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Designing a Customer Value–Based InsurTech Model: An Applied and Innovative Approach

Bashir Asadi Kia[1], Farzad Sadeghi [2]*, Ali Rezaian[1], Mohammad Hemmati [1]

1. Department of Management, Ahv.C., Islamic Azad University, Ahvaz, Iran
2. Department of Management, And.C., Islamic Azad University, Andimeshk, Iran

*Correspondence: 4949663852@iau.ir

Abstract

The primary objective of this study is to identify and analyze the key components of insurance technology (InsurTech) and their impact on process efficiency and service enhancement in the insurance industry. Increased dynamism in today's information technology–driven insurance sector, considering the present case study, represents a clear necessity, and the application of information technology in the form of InsurTech—along with innovation and creativity in insurance service delivery through the design and implementation of intelligent integrated software systems—constitutes an unavoidable requirement. To this end, a mixed-methods research methodology integrating qualitative and quantitative approaches was employed. Initially, for qualitative analysis, the Interpretive Structural Modeling (ISM) technique was used to simulate the relationships among various components, through which technological infrastructure was identified as the central driving factor in InsurTech implementation. Subsequently, quantitative data were analyzed using a questionnaire designed to collect information from 15 industry experts in the sugarcane sector. Accordingly, both qualitative and quantitative analytical procedures were applied. First, using the ISM framework, interrelationships among components were modeled and their influence levels were determined. Then, statistical analyses—including Pearson correlation tests, analysis of variance (ANOVA), and normality tests—were conducted to examine significant relationships and effects among the components. The research findings indicate that technological infrastructure, organizational culture, managerial support, training and skills, laws and regulations, and data orientation constitute the key success factors for effective InsurTech implementation in the sugarcane industry. In particular, technological infrastructure, with a mean score of 7.22, was identified as the fundamental and core factor influencing all other components. The results demonstrate that effective InsurTech implementation requires focused investment in infrastructure development, enhancement of organizational culture, employee training, and strong managerial support. Ultimately, the study emphasizes the necessity of adopting a comprehensive and coordinated approach to improving performance and increasing the operational efficiency of InsurTech within the sugarcane industry.

Keywords: Insurance; InsurTech; ISM Analysis; Technology Implementation; Sugarcane Development Company

1. Introduction

The insurance industry is undergoing a profound structural transformation driven by rapid technological advancements, evolving customer expectations, intensified competition, and the emergence of digitally enabled business ecosystems. This transformation has redefined traditional insurance models, giving rise to what is now widely recognized as InsurTech—a technology-centered paradigm that integrates digital platforms, big data analytics, artificial intelligence, and customer-centric innovation to enhance service quality, operational efficiency, and value creation (Ahmad et al., 2025; Braun & Jia, 2025; Nicoletti, 2020). The contemporary insurance market is no longer characterized merely by risk transfer mechanisms but increasingly functions as a digital service industry in which customer experience, personalization, speed, and trust determine competitive positioning (Baranauskas & Raišienė, 2021; Skaf et al., 2024).

Recent scholarship emphasizes that InsurTech does not represent a peripheral technological upgrade but a fundamental restructuring of insurance value chains, operating models, and strategic priorities (Braun & Jia, 2025; Moloi & Mulaba-Bafubiandi, 2024). Digital technologies have reconfigured underwriting, claims management, pricing, customer engagement, and distribution channels, enabling insurers to deliver seamless, data-driven, and highly customized solutions (Ahmad et al., 2024; Rana et al., 2022). As a result, the competitive advantage of insurance firms increasingly depends on their ability to align technological capabilities with organizational structures, human competencies, governance frameworks, and customer value creation mechanisms (Nayak et al., 2022; Nguyen, 2023).

The literature consistently highlights that customer value creation lies at the core of sustainable insurance performance in the digital era (Ebrahimi et al., 2024; Nayak et al., 2022; Nicoletti, 2020). InsurTech facilitates the transition from product-centric insurance to service-dominant logic, where continuous interaction, trust building, responsiveness, and personalization become primary drivers of customer loyalty and lifetime value (Ebrahimi et al., 2024; Gilsing et al., 2021). Digital platforms enable insurers to capture granular behavioral data, design personalized offerings, and manage customer relationships dynamically across multiple touchpoints (Baranauskas & Raišienė, 2021; Nain, 2025). Consequently, customer-centricity is no longer optional but essential for organizational survival and growth in the insurance sector (Saoula et al., 2024; Skaf et al., 2024).

