Evaluation measures

Selecting the appropriate metric is vital for evaluating neural network models. Different metrics are employed across various applications to monitor and measure model performance. In our case, specific metrics are used to assess the effectiveness of our classification model. We apply tenfold cross-validation, a standard method for evaluating the performance of a learning scheme on a given dataset. The classifier's performance (output IP) is evaluated using metrics such as true positive (TP), false positive (FP), true negative (TN), false negative (FN), accuracy (ACC), receiver operating characteristic (ROC), and F-score [2].

- The FP rate corresponds to a Type I error and is defined as:

$$\text{FP rate} = \frac{\text{FP}}{\text{FP} + \text{TN}} \tag{7}$$

--The FN rate represents a Type II error, calculated using the following formula:

$$\text{FNrate} = \frac{\text{FN}}{\text{FN} + \text{TP}} = 1 - \text{TP rat} \tag{8}$$

- The TN rate and TP rate are defined as:

$$\text{TN rate} = 1 - \text{FP} \qquad \text{TP rate} = 1 - \text{FN} \tag{9}$$

- Accuracy (ACC) measures the proportion of correctly classified instances (both TP and TN) out of the total number of instances.

$$\text{ACC} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{10}$$

-The F-score (or F1-score) is the harmonic mean of Precision and Recall (Sensitivity or TN), providing a balanced measure of a classifier's performance.

$$\text{F} - \text{score} = 2 * \frac{\text{Precision} * \text{TP}}{\text{Precision} + \text{TP}} \tag{11}$$

$$\text{where} \quad \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The ROC curve is a graphical representation of a classifier's performance, plotting TP against FP at various threshold settings. The ROC curve helps visualize the trade-off between sensitivity and specificity, and the Area Under the Curve (AUC) is often used as a performance metric.

4. Experimental Results

4.1 Data Description

This study employed a questionnaire survey approach, extending historical empirical studies involving DP, SG, FR, and IP. The questionnaire comprised two parts: the first captured respondents' demographic profiles, while the second included study variables measured on a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"). A pilot study was conducted to refine the questionnaire, with 40 questionnaires emailed to the target population. Of these, 32 were returned (80% response rate), and minor adjustments were made based on feedback to improve clarity and relevance. The dataset included responses from employees of Jordanian insurance companies. Out of 280 questionnaires distributed, 243 were used (87% adoption rate), while 37 were excluded due to incomplete responses or missing values. The sample size was critical for ensuring robust evaluation and interpretation of the findings.

4.2 Demographic Information

Table 1 provides demographic information about the study participants, categorized by age, education, experience, position, and technology level, including the distribution of males, females, and totals. In terms of age, the majority of respondents (46.91%, 114 out of 243) are between 25-35 years old (51 males and 63 females), followed by 40.74% (99 out of 243) in the 36-45 age group (57 males and 42 females). Only 7.41% (18 out of 243) are under 25 (0 males and 18 females), and 4.94% (12 out of 243) are between 46-55 years old (9 males and 3 females). Regarding education, most participants (79.01%, 192 out of 243) hold undergraduate degrees (99 males and 93 females), while 11.11% (27 out of 243) have diplomas (6 males and 21 females) and 9.88% (24 out of 243) have postgraduate qualifications (12 males and 12 females). For work experience, 24.69% (60 out of 243) have less than 5 years of experience (12 males and 48 females), 28.40% (69 out of 243) have 5-10 years (36 males and 33 females), 23.46% (57 out of 243) have 10-15 years (30 males and 27 females), 16.05% (39 out of 243) have 15-20 years (30 males and 9 females), and 7.41% (18 out of 243) have over 20 years (9 males and 9 females).

In terms of position, the majority (60.49%, 147 out of 243) are employees (57 males and 90 females), followed by heads (25.93%, 63 out of 243; 33 males and 30 females), managers (12.35%, 30 out of 243; 27 males and 3 females), and directors (1.23%, 3 out of 243; 0 males and 3 females). Finally, regarding the percentage of technology level used in the insurance company, 37.04% (90 out of 243) of respondents use technology at a 51-75% level (39 males and 51 females), while 34.57% (84 out of 243) use it at a 76-100% level (33 males and 51 females). Only 4.94% (12 out of 243) use technology at less than 25% (6 males and 6 females), and 23.46% (57 out of 243) use it at a 25-50% level (39 males and 18 females).

