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1301

Factors Influencing the Intention to Use Insurance Technology (Insurtech) Among Generation Z Using the Extended D-M Model

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Abstract

This study investigates the factors influencing Generation Z's intention to use Insurtech in Indonesia using an extended DeLone and McLean model. The research introduces two additional variables: perceived trust and regulatory expectancy. Data were collected via an online survey of 431 Generation Z respondents aged 17 and above, residing in ten major Indonesian cities: Jakarta, Bandung, Semarang, Yogyakarta, Surabaya, Denpasar, Palembang, Medan, Balikpapan, and Makassar, all with a basic understanding of Insurtech. The questionnaire included demographic questions and research variables measured on a five-point Likert scale. Data were analyzed using Structural Equation Modeling (SEM) through Smart PLS 4. Descriptive analysis revealed that most respondents were aged 25-28 years, predominantly female, residing in Jakarta, employed in private sectors, with monthly expenditures below USD 300, and holding a bachelor's degree. The analysis indicated that respondents viewed Insurtech positively, noting its organized information, flexible services, knowledgeable providers, honest services, and legal protection of personal data. Additionally, respondents expressed a strong interest in using Insurtech soon. The measurement model evaluation confirmed the validity and reliability of all indicators based on convergent validity, discriminant validity, and reliability tests. The structural model analysis showed that the independent variables explained 57% of the variance in intention to use Insurtech and 69% in perceived trust. Hypothesis testing revealed that information quality, system quality, service quality, and regulatory expectancy positively influenced both intentions to use Insurtech and perceived trust. However, contrary to expectations, perceived trust did not significantly affect the intention to use Insurtech. This finding suggests that for Generation Z, trust may be considered a baseline expectation, with factors like system and service quality playing a more direct role in their adoption decisions. Additionally, no significant mediation effects were found. The model demonstrated strong predictive relevance and good fit, confirmed by Q^2, NFI, and SRMR values.

Keywords: Information Quality, System Quality, Service Quality, Perceived Trust, Regulatory Expectancy, Intention to Use Insurtech, Generation Z

1. Introduction

The rapid development of digital technologies has significantly influenced various sectors, including the insurance industry. The advent of digital insurance, commonly referred to as insurtech, is driven by the widespread use of digital devices that have made it easier to offer services and reach potential consumers, offering solutions for the insurance industry [1]. Insurtech enables customers to access insurance products online directly, bypassing agents. This change is driven by widespread online access via gadgets and computers, allowing consumers to engage with insurance services conveniently. The insurance industry must adapt to rapid technological advancements and understand evolving consumer behaviors influenced by digital transformations [2]. Insurtech has gained significant traction since its inception in 2010, reshaping traditional insurance operations. However, some studies highlight challenges in adopting insurtech, with industry players hesitant to invest due to uncertainties about market acceptance [3]. Despite the challenges, understanding consumer behavior is critical, as the adoption of insurtech depends not only on the offerings of insurance companies but also on how consumers perceive these innovations. This underscores the importance of consumer perceptions and their willingness to embrace digital insurance solutions. The gap in knowledge about consumer behavior toward insurtech remains a major concern, especially in emerging markets like Indonesia [3]. In Southeast Asia, including Indonesia, the adoption of insurtech has been relatively slow compared to global trends.

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Despite the industry's potential, the slow uptake is often attributed to several factors, such as a lack of understanding of insurtech's operational mechanisms and the immediate benefits it provides [4]. These factors indicate a mismatch between the products offered by insurance companies and consumer expectations, highlighting the need for more targeted research to address consumer behavior toward insurtech. This gap in understanding presents a unique opportunity to explore how Gen Z perceives insurtech and its adoption drivers. Trust and regulatory factors are also underexplored, particularly in the context of Indonesia's evolving regulatory landscape [3]. Generation (Gen) Z, those born between 1997 and 2012, is recognized as a significant driver of digitalization and is considered a prime segment for digital products, including insurtech. Gen Z is often referred to as digital natives, highly proficient in using technology to access information and services [5]. This generation's significant engagement with digital platforms, especially social media, coupled with their preference for online services, makes them an appealing target market for Insurtech companies. In Indonesia, Gen Z spends a substantial amount of time online, with many dedicating 1-6 hours daily to social media [6]. This trend, combined with Indonesia's young and tech-savvy demographic, offers a unique opportunity for Insurtech to engage with a digitally literate and financially emerging segment of the population. With over 74 million Gen Z individuals in Indonesia, making up a significant portion of the nation's population, their high digital engagement and growing purchasing power position the country as an ideal market for expanding Insurtech services.

Given the rapid digital adoption among Gen Z, it is crucial for the insurance industry to adapt quickly by offering relevant, accessible, and trustworthy services. As Gen Z moves into the workforce, they will have greater disposable income, further increasing their potential as future consumers of insurtech products [6]. The potential for insurtech to capture this market is significant, especially as Indonesia's population is predominantly young and digitally connected. However, for insurtech to realize its potential, it must address the barriers to adoption, including lack of trust and regulatory uncertainties [7]. The integration of consumer trust and regulatory expectancy (RE) into models of insurtech adoption is critical, as these factors influence the willingness of consumers to adopt new technologies, making it essential to understand how these factors affect Gen Z's intention to use (INT) of insurtech. The DeLone and McLean (D and M) model, originally developed in 1992, is a well-established framework for evaluating the success of information systems, focusing on dimensions like system quality, information quality, service quality, user satisfaction, and net benefits. This study extends the D and M model by adding PT and RE to better capture the unique challenges of Insurtech adoption in Indonesia, where both trust in digital platforms and the regulatory landscape significantly impact consumer decisions. By incorporating these variables, the extended D and M model offers a more comprehensive understanding of the factors influencing Generation Z's intention to use Insurtech.

Limited empirical evidence exists on how factors like IQ, SQ, SV, and RE influence insurtech adoption in Indonesia, where the digital insurance market is underdeveloped. Studies on technology acceptance have focused on specific industries, leaving a gap in understanding insurtech from a consumer perspective. Despite regional e-commerce growth, insurtech adoption lags, with digital insurance premiums declining from 2% in 2022 to 1.3% in 2023. Gen Z, a digital-native demographic, has been sparsely researched regarding their attitudes toward digital insurance. Their digital fluency makes them an ideal target, yet their perception of insurtech and adoption factors remain unclear. Trust and regulatory expectations are also underexplored, with regulatory clarity lacking. This research uses the extended D-M model to integrate these factors, providing insights into insurtech adoption in Indonesia and contributing to academic literature and practical strategies for companies targeting Gen Z. The research aims to develop and validate a model to understand factors influencing Gen Z's intention to adopt insurtech in Indonesia. It examines the relationships between IQ, SQ, SV, PT, and RE, focusing on usability, effectiveness, trust, and regulatory expectations. The study also investigates how information, system, and service quality affect trust and adoption intention, with PT as a mediator. By addressing these objectives, the research seeks to provide insights into the drivers of insurtech adoption among Gen Z in Indonesia.