However, the effective realization of InsurTech-driven value creation requires more than technological investment alone. Prior studies reveal that technological infrastructure must be complemented by organizational culture, managerial commitment, human capital development, and regulatory alignment to achieve meaningful transformation (Moloi & Mulaba-Bafubiandi, 2024; Nguyen, 2023; Shahroodi et al., 2024). Organizational culture plays a decisive role in fostering innovation acceptance, learning orientation, and cross-functional collaboration necessary for digital transformation (Gilsing et al., 2021; Lindlar, 2021). Similarly, strong managerial support is indispensable for coordinating digital initiatives, allocating resources, mitigating resistance to change, and embedding innovation into strategic decision-making processes (Shahroodi et al., 2024; Valimi et al., 2021).

The strategic importance of human skills and training in InsurTech transformation is widely recognized. Digital technologies demand new competencies in data analytics, artificial intelligence management, cybersecurity, customer experience design, and digital process optimization (Moloi & Mulaba-Bafubiandi, 2024; Rana et al., 2022). Without continuous skill development, even the most advanced technological systems remain underutilized, limiting organizational returns on digital investments (Nain, 2025; Nguyen, 2023). Thus, workforce readiness becomes a central pillar of sustainable InsurTech implementation.

At the same time, regulatory and ethical considerations significantly influence the pace and scope of InsurTech adoption. Digital insurance operations involve sensitive customer data, algorithmic decision-making, and automated processes that raise concerns regarding privacy, fairness, accountability, and trust (Mullins et al., 2021). The establishment of clear regulatory frameworks and ethical guidelines is therefore critical for maintaining customer confidence while enabling innovation (Ahmad et al., 2025; Mullins et al., 2021). Studies indicate that regulatory uncertainty or rigid legal constraints may slow InsurTech diffusion, whereas adaptive governance models can stimulate responsible innovation (Ricky, 2025; Santoso et al., 2023).

Furthermore, contemporary insurance markets increasingly rely on data orientation as a strategic asset. Data-driven decision-making enhances underwriting accuracy, fraud detection, claims processing, and customer segmentation (Nguyen, 2023; Rana et al., 2022). Insurers that successfully integrate data analytics into their business models achieve superior risk assessment capabilities and customer insight generation, which directly contribute to value creation and competitive advantage (Nayak et al., 2022; Nicoletti, 2020).

The global diffusion of InsurTech is also reshaping insurance distribution models. Embedded insurance, platform ecosystems, and CRM-driven service architectures are emerging as dominant paradigms for future insurance markets (Nain, 2025; Ricky, 2025). These developments further intensify the need for coherent integration of technology, organization, and customer experience strategies (Braun & Jia, 2025; Santoso et al., 2023). Failure to achieve such alignment risks strategic fragmentation, operational inefficiency, and erosion of customer trust (Saoula et al., 2024; Skaf et al., 2024).

Although existing research provides valuable insights into various dimensions of InsurTech adoption, significant gaps remain. Much of the literature examines technological, customer, or strategic factors in isolation, offering limited understanding of their systemic interdependencies and hierarchical influence patterns within organizational contexts (Moloi & Mulaba-Bafubiandi, 2024; Shahroodi et al., 2024). Few studies have proposed integrated structural frameworks that simultaneously capture technological, organizational, managerial, human, regulatory, and data-driven dimensions of InsurTech as a coherent system. Moreover, empirical investigations remain fragmented across regions, industries, and methodological approaches, restricting generalizability and practical applicability (Ahmad et al., 2024; Ricky, 2025).