This indicates that the workers in insurance companies are predominantly young, with the majority aged between 25 and 45 years. Most workers hold undergraduate degrees, and their work experience is distributed across all ranges of years. Additionally, the majority of employees believe that their companies use technology at a level of above 50%.

Table 1: Demographic Profile of Study Participants

Variables	Items	Male	Female	Total	Percentage
Age (Years)	<25	0	18	18	7.41%
	25-35	51	63	114	46.91%
	36-45	57	42	99	40.74%
	46-55	9	3	12	4.94%
	Total	117	126	243	100%
Education	Diploma	6	21	27	11.11%
	Undergraduate	99	93	192	79.01%
	Postgraduate	12	12	24	9.88%
	Total	117	126	243	100%
Experience (Years)	<5	12	48	60	24.69%
	5.-10.	36	33	69	28.40%
	10.-15.	30	27	57	23.46%

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	15.-20.	30	9	39	16.05%
	>20	9	9	18	7.41%
	Total	117	126	243	100%
Position	Director	0	3	3	1.23%
	Manager	27	3	30	12.35%
	Head	33	30	63	25.93%
	Employee	57	90	147	60.49%
	Total	117	126	243	100%
Technology Level (For Insurance Company)	<25%	6	6	12	4.94%
	25-50%	39	18	57	23.46%
	51-75%	39	51	90	37.04%
	76-100%	33	51	84	34.57%
	Total	117	126	243	100%

4.3 Exploratory factor analysis

Table 2 illustrats the results of the exploratory factor analysis (AVE, CR, and Alpha) for the constructs DP, SG, and FR, including the number of items, factor loadings (Lambda), Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's Alpha. For DP, the four items show strong factor loadings (0.649 to 0.854), with an AVE of 0.5583, CR of 0.8333, and Cronbach's Alpha of 0.732, indicating adequate convergent validity and reliability. For SG, the four items exhibit very strong factor loadings (0.831 to 0.902), with an AVE of 0.7523, CR of 0.9238, and Cronbach's Alpha of 0.89, demonstrating excellent convergent validity and high reliability. For FR, the four items have strong factor loadings (0.733 to 0.866), with an AVE of 0.6335, CR of 0.8731, and Cronbach's Alpha of 0.805, confirming good convergent validity and high reliability. Overall, the results indicate that all constructs are robust, reliable, and suitable for further analysis. In terms of validity and reliability, the values of factor loadings are acceptable because all of them are above 0.50. Furthermore, the results indicate that CR values are above 0.70, AVE values are above 0.50, and alpha coefficients are no less than 0.7 [43, 44], confirming that all constructs are robust, reliable, and suitable for further analysis.

Table 2: Exploratory factor analysis (AVE, CR, and Alpah)

Facroes	**No. of items**	**Lamda**	**AVE**	**CR**	**Alpha**
DP	1	0.756	0.5583	0.8333	0.732
	2	0.649			
	3	0.854			
	4	0.715			
SG	1	0.831	0.7523	0.9238	0.89

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	2	0.902			
	3	0.894			
	4	0.84			
FR	1	0.733	0.6335	0.8731	0.805
	2	0.866			
	3	0.828			
	4	0.749			

4.4 Multiple Regression Model

The Correlation and Collinearity Statistics in Table 3 displays the correlation coefficients among DP, SG, FR, and IP, as well as collinearity diagnostics. DP exhibits a weak negative correlation with SG (-0.063, less than 0.5) and a weak positive correlation with FR (0.044, less than 0.5), as well as a weak positive correlation with IP (0.361, less than 0.5). SG has a weak positive correlation with FR (0.379), and a weak negative correlation with IP (-0.139). FR has a weak positive correlation with IP (0.272). The collinearity statistics (Tolerance > 0.10 and VIF < 10) confirm the absence of multicollinearity, with DP (Tolerance = 0.9910, VIF = 1.0090), SG (Tolerance = 0.8500, VIF = 1.1770), and FR (Tolerance = 0.8520, VIF = 1.1740) all within acceptable limits. In summary, the correlations reveal meaningful relationships between the variables, with DP and FR positively influencing IP and SG negatively influencing it, while the collinearity statistics ensure the reliability of the regression model. The model is statistically robust and free from multicollinearity issues.