2. Literature Review

2.1. Understanding the Impact of Information Quality (IQ)

IQ refers to the level of performance a system delivers to individual users [8]. It is a crucial aspect of the output standards of an information system and serves as an essential element that the system offers to end-users [9]. In the context of insurtech, IQ plays a significant role in how users interact with digital insurance platforms. It affects users' ability to access accurate, relevant, and clear information about insurance products and services, ultimately influencing their decision to engage with these platforms. For consumers in the insurance sector, particularly in the digital realm, the quality of information is vital for performing transactions and engaging in activities related to insurance. Research by [10] has demonstrated a significant positive impact of IQ on the behavioral INT of systems, particularly in contexts like online library systems. This study highlights that when users perceive the information provided by a system as accurate and helpful, their INT of the system increases. Similarly, [11] found that the perceived IQ significantly influences users' behavioral intention, suggesting that high-quality, reliable information leads to greater trust and willingness to engage with a platform. IQ significantly influences consumer behavior in the insurtech sector, especially for Gen Z in Indonesia. Their digital fluency and need for transparent information make the quality of data provided by insurtech platforms crucial for their adoption of these services.

2.2. Exploring the Factors Behind the Intention to Use (INT) of Insurtech

INT refers to an individual's desire to consistently use a product or service and share its benefits. It is commonly studied using theories such as TRA, TAM, TPB, and UTAUT. In the context of Insurtech, INT indicates the likelihood of consumers regularly using digital insurance products. Research by [12] highlighted that INT significantly influences consumer behavior in e-commerce platforms like Shopee, suggesting that understanding the factors affecting INT can help predict user engagement with digital services, including Insurtech. Studies by [13] found that perceived usefulness and ease of use are key drivers of behavioral intentions, as users are more likely to adopt technologies, they find both useful and easy to navigate. INT, as defined by [14], refers to an individual's interest or desire to engage with a particular behavior, which may evolve over time. This is especially relevant for understanding how Generation Z, a key target demographic for Insurtech in Indonesia, might adopt digital insurance services. Research by [15] further defines behavioral intention as the extent to which a person plans to engage in or avoid a particular behavior in the future, with users being more likely to adopt Insurtech if they perceive it as beneficial. Additionally, [16] posits that a person's attitude toward technology can be predicted by their intention to continue using it or recommend it to others. This underscores the importance of fostering a positive attitude toward Insurtech to drive adoption. INT in the context of Insurtech involves three components: action, target, and context. Action refers to the behavior following the intention, such as using the platform; target refers to the goal, which could be individual users, groups, or the market; and context involves the circumstances that support the behavior, such as interaction methods. Understanding these factors is crucial for fostering broader adoption of Insurtech.

2.3. The Role of System Quality (SQ) in User Adoption

SQ is crucial for assessing a system's reliability, usability, responsiveness, and availability. Positive user evaluations impact their attitude and behavior, with high SQ linked to system reliability, encouraging adoption and continued use [8]. In the context of insurtech, SQ plays a pivotal role in determining whether consumers perceive the platform as dependable and easy to use, which can directly affect their decision to engage with digital insurance services. Research by [17] examined the sustainable adoption of e-learning systems in Malaysia and found that SQ had a positive relationship with the INT of the system. This study highlights those efficient systems increase user adoption and continued use. In mobile learning, SQ positively affects engagement intentions with platforms [17]. Similarly, the quality of the insurtech will significantly impact how Gen Z users perceive their reliability and overall functionality. In the insurtech sector, SQ involves system reliability, user interface design, ease of navigation, and responsiveness. These ensure effective platform interaction, boosting satisfaction and INT. As digital insurance grows, robust and user-friendly systems are vital for attracting and retaining users, especially Gen Z in Indonesia. High SQ builds consumer confidence, while frequent technical issues or poor interfaces can decrease trust and adoption rates. A smooth, reliable system increases service embrace, highlighting SQ's impact on user satisfaction and INT.

2.4. Enhancing Service Quality (SV) for Better User Experience

SV refers to the customer's perception of the service experience, which can be compared to their expectations to determine the quality of service they perceive [18]. SV is key to distinguishing services and ensuring customer satisfaction. In insurtech, SV shapes users' perceptions and engagement with platforms. High-quality service in digital insurance involves responsiveness, professionalism, customer support, and user experience, building trust and making users feel valued. Research by [19] examined the INT of mobile banking services among Jordanian users and found that SV positively influenced users' behavioral intentions. This indicates that when users perceive high SV, they are more likely to adopt and engage with the service. Similarly, [20] identified SV as a promising predictor for the adoption of online transportation systems, highlighting its relevance across various digital platforms. The same logic applies to insurtech, where the SV of the platform can significantly affect users' intentions to use digital insurance products. For insurtech, SV includes customer support responsiveness, claims processing efficiency, platform navigation ease, and overall user experience. Fast, helpful responses, easy service access, and smooth transactions encourage continued use, while poor SV, like slow responses or lack of support, can deter users. SV is crucial for building consumer confidence and trust, influencing satisfaction, repeated use, and positive word-of-mouth, which are vital for digital insurance growth. As insurtech evolves, excellent service will be key to customer retention, especially with rising digital service expectations.

2.5. The Influence of Perceived Trust (PT) on Adopted Decisions

In technology adoption, risk is inherent, making PT a crucial element for consumer confidence. When consumers perceive risk, PT helps alleviate their concerns by assuring them that the system is reliable, safe, and beneficial. PT is the expectation that technology will function properly, and it helps individuals feel secure in their interactions, especially in situations where they rely on the behavior of others. This is particularly important in economic transactions, where PT reduces perceived risks and encourages consumers to engage in transactions [21]. As individuals believe in the system's ability to offer comfort and sustained usefulness, they develop a sense of security, which is critical for adopting new technologies. Trust is built through various sources such as the transparency of information, recommendations from peers, or feedback from other users, ensuring that the provided information is reliable and credible [22].