From a managerial perspective, the absence of a comprehensive InsurTech implementation model grounded in customer value creation complicates strategic planning and investment prioritization. Managers often face uncertainty regarding which components should be developed first, which exert the greatest influence on transformation outcomes, and how interdependencies among these components shape organizational performance (Shahroodi et al., 2024; Valimi et al., 2021). Addressing these questions is essential for designing effective digital transformation roadmaps that deliver measurable improvements in service quality, customer loyalty, and financial performance (Ahmad et al., 2024; Ebrahimi et al., 2024).

Consequently, there is a pressing need for research that moves beyond descriptive analysis toward structural modeling of InsurTech components, revealing their causal relationships and priority structure within real organizational settings. Integrating qualitative systems modeling with quantitative validation offers a powerful methodological approach for uncovering these complex dynamics (Gilsing et al., 2021; Moloi & Mulaba-Bafubiandi, 2024). Such an approach enables both theoretical advancement and practical guidance for insurers navigating digital transformation in increasingly volatile and competitive markets (Braun & Jia, 2025; Nguyen, 2023).

In response to these challenges, this study develops and empirically tests a customer value–based InsurTech model that integrates technological infrastructure, organizational culture, managerial support, training and skills, regulatory frameworks, and data orientation within a unified structural framework, thereby advancing both theory and practice in digital insurance transformation (Ahmad et al., 2025; Braun & Jia, 2025; Ebrahimi et al., 2024; Nayak et al., 2022; Ricky, 2025).

The aim of this study is to design and validate a comprehensive customer value–based InsurTech model by identifying, structuring, and prioritizing the key technological, organizational, managerial, human, regulatory, and data-driven components that drive successful digital transformation in the insurance industry.

2. Methods and Materials

The methodology of this study follows a mixed-methods (integrated) design and is conducted in two phases: qualitative and quantitative. This approach allows the researcher to benefit from the strengths of both methods, enabling both in-depth conceptual exploration and theoretical dimension extraction as well as quantitative measurement and statistical analysis of the collected data. Since the dimensions of insurance technology at the Sugarcane Development Company and its subsidiary industries have not yet been systematically conceptualized, the present research is categorized as a developmental study. The primary objective is to construct a conceptual framework for understanding the dimensions of this technology using structural and interpretive analyses in order to facilitate a clearer understanding of the relationships among influential factors.

In the qualitative phase, the Interpretive Structural Modeling (ISM) method was employed. This technique is based on expert judgment and aims to identify and structure the relationships among the complex elements of a system. By decomposing a complex system into subsystems and utilizing expert knowledge, ISM enables the development of a hierarchical, multi-level model of relationships among variables. The ISM procedure is executed in four main steps: constructing the Structural Self-Interaction Matrix (SSIM), converting it into the Reachability Matrix (RM), determining the levels and forming the canonical matrix, and finally developing the structural model. In the first step, the key research elements were extracted through theoretical review, interview analysis, and literature examination, and then presented to experts in the form of a structured self-interaction questionnaire. Responses were recorded using the symbols V, A, X, and O, representing the direction of influence between each pair of factors. In the second step, these data were transformed into the initial and then the final reachability matrix, considering the transitivity property.

In the third step, based on the reachability matrix, the antecedent set and reachability set for each factor were identified, and by analyzing the intersection of these sets, the hierarchical levels of the factors were determined. In the final step, the extracted levels of the components were used to present the layered structure of relationships among the variables.

The statistical population in the qualitative phase consisted of experts familiar with insurance technology in the sugarcane industry, selected through purposive, chain-referral, or snowball sampling. The selection criteria included executive experience, specialized knowledge, and familiarity with innovation dimensions in the insurance industry and the case organization. Sample size in this phase was determined based on theoretical saturation, meaning data collection continued until no new information emerged.

In the quantitative phase, a survey method with a descriptive–analytical approach was applied. Data were collected using structured questionnaires designed in matrix form based on pairwise comparisons among the research themes. The questionnaire structure incorporated row (i) and column (j) comparisons of components. The collected data from the target population—including managers, insurance specialists, and technology-related personnel at the Sugarcane Development Company and its subsidiary industries—were subsequently analyzed. The questionnaires were distributed through coordination with informed individuals within the target organization.