Table 3: The multicollinearity tests

	Correlation				**Collinearity Statistics**	
	DP	SG	FR	IP	Tolerance	VIF
DP	1	-0.063	0.044	0.361	0.991	1.009
SG		1	0.379	-0.139	0.850	1.177
FR			1	0.272	0.852	1.174
IP				1		

Table 4 presents the results of the Ordinary Least Squares (OLS) regression model, showing the impact of DP, SG, and FR on IP. The unstandardized coefficients (B) indicate that a one-unit increase in DP increases IP by 0.2870, while a one-unit increase in FR increases IP by 0.2780, and a one-unit increase in SG decreases IP by 0.1810. The standardized coefficients (Beta) reveal FR as the strongest predictor (Beta = 0.3530), followed by DP (Beta = 0.3300) and SG (Beta = -0.2520). The t-values (all significant at $p < 0.05$) confirm the statistical significance of DP (t = 5.8580), SG (t = -4.1450), and FR (t = 5.8210). The R Square (0.2500) and Adjusted R Square (0.2410) show that the model explains 25% of the variance in IP, while the Durbin-Watson statistic (1.9690) suggests no autocorrelation. The F-statistic (26.5650) confirms the model's overall significance. Regarding hypothesis testing at the 5% significance level, H_{01} (no impact of DP on IP) is rejected, as DP has a significant positive effect; H_{02} (no impact of SG on IP) is rejected, as SG has a significant negative effect; and H_{03} (no impact of FR on IP) is rejected, as FR has a significant positive effect. In summary, DP and FR positively affect IP, while SG negatively affects it.

Table 4: The OLS model for the effect of DP, SG, and FR on IP

Factors	Unstandardized Coefficients		Standardized Coefficients		Collinearity Statistics	
	B	Std. Error	Beta	t	Tolerance	VIF
(Constant)	1.9410	0.2630		7.3740***		
DP	0.2870	0.0490	0.3300	5.8580***	0.9910	1.0090
SG	-0.1810	0.0440	-0.2520	-4.1450***	0.8500	1.1770
FR	0.2780	0.0480	0.3530	5.8210***	0.8520	1.1740
R Square	Adjusted R Square	Std. Error	Durbin-Watson	F		
0.2500	0.2410	0.5898	1.9690	26.5650***		

Signif. codes: ‘*’ 0.01 ‘**’ 0.05 ‘*’ 0.1**

4.5 ANOVA test

ANOVA is a collection of statistical models designed to analyze differences among group means within a sample, along with their associated estimation methods (such as assessing the "variation" between groups). Developed by [45], ANOVA operates on the principle of the law of total variance, which partitions the observed variance into components attributable to different sources of variation in a given variable. The null hypothesis ($H_0: \mu_1 = \mu_2 = \mu_3$) in an ANOVA test posits that there are no significant differences between the group means, while the alternative hypothesis ($H_1: \mu_1 \neq \mu_2 \neq \mu_3$) suggests that at least one group mean differs. Here, μ_1, μ_2, and μ_3 represent the means of group one, group two, and group three, respectively. The null hypothesis is rejected if the significance level (p-value) is less than 5%.

The ANOVA analysis for DP, SG, FR, and IP in the table 5 examines the differences in these variables across experience groups. For DP, the between-groups sum of squares is 12.323 with a mean square of 3.081, resulting in an F-value of 5.477 and a significance level of 0.000, indicating significant differences in DP across experience groups. For SG, the between-groups sum of squares is 14.390 with a mean square of 3.598, yielding an F-value of 4.299 and a significance level of 0.002, suggesting significant differences in SG based on experience. For FR, the between-groups sum of squares is 8.192 with a mean square of 2.048, producing an F-value of 2.851 and a significance level of 0.025, indicating moderate differences in FR across experience groups. For IP, the between-groups sum of squares is 6.162 with a mean square of 1.540, resulting in an F-value of 3.502 and a significance level of 0.008, showing significant differences in IP based on experience. Regarding hypothesis testing at the 0.05 significance level, H_{04} (no significant difference in the mean responses for DP, SG, and FR on IP based on experience) is rejected, as the results show significant effects of experience on DP ($p = 0.000$), SG ($p = 0.002$), FR ($p = 0.025$), and IP ($p = 0.008$).