In the context of online transactions, especially with the increasing frequency of fraud, PT plays a vital role in fostering consumer confidence [23]. A lack of trust can lead to hesitation and reluctance to engage with online platforms, which ultimately reduces the intention to use digital services. The Social Exchange Theory [24] explains that trust is a fundamental element in exchanges, particularly in situations where knowledge and resources are shared between parties [25]. Trust facilitates smoother interactions, reduces risks, and assures consumers that they are not being exploited [28]. In the realm of insurtech, where transactions occur online without direct personal interaction, PT becomes even more critical in shaping consumer decisions. It acts as a mediator for successful transactions and influences consumer purchases by reducing uncertainty.

Several dimensions of PT—such as Trusting Belief, Benevolence, Integrity, and Competence—are crucial in a consumer's relationship with an e-commerce system. Key indicators of PT include security, privacy, and reliability. To build trust in digital transactions, insurtech companies must prioritize protecting user information, maintaining transparency, avoiding negative criticism of competitors, and conducting business with integrity. These strategies are essential for fostering consumer engagement and ensuring the success of insurtech platforms. While perceived trust was initially expected to mediate the relationships between IQ, SQ, and SV, the lack of mediation in these relationships suggests that these factors directly influence adoption decisions, independent of trust.

2.6. Regulatory Expectancy (RE) and Its Role in Shaping User Trust

RE refers to the extent to which the performance of regulations meets expectations and continues to improve due to the use of technology or systems [29]. RE refers to performance improvements in insurtech for insurance activities. This is seen in potential users' expectations for laws protecting their interests from disputes or misuse of personal information [30]. RE is vital for technology adoption, particularly in sectors like insurance, where consumer protection and data security are key. Technology and internet penetration offer innovation and product development opportunities, but regulations are essential to prevent misuse and ensure ethical data handling [31]. In the insurtech sector, regulations should balance innovation with consumer protection. Overly strict or poorly designed regulations may hinder insurtech development and adoption, while a well-structured environment can boost consumer trust and promote technology use. RE is vital for insurtech's success and sustainability. Consumers need confidence in regulations to protect their data and rights. Without it, they may avoid insurtech due to privacy or financial concerns. Clear, fair regulations are essential for insurtech growth, especially in Indonesia, where tech regulations are still developing. Effective management and

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flexibility in regulations are necessary to keep pace with technology, align with industry advancements, and meet consumer expectations. This supports market stability, innovation, and consumer protection, driving insurtech adoption.

3. Methodology

3.1. Research Design and Data Collection

This study uses quantitative research to examine factors affecting insurtech interest (INT) among Gen Z in Indonesia. It builds on empirical studies linking INT to independent variables (IQ, SQ, SV, RE), a mediating variable (PT), and tests these relationships with Structural Equation Modeling (SEM). Data is collected via a survey, a common method for large populations. Non-probability purposive sampling is used, targeting Gen Z aged 17 to 28 in ten major cities: DKI Jakarta, Bandung, Semarang, Yogyakarta, Surabaya, Denpasar, Palembang, Medan, Balikpapan, and Makassar. These cities are selected for their economic activity and digital infrastructure, and respondents must be familiar with insurtech products. The sample size for this study is determined using a formula based on the number of indicators in the model. According to [32], the minimum sample size required for multivariate analysis in SEM is calculated as the number of indicators multiplied by a factor of 5 to 10. With 36 indicators in the model, the minimum sample size is calculated as 360 respondents. However, to ensure more robust results, the target sample size is set to around 500 respondents, as recommended by [33]. This sample size is adequate for ensuring statistical power and reliable results for SEM analysis. Data was collected via an online Google Forms survey distributed on social media platforms like WhatsApp, Instagram, Twitter, and Line, targeting Gen Z. This cost-effective method ensured a broad reach. The survey covered key variables (IQ, SQ, SV, RE, PT) and demographics. Data was analyzed using SEM to assess hypothesized relationships and insights into insurtech adoption factors among Gen Z in Indonesia.

3.2. Research Model and Hypothesis Development

The research model examines variables affecting Gen Z's intention to adopt insurtech in Indonesia, using theories like TAM, TRA, and UTAUT. It suggests that IQ, SQ, SV, PT, and RE are key influences, with PT mediating their relationship to the intention to adopt insurtech.

H1: IQ significantly affects the intention to use insurtech.

The quality of information provided by insurtech platforms plays a crucial role in consumer decision-making. According to [8], IQ is a key determinant in the success of information systems. High-quality information ensures that users can easily understand the benefits, terms, and conditions of insurance products, which increases their likelihood of adopting the technology. Research [10] and [11] both found that perceived IQ positively affects consumers' behavioral intentions, supporting the hypothesis that better quality information will enhance users' intention to use insurtech.

H2: SQ significantly influences the intention to adopt insurtech.

SQ refers to the reliability, usability, and performance of the digital platform. Research by [17] demonstrated that high SQ, characterized by stable performance and user-friendly interfaces, significantly impacts users' intention to adopt technology. In the context of insurtech, a reliable and easy-to-navigate platform will encourage users to engage with the service. This hypothesis is grounded in the theory of technology adoption, which emphasizes that perceived ease of use and system reliability are critical to consumers' decisions to use a new technology.

H3: SV significantly affects the intention to use insurtech.

SV encompasses factors like customer support, responsiveness, and the overall experience of using the platform. According to [18], SV is essential in differentiating services and ensuring customer satisfaction. In the insurtech context, high SV can build trust and encourage continued use of digital insurance platforms. Research [19] found that SV positively impacts the intention to adopt mobile banking services, suggesting that a similar relationship exists in the adoption of insurtech.

H4: PT significantly influences the intention to use insurtech.

Trust is a central factor in technology adoption, especially when it involves sensitive data such as personal and financial information. In digital platforms, trust reflects the user's confidence that the platform will handle their data securely and deliver promised services [34]. Consumers who trust the insurtech platform are more likely to adopt and continue using it. This hypothesis is supported by research in e-commerce and online banking, where PT was found to be a strong predictor of user behavior [21].

H5: RE significantly influences the intention to use insurtech.

RE refers to the consumer's confidence in the legal framework surrounding insurtech. In emerging markets like Indonesia, clear and supportive regulations are necessary to ensure consumer protection and platform reliability [29]. Research indicates that favorable regulations not only ensure market stability but also boost consumer confidence in adopting new technologies. Thus, RE is expected to significantly influence the intention to use insurtech.

H6: IQ significantly affects PT in insurtech.

High-quality, accurate, and transparent information fosters trust in digital platforms. Consumers are more likely to trust an insurtech service when the information provided is clear, reliable, and understandable. This relationship is supported by previous studies, such as those by [10] and [11], which found that IQ enhances trust in the platform, thereby increasing the likelihood of adoption.