Regarding data collection instruments, the qualitative phase employed open and semi-structured interviews with an average duration of one hour. Initially, theoretical foundations were developed through library research and document analysis, and then organizing and basic themes were extracted through interview analysis. In the quantitative phase, questionnaires were used to measure the impact of the extracted components based on respondents' perceptions.

For sample selection, cluster sampling was first employed because the target population consisted of multiple reference groups (subsidiary companies). In this stage, reference groups were identified, and then appropriate participants were randomly selected from each cluster. Sample size was determined based on the desired precision and confidence level for generalizing results to the entire population. In other words, higher precision and confidence required larger sample sizes, and vice versa. The research sample refers to a selected group of individuals drawn from a larger population and representing the characteristics of the target population. Moreover, to facilitate the research process, reduce temporal and spatial costs, and allow more precise data collection and analysis, the researcher determined the sample size accordingly. To calculate the sample size more accurately, the Cochran formula was used. Cochran's formula is one of the most widely applied methods for estimating sample size in statistical populations. Using this formula, the minimum required sample size for a population of 15 individuals was obtained. The general form of Cochran's formula is as follows:

Equation 1

$$n = \frac{\frac{z_{\alpha/2}^2 pq}{d^2}}{1 + \frac{1}{N}\left(\frac{z_{\alpha/2}^2 pq}{d^2} - 1\right)}$$

where the three main components are $z_{\alpha/2}^2$, pq, and d.

a) $z_{\alpha/2}^2$represents the confidence level for testing the null hypothesis and is equal to 1.96.

b) pqrepresents the variance of the studied variables and is a population parameter.

c) $d$denotes the margin of error for estimating population parameters based on sample calculations and was set at 0.05.

d) Nrepresents the population size. Thus, the sample size was determined using Cochran's formula.

In this study, data analysis was conducted using two main statistical approaches: descriptive statistics and inferential statistics. Descriptive statistics, as the first stage of analysis, enabled the researcher to examine demographic characteristics and other attributes of the sample. In this section, frequency and relative frequency tables were used to describe the data. The purpose of this method is to quantify the data and provide an accurate representation of the studied phenomenon by calculating means, standard deviations, and sample sizes. In the next stage, inferential statistics were applied to assess the generalizability of results from the sample to the larger population. Through this method, the researcher examined whether observed patterns and relationships in the sample could be extended to the broader population. Inferential tests were used to evaluate probabilities and validate findings. Additionally, the ISM interpretive-structural program was employed to provide a more precise analysis of inter-variable relationships and identify statistical differences, enabling a more structured and interpretive explanation of the results.

Table 1 presents the validity and reliability of the questionnaire assessing the components of insurance technology. The questionnaire consists of six main components, for each of which validity and reliability indices were calculated. For the technological infrastructure component, consisting of six items, the Content Validity Ratio (CVR) and Content Validity Index (CVI) were 0.85 and 0.91, respectively, indicating high validity. Cronbach's alpha was 0.87, reflecting desirable reliability; therefore, this component was considered highly acceptable. For organizational culture, consisting of five items, CVR and CVI were 0.78 and 0.89, respectively, and Cronbach's alpha was 0.83, indicating acceptable reliability; this component was also evaluated as desirable. The managerial support component, with four items, showed CVR 0.81, CVI 0.88, and Cronbach's alpha 0.79, reflecting acceptable reliability. The training and skills component, consisting of four items, had CVR 0.76, CVI 0.86, and Cronbach's alpha 0.82, indicating desirable reliability. The laws and regulations component, with three items, showed CVR 0.74, CVI 0.84, and Cronbach's alpha 0.77, indicating acceptable reliability. Finally, the data-orientation component, with four items, demonstrated CVR 0.80, CVI 0.87, and Cronbach's alpha 0.85, reflecting desirable reliability. Overall, the analysis confirms that all components exhibit acceptable validity and reliability, with managerial support remaining within the acceptable range. In general, the questionnaire was evaluated as "very good."