The ANOVA analysis for DP, SG, FR, and IP in the table 5 examines the differences in these variables across technology level groups. For DP, the between-groups sum of squares is 12.162 with a mean square of 4.054, resulting in an F-value of 7.229 and a significance level of 0.000, indicating significant differences in DP across technology level groups. For SG, the between-groups sum of squares is 6.139 with a mean square of 2.046, yielding an F-value of 2.358 and a significance level of 0.072, suggesting no significant differences in SG based on technology level. For FR, the between-groups sum of squares is 9.670 with a mean square of 3.223, producing an F-value of 4.545 and a significance level of 0.004, indicating significant differences in FR across technology level groups. For IP, the between-groups sum of squares is 15.327 with a mean square of 5.109, resulting in an F-value of 12.782 and a significance level of 0.000, showing significant differences in IP based on technology level. Regarding hypothesis testing at the 0.05 significance level, H_{05} (no significant difference in the mean responses for DP, SG, and FR on IP based on technology level) is partially rejected, as the results show significant effects of technology level on DP ($p = 0.000$), FR ($p = 0.004$), and IP ($p = 0.000$), but no significant effect on SG ($p = 0.072$).

Table 5: ANOVA analysis of Experience and Technology Level for DP, SG, FR, and IP

Variables	**Factors**		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Experiance	DP	Between Groups	12.323	4	3.081	5.477	0.000
		Within Groups	133.875	238	0.563		
		Total	146.198	242			
	SG	Between Groups	14.390	4	3.598	4.299	0.002
		Within Groups	199.151	238	0.837		
		Total	213.542	242			
	FR	Between Groups	8.192	4	2.048	2.851	0.025
		Within Groups	170.980	238	0.718		
		Total	179.171	242			
	IP	Between Groups	6.162	4	1.540	3.502	0.008
		Within Groups	104.690	238	0.440		
		Total	110.852	242			
Technology level	DP	Between Groups	12.162	3	4.054	7.229	0.000
		Within Groups	134.036	239	0.561		
		Total	146.198	242			
	SG	Between Groups	6.139	3	2.046	2.358	0.072
		Within Groups	207.403	239	0.868		
		Total	213.542	242			

FR	Between Groups	9.670	3	3.223	4.545	0.004
	Within Groups	169.501	239	0.709		
	Total	179.171	242			
IP	Between Groups	15.327	3	5.109	12.782	0.000
	Within Groups	95.525	239	0.400		
	Total	110.852	242			

4.6 MLP results

The dataset is split into two configurations: 80% (195 respondents) for training and 20% (48 respondents) for testing, and 60% (146 respondents) for training and 40% (97 respondents) for testing. The input variables (DP, SG, and FR) were then used to predict IP using the MLP model, as shown in Table 6. The table presents the classification results for training and testing datasets across different iterations (n=50, n=500, n=1000) using a 80/20 split. For training alone, the model shows varying performance: at n=50, the True Positive (TP) rate for low IP is 0.420, and the True Negative (TN) rate for high IP is 0.906, with a False Positive (FP) rate of 0.094 and a False Negative (FN) rate of 0.580. At n=500, the TP rate for low IP improves to 0.490, and the TN rate for high IP remains strong at 0.866, with FP and FN rates of 0.134 and 0.510, respectively. At n=1000, the TP rate for low IP further improves to 0.495, and the TN rate for high IP is 0.846, with FP and FN rates of 0.154 and 0.505, respectively. For testing alone, the model also shows consistent performance: at n=50, the TP rate for low IP is 0.324, and the TN rate for high IP is 0.786, with FP and FN rates of 0.214 and 0.676, respectively. At n=500, the TP rate for low IP improves to 0.480, and the TN rate for high IP increases to 0.913, with FP and FN rates of 0.087 and 0.520, respectively. At n=1000, the TP rate for low IP further improves to 0.522, and the TN rate for high IP reaches 0.920, with FP and FN rates of 0.080 and 0.478, respectively. Overall, the model demonstrates improved performance with increasing iterations, particularly in the testing dataset, where higher iterations (n=1000) yield better TP and TN rates and lower FP and FN rates compared to lower iterations (n=50). This indicates that the MLP model becomes more accurate and reliable as the number of iterations increases.