H7: SQ significantly affects PT in insurtech.

SQ also plays a significant role in building trust. A well-functioning system, which is free from technical issues and easy to navigate, can enhance users' confidence in the platform. According to [17], users are more likely to trust a system that performs reliably and efficiently. In the case of insurtech, consumers are more inclined to trust platforms that ensure smooth functionality and stable performance.

H8: SV significantly affects PT in insurtech.

SV, particularly the responsiveness of customer support and the professionalism of the service provider, is crucial in fostering trust. When users experience high-quality customer service, it enhances their belief that the platform is trustworthy. Research in other sectors, such as mobile banking [19], has shown that positive service experiences significantly enhance PT, which is expected to hold true for insurtech platforms as well.

H9: RE significantly affects PT in insurtech.

When users believe that there is strong regulatory support for the platform, they are more likely to trust the service. Regulations that protect consumer data and ensure fairness increase consumer confidence in using insurtech. Research [29] highlighted that a well-established regulatory framework helps build trust in digital platforms, which is essential for user adoption.

H10: IQ significantly affects the intention to use insurtech, mediated by PT.

PT plays a mediating role between IQ and the intention to use insurtech. High-quality information not only directly affects users' intention to adopt insurtech but also builds trust, which in turn influences adoption. This mediation effect is consistent with studies that highlight the central role of trust in online consumer behavior [11].

H11: SQ significantly affects the intention to use insurtech, mediated by PT.

As with IQ, SQ is expected to influence the intention to use insurtech through PT. A high-quality, reliable platform enhances trust, which then positively impacts the user's intention to adopt the service. This mediation effect supports the idea that users are more likely to adopt technology when they trust the platform [17].

H12: SV significantly affects the intention to use insurtech, mediated by PT.

SV is hypothesized to affect the intention to use insurtech through its impact on PT. Positive service experiences build trust, which in turn increases the likelihood of adoption. This mediation effect is supported by research in various sectors, including e-commerce and banking [19] where SV directly influences trust and adoption. Figure 1 visually represents the hypothesized relationships between the variables in the research model.

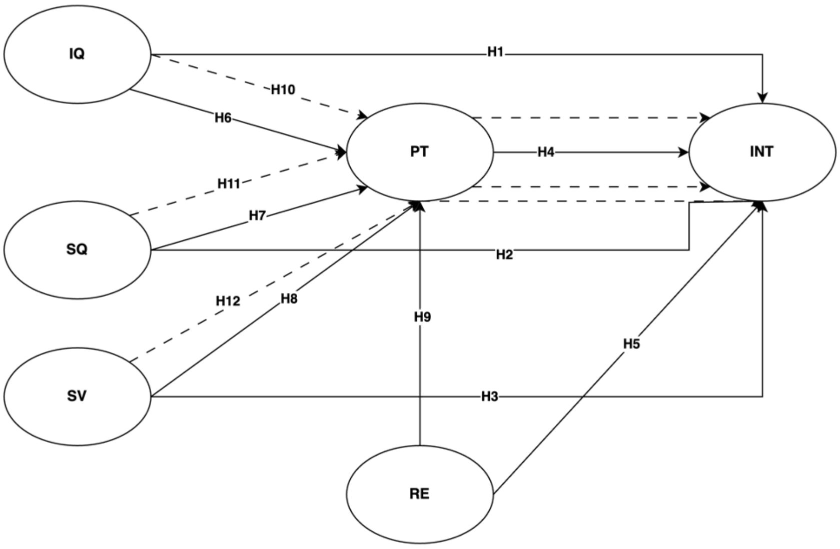

Figure 1. Research Model Framework

3.3. Measurement Instruments

The measurement instruments for each variable in this study, shown in Table 1, were developed and adapted from existing scales used in prior research. The purpose of adapting these instruments is to ensure they are relevant to the context of insurtech adoption, specifically among Gen Z in Indonesia.

Table 1. Questionnaire Items

Item*)		Questionnaire	Source
	IQ1	The insurance information provided by insurtech is understandable.	
	IQ2	Insurance information is reliable on the insurtech platform.	
	IQ3	The insurance information provided by insurtech is interesting	
IQ	IQ4	insurtech provides the information I want	Adapted from [35]
	IQ5	insurtech provides me with organized information content.	
	IQ6	insurtech provides up-to-date information content	
	IQ7	The information provided by the insurtech company is complete	
	SQ1	Insurtech's services are well structured	
	SQ2	Insurtech's services are easy to use	
SQ	SQ3	Insurtech provides interactive features between users and the system	Adapted from [35]
	SQ4	Insurtech provides flexible services	
	SQ5	It is very easy to access insurtech services	
	SV1	Insurtech service providers provide personal attention when I experience problems.	
	SV2	Insurtech service providers provide services at the promised time	
	SV3	Insurtech service providers have enough knowledge to answer my questions.	
SV	SV4	Insurtech provided the right explanation online	Adapted from [35]
	SV5	Insurtech gave me the opportunity to express my opinion	
	SV6	In general, insurtech can provide services as expected	
	SV7	In general, insurtech's service management is good	

Item*)		Questionnaire	Source
PT	PT1	Insurtech has enough protection that makes me comfortable using it.	Adapted from [36]
	PT2	I believe insurtech's technology makes me safe to use it.	
	PT3	In general, I am confident in insurtech's services.	
	PT4	Insurtech's services are competent in handling transactions	
	PT5	Insurtech provides reliable services.	
	PT6	Insurtech is always kind to customers	
	PT7	Insurtech is honest in providing services	
RE	RE1	I believe that the law can protect me from disputes.	Adapted from [36]
	RE2	I believe that the law should regulate how insurtech should use personal information.	
	RE3	I believe that the law should regulate how insurtech should protect my personal information.	
	RE4	I believe that the law can address violations committed by insurtech companies.	
	RE5	Enforcement of the rule of law for insurtech companies is what I expect.	
INT	INT1	If I have used insurtech's services, then I will continue to use them.	Adapted from [37]
	INT2	I want to use insurtech services for insurance transactions.	
	INT3	I would recommend insurtech services for insurance transactions.	
	INT4	I hope to use insurtech services soon.	
	INT5	My future projection will use insurtech services	

(IQ: Information Quality, SQ: System Quality, SV: Service Quality, PT: Perceived Trust, RE: Regulatory Expectancy, INT: Intention to Use)

3.4. Data Analysis

Data analysis in this study was conducted using SPSS and SmartPLS version 4. SPSS was employed to perform descriptive statistics and data tabulation, while SmartPLS was used to test the measurement and structural models, as well as hypotheses. The analysis process began with data cleaning, addressing any missing values. SPSS then generated descriptive statistics to summarize the sample data, including the mean, standard deviation, and frequency distributions. SmartPLS conducted Structural Equation Modeling (SEM) to evaluate both the measurement and structural models.