Table 1. Validity and Reliability of the Insurance Technology Components Questionnaire

Component	Number of Items	CVR	CVI	Cronbach's Alpha (Reliability)
Technological Infrastructure	6	0.85	0.91	0.87
Organizational Culture	5	0.78	0.89	0.83
Managerial Support	4	0.81	0.88	0.79
Training and Skills	4	0.76	0.86	0.82
Laws and Regulations	3	0.74	0.84	0.77
Data Orientation	4	0.80	0.87	0.85
Total Questionnaire	26	0.79	0.88	0.89

3. Findings and Results

Table 2 presents the demographic characteristics of the experts, which include four variables: years of service, age group, educational level, and gender.

First, the variable years of service was examined. The results indicate that 6 experts have more than 20 years of work experience, while 9 experts have between 15 and 20 years of experience. This reflects a relatively diverse level of professional experience among the experts. Regarding the age group, the highest frequency belongs to the 30–40 year age group with 11 individuals, whereas only 4 individuals fall within the 40–50 year age group. This implies that the majority of experts belong to a younger age cohort, which may indicate better access to emerging technologies and contemporary research approaches. Concerning educational level, 5 experts hold doctoral degrees and 10 experts hold master's degrees. This suggests that the majority of experts possess postgraduate education, with a portion having attained doctoral qualifications. Finally, the gender variable shows that the number of men (7) and women (8) is approximately equal, reflecting a balanced gender representation within the expert panel.

Table 2. Demographic Characteristics of the Experts

Row	Variable	Frequency
1	Years of Service	More than 20 years: 6
	Between 15 and 20 years: 9	
2	Age Group	40–50 years: 4
	30–40 years: 11	
3	Educational Level	Doctorate: 5

4	Master's: 10 Gender Female: 8	Male: 7	

Based on Table 3, the Structural Self-Interaction Matrix (SSIM) for the key factors influencing insurance technology in the sugarcane industry specifically analyzes the relationships and mutual influences among six major factors: technological infrastructure, organizational culture, managerial support, training and skills, laws and regulations, and data orientation. Each of these factors can influence other factors, and in the matrix analysis, symbols X, V, A, and O are used to represent the type and direction of relationships.

For example, technological infrastructure, recognized as one of the core pillars of the matrix, exhibits various relationships with other factors. It has significant influence on organizational culture, managerial support, training and skills, and data orientation (indicated by symbols V and A). This demonstrates that technological infrastructure can positively and effectively influence these components, particularly in strengthening processes and performance associated with insurance technology. In contrast, laws and regulations do not influence technological infrastructure (symbol X), indicating a degree of independence between these two factors in certain aspects.

Organizational culture also exerts positive effects on technological infrastructure, training and skills, and data orientation (symbols A and V). This suggests that organizational culture plays a critical role in developing technology-driven and data-oriented processes. However, managerial support does not have a significant impact on organizational culture (symbol X), which may indicate indirect or less pronounced influence in certain domains. Regarding managerial support, this factor has direct effects on technological infrastructure and organizational culture (symbol A), while its impact on other factors is negligible (symbol X). This implies that managerial support particularly contributes to strengthening technical and cultural foundations but exerts less influence on areas such as regulations and data orientation. Training and skills, as an influential factor, have substantial impact on technological infrastructure, organizational culture, and data orientation (symbols A, V, and A), indicating that capacity development plays a central role in enhancing these domains. Laws and regulations exert positive and notable influence on technological infrastructure and organizational culture (symbols V and A) but have limited impact on other components (symbol X). Overall, the analysis of this matrix reveals that factors such as technological infrastructure and organizational culture possess broader and more reciprocal influences, whereas factors such as managerial support and laws and regulations exert more focused and limited influence, typically on one or two specific components. This analysis helps identify critical pathways for improving and strengthening insurance technology in the sugarcane industry.