The table also provides the classification results for training and testing datasets across different iterations (n=50, n=500, n=1000) using a 60/40 split. For training alone, the model shows varying performance: at n=50, the TP rate for low IP is 0.350, and the TN rate for high IP is 0.808, with a FP rate of 0.192 and a FN rate of 0.650. At n=500, the TP rate for low IP improves to 0.479, and the TN rate for high IP increases to 0.840, with FP and FN rates of 0.160 and 0.521, respectively. At n=1000, the TP rate for low IP further improves to 0.500, and the TN rate for high IP is 0.838, with FP and FN rates of 0.163 and 0.500, respectively. For testing alone, the model also shows consistent performance: at n=50, the TP rate for low IP is 0.346, and the TN rate for high IP is 0.947, with FP and FN rates of 0.053 and 0.654, respectively. At n=500, the TP rate for low IP improves to 0.473, and the TN rate for high IP remains strong at 0.929, with FP and FN rates of 0.071 and 0.527, respectively. At n=1000, the TP rate for low IP remains at 0.500, and the TN rate for high IP is 0.898, with FP and FN rates of 0.102 and 0.500, respectively. Overall, the model demonstrates improved performance with increasing iterations, particularly in the testing dataset, where higher iterations (n=1000) yield better TP and TN rates and lower FP and FN rates compared to lower iterations (n=50). This indicates that the MLP model becomes more accurate and reliable as the number of iterations increases, even with a 60/40 split.

Table 6: Statistical criteria to classify insurance performance (IP) in MLP model

Iterations	Size	Matrix			TP rate	TN rate	FP rate	FN rate
			Low	High				
n=50	Train (80%)	Low	55	6	0.420	0.906	0.094	0.580
		High	76	58				
	Test (20%)	Low	11	3	0.324	0.786	0.214	0.676
		High	23	11				
n=500	Train (80%)	Low	48	13	0.490	0.866	0.134	0.510
		High	50	84				
	Test (20%)	Low	12	2	0.480	0.913	0.087	0.520
		High	13	21				
n=1000	Train (80%)	Low	45	16	0.495	0.846	0.154	0.505
		High	46	88				
	Test (20%)	Low	12	2	0.522	0.920	0.080	0.478
		High	11	23				
n=50	Train (60%)	Low	42	5	0.350	0.808	0.192	0.650
		High	78	21				
	Test (40%)	Low	27	1	0.346	0.947	0.053	0.654
		High	51	18				
n=500	Train (60%)	Low	34	12	0.479	0.840	0.160	0.521
		High	37	63				
	Test (40%)	Low	26	3	0.473	0.929	0.071	0.527
		High	29	39				
n=1000	Train (60%)	Low	33	13	0.500	0.838	0.163	0.500
		High	33	67				
	Test (40%)	Low	24	5	0.500	0.898	0.102	0.500
		High	24	44				

Some Statistical Criteria for Detecting High/Low IP in the MLP Model presents the performance metrics for training and testing datasets across different iterations (n=50, n=500, n=1000) using split data 80/20 in Table 7. For training alone, the model shows consistent performance: at n=50, the ACC is 0.663, ROC is 0.663, and F-score is 0.573. At n=500, the accuracy improves to 0.678, ROC to 0.678, and F-score to 0.604. At n=1000, the accuracy is 0.670, ROC is 0.670, and F-score is 0.592. For testing alone, the model also shows improved performance: at n=50, the accuracy is 0.555, ROC is 0.555, and F-score is 0.458. At n=500, the accuracy increases to 0.697, ROC to 0.697, and F-score to 0.615. At n=1000, the accuracy further improves to 0.721, ROC to 0.721, and F-score to 0.649. Overall, the model demonstrates better performance with increasing iterations, particularly in the testing dataset, where higher iterations (n=1000) yield higher accuracy, ROC, and F-score values compared to lower iterations (n=50). This indicates that the MLP model becomes more accurate and reliable as the number of iterations increases, with the testing dataset showing significant improvements in performance metrics.