The measurement model was evaluated to assess the reliability and validity of the latent constructs. For convergent validity, the Average Variance Extracted (AVE) for each latent variable was calculated, ensuring that it was above 0.5, meaning the indicators explained at least 50% of the variance in the latent variable. Composite reliability and Cronbach’s alpha values were also assessed, with values exceeding 0.7 considered acceptable, indicating internal consistency of the measurement items. For discriminant validity, the square root of the AVE was compared to the correlations between latent constructs, ensuring that each construct was distinct. Additionally, the loading factor for each indicator was required to be above 0.7, indicating reliable measurement of each construct.

The structural model was then tested to evaluate the relationships between the latent variables. Path coefficients were analyzed to determine the strength and direction of these relationships. A key output from SmartPLS was the R-squared (R^2) value, which indicated the proportion of variance in the dependent variable explained by the independent variables. R^2 values of 0.75, 0.50, and 0.25 were considered strong, moderate, and weak, respectively. Hypothesis testing was conducted using the bootstrapping method, generating t-statistics and p-values to assess the significance of the path coefficients. A t-value greater than 1.96 and a p-value less than 0.05 indicated statistical significance. Model fit indices, such as the Goodness of Fit (GoF), were also examined to ensure the overall fit of the model. The GoF index combines the fit of both the measurement and structural models, with values above 0.36 indicating a good fit. Lastly, f^2 effect sizes were calculated to evaluate the magnitude of the effect of each independent variable on the dependent variable.It is important to note that, given the cross-sectional and self-reported nature of the data, potential issues like common method bias and endogeneity were considered. Common method bias was addressed by ensuring that the survey design minimized leading or biased questions, and statistical controls were employed to mitigate the impact of endogeneity. These efforts help ensure the robustness and reliability of the findings.

4. Results and Discussion

4.1. Descriptive Statistics

This section presents the demographic characteristics of the study respondents, including age, gender, income, education, occupation, and location, as shown in Table 2.

Table 2. Demographic Data

Demography Characteristic	Category	Frequency	Percentage (%)
Age	17-20	76	17.6%
	21-24	139	32.3%
	25-28	216	50.1%
Location	DKI Jakarta	255	59.3%
	Bandung	12	2.8%
	Semarang	17	4.0%
	Yogyakarta	17	4.0%
	Surabaya	30	7.0%
	Denpasar	13	3.0%
	Palembang	11	2.6%
	Medan	32	7.4%
	Balikpapan	11	6.5%
	Makassar	32	7.4%
Gender	Male	172	39.9%
	Female	259	60.1%
Occupation	Students	154	35.7%
	Public Employee	18	4.2%
	Private Employee	179	41.5%
	Entrepreneur	13	3.0%
	Other	67	15.6%
Income Level	< USD 300	221	51.3%
	USD 300 - 600	169	39.2%
	USD 600 - 900	31	7.2%
	USD 900 - 1200	3	0.7%
	> USD 1200	7	1.6%
Education Level	High School/Equivalent	64	14.8%
	Diploma	54	12.5%
	Bachelor	296	68.6%
	Master	16	3.7%
	Master (Ongoing)	1	0.2%

The majority of respondents are aged 25 to 28, representing 50.1% of the total sample. The next largest group is aged 21 to 24, making up 32.3%, and 17.6% are aged 17 to 20. This indicates that a significant portion of the respondents are in the older segment of Gen Z. DKI Jakarta has the highest number of respondents, at 59.3% of the total sample. Other cities, including Surabaya, Medan, and Makassar, have smaller but still notable representation, ensuring geographical diversity in the research. The survey shows that 60.1% of respondents are female, while 39.9% are male, reflecting the general trend in the respondent pool. In terms of employment, 41.5% of respondents work in the private sector, followed by students at 35.7%. A smaller percentage are self-employed or work in the public sector, highlighting the dominant working demographic of Gen Z, which includes students and young professionals. Regarding monthly income, 51.3% of respondents earn less than USD 300, indicating a relatively lower-income group. Only 1.6% earn above USD 1200, and 39.2% fall within the USD 300-500 income bracket. A large majority of respondents have completed their bachelor's degree, at 68.68% of the sample. Other respondents have completed high school or have a diploma, while only a small proportion hold a master's degree.

Multicollinearity occurs when independent variables are highly correlated with one another, which can affect the reliability of the regression coefficients. To assess multicollinearity, the Variance Inflation Factor (VIF) was calculated. A VIF value greater than 5 indicates problematic multicollinearity. In this study, all VIF values are below 5, indicating that multicollinearity is not a concern in the structural model. The VIF values for the constructs in this study are shown in Table 3. Since all VIF values are below 5, the model does not suffer from multicollinearity issues, and the relationships between the variables are stable.

Table 3. Inner Variance Inflation Factor (VIF) Results

Path	VIF Value
IQ → INT	3.323
RE → INT	1.759
SV → INT	3.635
SQ → INT	3.685
PT → INT	3.193
IQ → PT	3.141
RE → PT	1.636
SV → PT	3.373
SQ → PT	3.524

4.2. Measurement Model Evaluation

The measurement model evaluation is vital for assessing the validity and reliability of study constructs. It ensures indicators effectively measure latent variables. Reliability testing is used to assess the consistency of the measurement model. It ensures that the indicators used in the study provide consistent results. Two primary measures of reliability are Cronbach's Alpha and Composite Reliability. Cronbach's Alpha is a measure of internal consistency, indicating how closely related a set of items are as a group. A Cronbach's Alpha value greater than 0.70 is considered acceptable. In this study, all constructs show Cronbach's Alpha values well above 0.70, as shown in Table 4, indicating high internal consistency among the indicators for each latent variable. For example, IQ has a Cronbach's Alpha of 0.942, which is well above the acceptable threshold, ensuring the reliability of this construct. Composite Reliability is another measure of reliability that is less sensitive to the number of items in the scale than Cronbach's Alpha. A value greater than 0.70 is considered good. The results show that all constructs have Composite Reliability values exceeding the threshold of 0.70, as shown in Table 3, with IQ having a value of 0.953, confirming that the measurement model is reliable and the indicators consistently measure their respective constructs. These reliability measures demonstrate that the model's constructs and indicators are stable and dependable, ensuring the validity of the conclusions drawn from the data.