Table 7 also provides the performance metrics for training and testing datasets across different iterations (n=50, n=500, n=1000) using a 60/40 split data. For training alone, the model shows consistent performance: at n=50, the ACC is 0.579, ROC is 0.579, and F-score is 0.503. At n=500, the accuracy improves to 0.659, ROC to 0.659, and F-score to 0.581. At n=1000, the accuracy further increases to 0.669, ROC to 0.669, and F-score to 0.589. For testing alone, the model also shows improved performance: at n=50, the accuracy is 0.647, ROC is 0.647, and F-score is 0.509. At n=500, the accuracy increases to 0.701, ROC to 0.701, and F-score to 0.619. At n=1000, the accuracy is 0.699, ROC is 0.699, and F-score is 0.623. Overall, the model demonstrates better performance with increasing iterations, particularly in the testing dataset, where higher iterations (n=500 and n=1000) yield higher accuracy, ROC, and F-score values compared to lower iterations (n=50). This indicates that the MLP model becomes more accurate and reliable as the number of iterations increases, with the testing dataset showing significant improvements in performance metrics even with a 60/40 split data.

Table 7: Statistical Metrics for Classifying High and Low IP

Iterations	Size (Percentage)	ACC	ROC	F-score
n=50	Train (80%)	0.663	0.663	0.573
	Test (20%)	0.555	0.555	0.458
n=500	Train (80%)	0.678	0.678	0.604
	Test (20%)	0.697	0.697	0.615
n=1000	Train (80%)	0.670	0.670	0.592
	Test (20%)	0.721	0.721	0.649
n=50	Train (60%)	0.579	0.579	0.503
	Test (40%)	0.647	0.647	0.509
n=500	Train (60%)	0.659	0.659	0.581
	Test (40%)	0.701	0.701	0.619
n=1000	Train (60%)	0.669	0.669	0.589
	Test (40%)	0.699	0.699	0.623

Figure 3 illustrates the performance of MLP model using an 80% training and 20% testing dataset split with iteration (n=1000). It shows the Weighted SSE (Sum of Squared Errors) decreasing over iterations (ranging from 0.0 to 1.0), indicating that the model is learning and improving its predictions as it minimizes errors. The steps axis represents incremental progress during training, while the targets axis reflects the desired output values the model aims to predict. The speed metric highlights the model's convergence rate, with faster convergence suggesting efficient learning. Additionally, the 1 - Specificity (1 - Spec) metric, representing the FP rate, evaluates the model's classification performance, showing how well it minimizes FP over time. Overall, the figure demonstrates the model's effective learning process, with the 80-20% split providing a robust framework for training and evaluation, as evidenced by the decreasing SSE and improved classification performance.

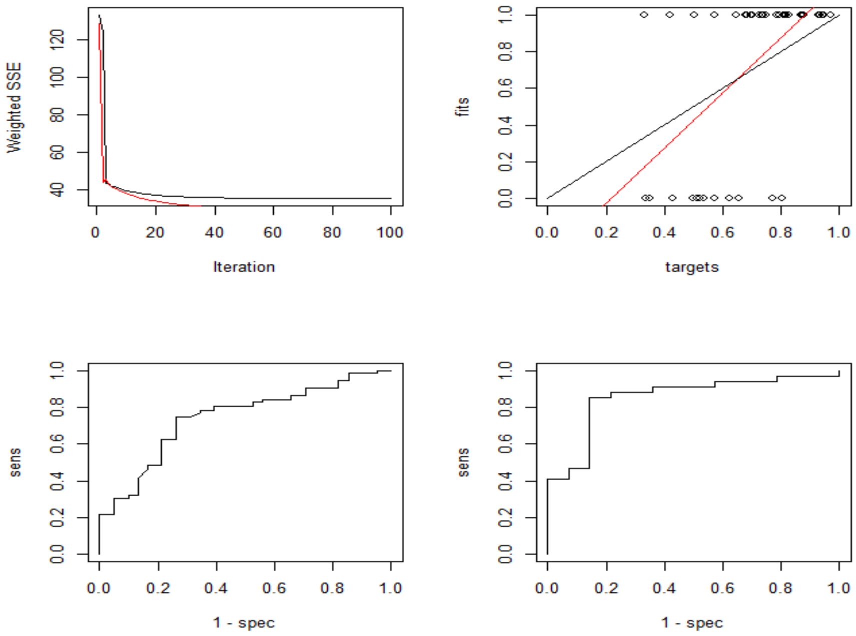

Figure 3. The performance of MLP model using 80/20 split data and iteration 1000.

5. Empirical Discussion and Recommendations

The study evaluates the influence of technology risks on IP through Insurtech innovation, focusing on strategies to address IT skills gaps, the use of data analysis or AI for risk prediction, emergency plans for technological risks, and the maintenance of DP to enhance reputation and attract customers. DP, measured through four questions assessing its role in preserving customer information, reducing unauthorized access, and mitigating misuse, has a significant positive impact (28.70%) on IP. This means that 28.7% of the variation in IP can be attributed to a company's commitment to and effectiveness in maintaining DP. This strong relationship exists because robust data privacy practices enhance customer trust, ensure regulatory compliance, reduce data breach risks, and provide a competitive advantage, all of which contribute to improved performance. By prioritizing DP, insurance companies align with Insurtech innovation goals, fostering customer-centricity, operational efficiency, and long-term growth, ultimately driving better business outcomes.

Similarly, SG is assessed through four questions highlighting perceived gaps in cybersecurity, big data analysis, software development, and network management skills among employees.The findings reveal that SG has a significant negative impact (-18.10%) on IP, as insufficient technological competencies hinder the adoption of Insurtech innovations, limit risk prediction and management capabilities, and reduce operational efficiency. This skills deficiency increases vulnerability to cyber threats, leads to poor data management, and restricts the ability to leverage advanced technologies, ultimately diminishing performance and competitiveness. Addressing these gaps through targeted training, strategic hiring, and partnerships is crucial for improving IP and ensuring sustainable growth.

FR is assessed through four questions focusing on the perceived impact of technological risks on financial performance, including increased likelihood of financial losses, higher operational costs, and revenue losses. Surprisingly, FR has a significant positive effect (27.80%) on IP. This counterintuitive result may stem from the

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fact that heightened financial risks compel companies to adopt more robust risk management strategies, invest in advanced technologies like Insurtech, and enhance operational efficiencies to mitigate these risks. Such proactive measures can lead to improved performance, as companies become more resilient, innovative, and customer-focused. Additionally, the awareness of financial risks may drive companies to prioritize data privacy and cybersecurity, further strengthening their reputation and competitive advantage. Thus, while financial risks pose challenges, they can also act as a catalyst for positive change and performance improvement in the insurance sector.

The importance of protecting insurance companies from information technology risks, we recommend implementing several key measures: Establish specialized departments focused on IT development and data protection to coordinate operations, develop modern software, monitor malfunctions, and oversee system implementations. Enhance cybersecurity by encrypting sensitive data, utilizing firewalls and intrusion detection systems, protecting against malicious software, and regularly updating systems to patch vulnerabilities. Manage permissions effectively by granting minimum necessary access, implementing Multi-Factor Authentication (MFA), and monitoring high-privilege accounts. Protect customer data and ensure regulatory compliance by adhering to standards like ISO 27001 and GDPR, maintaining regular backups in secure locations, and establishing strict data governance policies. Prioritize employee awareness and training by educating staff on new systems, phishing frauds, and cyber risks, conducting simulated cyberattack tests, and raising awareness about the dangers of sharing sensitive information. Finally, consider purchasing cyber risk insurance to cover damages from cyberattacks, such as data theft or system disruptions, ensuring comprehensive protection against evolving technological threats.

6. Conclusion and Future Work

In this study, we predicted the performance (IP) of Jordanian insurance firms using MLP model, classifying IP as high or low based on a threshold of 3. Input variables—subrogation, DP , SG , and FR —were selected after multicollinearity tests (VIF < 10, tolerance > 0.1) and multiple regression analysis, which showed DP and FR positively impacted IP, while SG had a negative effect ($p < 0.05$). The dataset included 243 responses, with validity and reliability confirmed via AVE, CR, and Cronbach's Alpha. ANOVA tests revealed significant differences in DP, SG, FR, and IP across experience and technology levels. The MLP model achieved prediction accuracy of up to 72%. Additionally, the model's performance enhances as the number of iterations rises from 50 to 1000. The study highlights the importance of SG, FR, and DP in enhancing insurance firm performance. It also underscores the potential of machine learning and Insurtech innovations to address technology risks and improve decision-making. These findings provide valuable insights for industry stakeholders and policymakers, emphasizing the need for data-driven strategies to achieve sustainable growth and competitiveness in the insurance sector.

Future research could expand the dataset, explore additional machine learning models, and investigate the integration of advanced Insurtech solutions to further enhance predictive accuracy and operational efficiency. Additionally, the impact of external factors, such as economic conditions, regulatory changes, and market competition, could be examined to better understand their influence on insurance firm performance and adaptability in dynamic environments.

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