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Table 4. Reliability Analysis and Convergent Validity

Construct	Item	Factor Loading	AVE	Composite Reliability	Cronbach's Alpha
INT	INT1	0.876	0.879	0.944	0.925
	INT2	0.900			
	INT3	0.909			
	INT4	0.928			
	INT5	0.773			
IQ	IQ1	0.840	0.862	0.953	0.942
	IQ2	0.901			
	IQ3	0.905			
	IQ4	0.871			
	IQ5	0.844			
	IQ6	0.828			
	IQ7	0.841			
PT	PT1	0.792	0.832	0.940	0.926
	PT2	0.795			
	PT3	0.836			
	PT4	0.784			
	PT5	0.877			
	PT6	0.863			
	PT7	0.870			
RE	RE1	0.821	0.871	0.940	0.920
	RE2	0.900			
	RE3	0.868			
	RE4	0.907			
	RE5	0.859			
SQ	SQ1	0.826	0.862	0.935	0.913
	SQ2	0.878			
	SQ3	0.876			
	SQ4	0.848			
	SQ5	0.880			
SV	SV1	0.802	0.820	0.935	0.919
	SV2	0.817			
	SV3	0.811			
	SV4	0.824			
	SV5	0.810			
	SV6	0.847			
	SV7	0.832			

Convergent validity is assessed by examining how well each indicator correlates with its corresponding latent variable. In PLS-SEM, a common threshold for an acceptable loading factor is 0.70, which means that the indicator explains 70% of the variance in the latent variable. In this study, all indicator loadings exceeded the 0.70 threshold, confirming that the indicators are effectively representing their latent constructs. The high loading factors suggest that the items used for each construct are strongly aligned with their respective variables, ensuring that each construct is well-defined and understood by respondents. For example, the loading factors for the intention to use Insurtech (INT) range from 0.773 to 0.928, demonstrating a solid correlation between the indicators and the construct. Similarly, the information quality (IQ) construct shows loading factors between 0.828 and 0.905, further validating the model's convergent validity.

The Average Variance Extracted (AVE) is another important metric in this evaluation. AVE values greater than 0.50 suggest that the latent variable explains more than 50% of the variance in its indicators, indicating a strong link between the construct and its measures. In this study, the AVE values for all constructs exceed 0.50, with the IQ construct showing an AVE of 0.862. This reinforces the convergent validity of the model, highlighting that the constructs are well explained by their indicators and are distinct from other constructs. To further ensure discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) was used, which is a more advanced method to detect potential overlap between constructs. The recommended threshold for HTMT values is below 0.90. In this study, all HTMT values are below this threshold, with the highest being 0.823 between IQ and service quality (SV), confirming that the constructs are sufficiently distinct. These results demonstrate that the model effectively differentiates between constructs, ensuring that each one is measuring a unique concept. Therefore, the overall evaluation of convergent and discriminant validity not only meets the numeric thresholds but also provides a comprehensive understanding of the model's robustness.

Discriminant validity assesses whether each construct is distinct from the others in the model. It ensures that the indicators of one construct do not correlate too highly with those of other constructs. Discriminant validity was evaluated using three methods: cross-loading, Average Variance Extracted (AVE), and Heterotrait-Monotrait ratio (HTMT). The cross-loading approach evaluates the correlation between each indicator and its respective latent construct, ensuring that each item is more strongly correlated with its own construct than with other constructs. In this analysis, the results show that the cross-loadings of each indicator are higher with their corresponding constructs than with other constructs, as shown in Table 5, confirming the validity of discriminant validity. For example, the INT indicators such as INT1, INT2, and INT3 have higher correlations with INT (values ranging from 0.773 to 0.928) than with other constructs, confirming the distinctiveness of this construct.

Table 5. Discriminant Validity

	IQ	INT	RE	SV	SQ	PT
IQ	0.862					
INT	0.666	0.879				
RE	0.591	0.632	0.871			
SV	0.770	0.657	0.558	0.820		
SQ	0.779	0.660	0.574	0.805	0.862	
PT	0.749	0.631	0.625	0.759	0.752	0.832

The measurement model evaluation reveals that the constructs used in this study exhibit strong convergent validity, meaning that the indicators reliably represent the latent variables. Discriminant validity tests indicate that each construct is sufficiently distinct from the others, ensuring that the model accurately reflects different aspects of the theoretical framework. Furthermore, the reliability tests confirm that the scales used to measure the constructs are consistent and dependable.

4.3. Structural Model Evaluation and Hypothesis Testing Results

The evaluation of the structural model (inner model) is essential to assess the relationships between latent variables as hypothesized in the research framework. The evaluation focuses on several key aspects, including the R-squared values, Effect Size (f^2), Multicollinearity (VIF), and hypothesis testing results based on path coefficients (β), t-values, and significance levels. The results presented below highlight the overall fit of the structural model and the statistical significance of the hypotheses.

The R^2 value represents the proportion of variance in the dependent variable that is explained by the independent variables. Higher R^2 values indicate a stronger explanatory power of the model. In this study, the R^2 values for the two key dependent variables, INT and PT, were calculated. INT has an R^2 value of 0.569, which indicates that the independent variables in the model explain approximately 57% of the variation in users' intention to use insurtech. This is considered a strong model fit. PT shows an R^2 value of 0.687, which means that 69% of the variance in PT can be explained by the independent variables in the model, signifying a strong explanatory power. These R^2 values suggest that the model explains a significant portion of the variance in the dependent variables, which supports the robustness of the structural model.

Effect size (f^2) is used to assess the magnitude of the relationship between the independent variables and the dependent variables. It quantifies how much the inclusion of a particular independent variable improves the explanatory power of the model. According to [32], f^2 values are interpreted as follows: values of 0.02 indicate a small effect, 0.15 indicate a moderate effect, and 0.35 indicate a large effect. The f^2 values for the relationships between the independent variables and their respective dependent variables in the study are as follows. IQ has a small effect on INT ($f^2 = 0.027$) and a small effect on PT ($f^2 = 0.058$). SQ has a small effect on INT ($f^2 = 0.017$) and a small effect on PT ($f^2 = 0.045$). SV has a small effect on INT ($f^2 = 0.020$) and a moderate effect on PT ($f^2 = 0.078$). RE has a moderate effect on INT ($f^2 = 0.118$) and a moderate effect on PT ($f^2 = 0.075$). While these effects are generally small to moderate, they still significantly contribute to explaining the variance in the dependent variables. However, it is important to note that the small effect sizes, particularly for relationships like SQ → INT ($f^2 = 0.017$), indicate that the influence of these independent variables on the dependent variables is limited. The practical significance of these relationships should be carefully considered, as even though they are statistically significant, their impact may not be substantial enough to drive large-scale changes in the context of Insurtech adoption. This highlights the need for further investigation into other factors that may have a stronger effect or may interact with these variables to produce more meaningful outcomes in the adoption of Insurtech.

Hypothesis testing was conducted using bootstrapping in SmartPLS to assess the path coefficients, t-statistics, p-values, and significance levels. The hypotheses were evaluated at a 95% confidence level, with t-statistics greater than 1.96 indicating significance and p-values less than 0.05 indicating statistical significance. The results of hypothesis testing are summarized in Table 6 below.

Table 6. Inner Model Results (Summary)

Hypothesis	Path	Coefficient	t-statistics	p values	f2	Supported
H1	IQ → INT	0.196	3.417	0.001	0.027	Yes
H2	SQ → INT	0.163	3.172	0.002	0.017	Yes
H3	SV → INT	0.178	2.862	0.004	0.020	Yes
H4	PT → INT	0.039	0.650	0.516	0.001	No
H5	RE → INT	0.299	6.212	0.000	0.118	Yes
H6	IQ → PT	0.238	4.085	0.000	0.058	Yes
H7	SQ → PT	0.224	3.925	0.000	0.045	Yes
H8	SV → PT	0.286	5.055	0.000	0.078	Yes
H9	RE → PT	0.196	4.846	0.000	0.075	Yes
H10	IQ → PT → INT	-	0.616	0.538	-	No
H11	SQ → PT → INT	-	0.614	0.539	-	No
H12	SV → PT → INT	-	0.631	0.528	-	No

The structural model demonstrates strong explanatory power, with significant path coefficients for most of the hypothesized relationships. The model fit indices (R^2) suggest a good fit, with the model explaining 57% of the variance in INT and 69% in PT, as shown in Figure 2. The hypotheses testing results indicate that IQ, SQ, SV, and RE all have significant effects on INT and PT, with the exception of PT influencing INT. These findings provide strong empirical support for the proposed model, confirming the importance of both direct and indirect effects of the independent variables on the intention to use insurtech among Gen Z in Indonesia. H1 shows that IQ positively impacts the intention to use insurtech (path coefficient = 0.196, t-statistics = 3.417, p-value = 0.001), emphasizing the importance of clear, complete, and reliable insurance data, which aligns with prior studies that stress the value of transparency and clarity in digital platforms [11]. H2 supports the significant influence of SQ, with user-friendly and reliable systems increasing adoption (path coefficient = 0.163, t-statistics = 3.172, p-value = 0.002). H3 confirms that SV significantly affects the intention to use insurtech (path coefficient = 0.178, t-statistics = 2.862, p-value = 0.004). This highlights the role of responsive, personalized, and efficient customer service in driving adoption, consistent with findings by [19]. However, H4 reveals that PT does not have a significant effect on the intention to use insurtech (t-statistics = 0.650, p-value = 0.516), challenging the assumption that trust is a primary determinant in technology adoption [9]. This may be explained by Gen Z's high technological literacy, where they may prioritize functional factors such as SQ over trust.

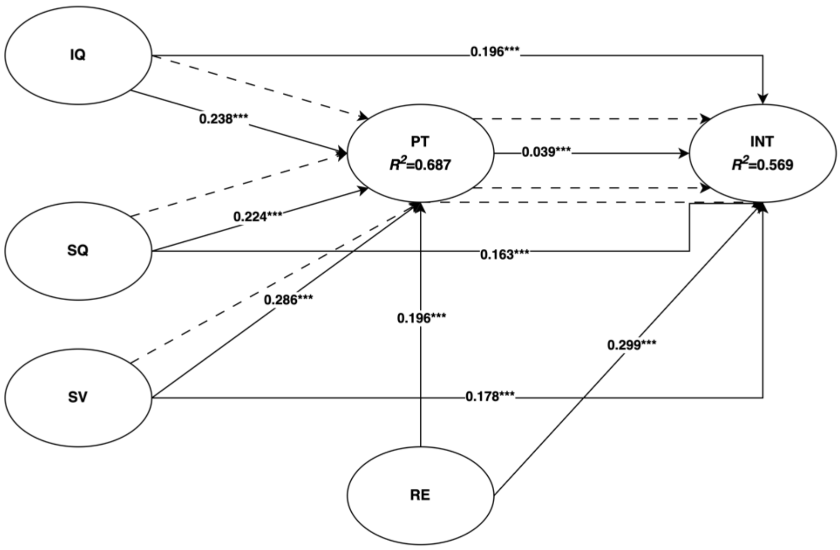

Figure 2. Structural Model Results Framework

H5 demonstrates that RE positively influences the intention to use insurtech (β = 0.299, t-statistics = 6.212, p-value = 0.000), highlighting the importance of regulatory assurance in driving user adoption. This is in line with studies suggesting that clear legal frameworks and consumer protection mechanisms are crucial for building trust and promoting digital adoption [10]. H6 tests the impact of IQ on PT, and the results show a significant positive effect (β = 0.238, t-statistics = 4.085, p-value = 0.000). This suggests that high-quality information improves users' trust in insurtech. For example, clear product details, including technical explanations, can enhance customer confidence. The effect size (f^2 = 0.058) indicates a moderate influence. These findings align with previous research by [38], who also found that IQ is a significant factor in building trust in digital platforms. H7 explores the relationship between SQ and PT. The analysis reveals a positive and significant influence (β = 0.224, t-statistics = 3.925, p-value = 0.000). Users are more likely to trust a system that is reliable and secure. This finding emphasizes the importance of strong data security measures, such as two-factor authentication and regular system audits. The effect size (f^2 = 0.025) indicates a moderate influence, consistent with studies by [11] that emphasize the role of SQ in fostering PT. H8 tests the effect of SV on PT, and the results show a significant and positive effect (β = 0.286, t-statistics = 5.055, p-value = 0.000). Professional customer service, such as quick resolution of user complaints, enhances users' trust in insurtech services. The effect size (f^2 = 0.078) indicates a moderate influence. This finding is supported by research from [39], who found that high SV is crucial for building trust in digital services. H9 examines the impact of RE on PT, revealing a significant positive effect (β = 0.196, t-statistics = 4.846, p-value = 0.000). Clear regulations, such as legal compensation guarantees, boost users' trust in insurtech. The effect size (f^2 = 0.075) indicates a moderate influence, aligning with the findings of [40], who highlighted the importance of regulatory clarity in fostering trust.

Hypotheses H10-H12 explore the potential mediating role of PT in the relationships between IQ, SQ, SV, and INT. However, the results from all three hypotheses indicate no significant mediation effect. For H10, the relationship between IQ and INT shows no significant mediation by PT, with t-statistics of 0.616 (less than 1.96) and a p-value of 0.538 (greater than 0.05). Similarly, H11, which investigates the mediating role of PT between SQ and INT, also reveals no significant mediation, with t-statistics of 0.614 (less than 1.96) and a p-value of 0.539 (greater than 0.05). Lastly, H12, which examines the mediating effect of PT between SV and INT, also finds no significant mediation, with t-statistics of 0.631 (less than 1.96) and a p-value of 0.528 (greater than 0.05). Despite these results, the direct impacts of IQ, SQ, and SV on INT remain significant, suggesting that these variables influence users' intention to adopt Insurtech directly, without mediation by PT. These findings contradict previous research [11], [41], and [42], which found significant mediating effects of PT on the relationships between IQ and INT, SQ and INT, and SV and INT, respectively. The lack of significant mediation in this study can be attributed to the unique characteristics of Generation Z, who are highly digitally savvy and may place more value on direct system quality and information reliability rather than relying on trust as a mediator. Moreover, the regulatory environment and the trust users have in Insurtech services might not be as critical in the decision-making process for Gen Z as expected, given their comfort with digital platforms and online services. Additionally, Gen Z's adoption of Insurtech may be driven more by the direct benefits they perceive from the service—such as convenience, accessibility, and cost-effectiveness—rather than the trustworthiness of the platform. This insight challenges the assumption that trust always plays a central role in adoption decisions, particularly for younger, digitally native consumers. Moreover, the lack of a mediating effect could point to other factors influencing Gen Z's decision-making, such as RE, which may serve as a more direct influencer for this group, particularly in ensuring security and data privacy in digital transactions. Given these dynamics, it's crucial for future research to explore alternative mediators or moderators that could better explain Gen Z's decision-making processes regarding Insurtech. For instance, understanding how perceived value or user experience affects adoption could provide more insight. To better illustrate these relationships, a visual mediation diagram could help clarify how the various factors interact, providing a clearer understanding of the complex decision-making process of Gen Z in adopting

4.4. Goodness of Fit Test

The Goodness of Fit (GoF) test is a critical evaluation used to determine how well the proposed research model fits the observed data. It helps assess whether the model can accurately represent the real-world data. In this study, the GoF test is conducted by examining the Prediction Test Result (Q^2), Normed Fit Index (NFI), and Standardized Root Mean Square Residual (SRMR) values. First, the Q^2 test measures how well the model's observed values match the parameter estimations in the structural model. A Q^2 value greater than 0 indicates that the model has good predictive relevance, meaning it can predict or explain variations in the observed data better than a model that only uses average values as predictors. In this research, both INT and PT have positive Q^2 values, indicating that the model performs well in predicting these variables. Specifically, the Q^2 value for INT is 0.559, which is considered strong, suggesting that the exogenous latent variables—such as IQ, SQ, SV, and RE—are effective in predicting INT. Similarly, the Q^2 value for PT is 0.678, which is also strong, confirming that PT serves as a robust predictor of INT. This shows that the model has strong predictive relevance and effectively explains the data variations. Further validation of the model's fit is done through the Normed Fit Index (NFI) and Standardized Root Mean Square Residual (SRMR). The NFI value ranges from 0 (no fit) to 1 (perfect fit), with values greater than 0.8 indicating that the model fits the data well. In this study, the NFI value is 0.797, which is close to 0.8, indicating that the model has an adequate fit. The SRMR, which measures the average difference between the observed and predicted correlations, should ideally be less than 0.08 to suggest a good fit. The SRMR value in this case is 0.063, which is below the threshold, confirming that the model fits the data well.

5. Conclusion

This study explored the factors influencing Generation Z's intention to adopt insurtech in Indonesia, utilizing a modified DeLone and McLean (D and M) model with the inclusion of PT and RE. The findings, drawn from a survey of 431 respondents across ten major cities, highlighted Gen Z as a key consumer group for insurtech services. The majority of respondents were based in DKI Jakarta, underscoring the potential for insurtech in urban areas with robust digital infrastructure. The results revealed that Gen Z's intention to use insurtech is heavily influenced by the quality of information, system performance, service quality, and RE, all of which positively impacted both their intention to use insurtech and their perceived trust in these services. However, the study found that while trust plays a role in shaping consumer behavior, it did not significantly influence Gen Z's intention to adopt insurtech. This suggests that, as digital natives, Gen Z places higher value on the functional aspects of services, such as system performance, user experience, and transparency, rather than abstract trust concepts. Their high expectations for technology imply that they assume services that adhere to legal and regulatory standards are inherently trustworthy, diminishing the role of trust as a differentiating factor in their decision-making process.

In light of these findings, insurtech providers should adjust their strategies to focus on improving the practical and functional aspects of their offerings. Companies must prioritize delivering organized, transparent information, efficient system performance, flexible services, and strong data protection to meet Gen Z's expectations. Additionally, enhancing the user experience, optimizing system usability, and ensuring service reliability should be at the core of their product offerings. While trust remains a foundational element, it should not be the primary focus for attracting Gen Z users. Instead, insurtech companies should focus on fostering consumer confidence through transparency, effective communication, and robust security measures. Moreover, collaboration with regulators to ensure adherence to laws and regulations is crucial in creating a legally compliant and secure environment that appeals to this demographic. For the government, promoting conducive regulatory frameworks that enhance data security and consumer protection is essential for building trust and facilitating the growth of the insurtech industry. The government should also play an active role in enforcing these regulations and ensuring that consumers are aware of their rights. Lastly, future research could explore other factors that influence insurtech adoption, such as digital literacy, and the role of RE as a moderator. It would also be beneficial to conduct cohort-based comparisons across regions or demographic groups to further understand how these factors shape consumer behavior in the evolving digital ecosystem.

6. Declarations

6.1. Author Contributions

Conceptualization: M.F.U., H.M., A.P.I., A.M.S.; Methodology: A.M.S.; Software: M.F.U.; Validation: M.F.U., A.M.S., and A.P.I.; Formal Analysis: M.F.U., A.M.S., and A.P.I.; Investigation: M.F.U.; Resources: A.M.S.; Data Curation: A.M.S.; Writing Original Draft Preparation: M.F.U., A.M.S., and A.P.I.; Writing Review and Editing: A.M.S., M.F.U., and A.P.I.; Visualization: M.F.U.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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