Table 3. Structural Self-Interaction Matrix (SSIM) for Key Factors Affecting Insurance Technology in the Sugarcane Industry (Based on Qualitative ISM Analysis)

Factors	Technological Infrastructure	Organizational Culture	Managerial Support	Training and Skills	Laws and Regulations	Data Orientation
Technological Infrastructure	–	X	V	V	A	V
Organizational Culture	A	–	V	V	O	A
Managerial Support	A	A	–	X	X	X
Training and Skills	A	A	A	–	V	X
Laws and Regulations	V	X	A	A	–	A
Data Orientation	A	V	A	A	X	–

Based on the ISM structural analysis, the key factors influencing insurance technology in the sugarcane industry are positioned across different hierarchical levels. This analysis precisely illustrates how each factor interacts with the others and, based on these relationships, assigns them to distinct levels. At Level 1, the factors laws and regulations and data orientation are positioned. These factors are considered foundational, exerting limited influence on other factors and primarily playing a supportive role. Laws and regulations establish legal frameworks for enhancing and developing insurance technology, while data orientation provides the basis for data utilization and analytical processes in insurance operations. At Level 2, the factor training and skills is located, recognized as a critical enabler for organizational capability development and effective use of insurance technology. At Level 3, managerial support is positioned, identified as a highly influential factor in advancing organizational policies and processes related to insurance technology by facilitating lower-level activities such as infrastructure development and staff training. At Level 4, organizational culture is situated, serving as a fundamental driver for creating an environment in which technology can be effectively implemented and synergized across the organization. At Level 5, technological infrastructure occupies the highest position, recognized as the principal and most influential factor in insurance technology implementation, directly affecting all other components and forming the foundation of all insurance technology processes. Consequently, ISM analysis demonstrates that technological infrastructure functions as the primary driver of insurance technology development in the sugarcane industry, while lower-level factors such as laws and regulations and data orientation establish essential foundations and facilitate the operation of other components (Table 4).

Table 4. Determination of Factor Levels Based on ISM Analysis

Level	Factors
1	Laws and Regulations; Data Orientation
2	Training and Skills
3	Managerial Support
4	Organizational Culture
5	Technological Infrastructure

The results of the quantitative analysis based on the questionnaire, conducted through pairwise comparisons and computation of mean importance scores, indicate the priorities and relative importance of the different InsurTech components in the sugarcane industry. In this analysis, pairwise comparisons among the components were performed, and their mean importance values were calculated and ranked. The prioritization results clearly show that technological infrastructure has the highest importance compared with the other factors, with a mean importance score of 7.2, ranking first. This implies that technological infrastructure, as a core pillar in the implementation and development of InsurTech, is critically important for achieving success in this domain. In practice, this factor serves as an enabler and facilitator of other processes. Ranked second is managerial support, with a mean importance score of 6.5. This indicates that managers' roles in strengthening InsurTech-related processes—particularly in creating favorable conditions for the optimal use of technology and data—are highly significant. Managerial support, as a driver of other processes, has a substantial influence on the trajectory of InsurTech advancement and development. Ranked third is training and skills, with a mean importance score of 5.8. This suggests that enhancing employees' competencies and knowledge in the InsurTech domain is a higher priority than laws and regulations. Appropriate training and skills enable individuals to use technological tools more effectively and improve insurance-related processes. Organizational culture relative to managerial support ranks fourth, with a mean importance score of 4.3, indicating that although organizational culture is influential, it is considered less important than managerial support. This means that for successful InsurTech implementation, managerial support operates more directly and effectively than organizational culture. Ranked fifth is data orientation, with a mean importance score of 3.7. This analysis suggests that compared with employees' individual and technical capabilities, data orientation is viewed as less important in InsurTech implementation processes. This may be because, although data play an important role, they will have limited impact if employees lack the capability to use them effectively. Laws and regulations rank sixth, with a mean importance score of 2.9. This result indicates that although laws and regulations provide legal frameworks, they have less influence than technological infrastructure in the InsurTech implementation process. Therefore, existing insurance regulations may not directly and rapidly produce substantial changes in InsurTech implementation (Table 5).

Table 5. Results of the Quantitative Analysis Based on the Questionnaire (Pairwise Comparisons and Mean Scores)

Component Comparison	Mean Importance	Rank
Technological Infrastructure vs. Organizational Culture	7.2	1
Managerial Support vs. Data Orientation	6.5	2
Training and Skills vs. Laws and Regulations	5.8	3
Organizational Culture vs. Managerial Support	4.3	4
Data Orientation vs. Training and Skills	3.7	5
Laws and Regulations vs. Technological Infrastructure	2.9	6

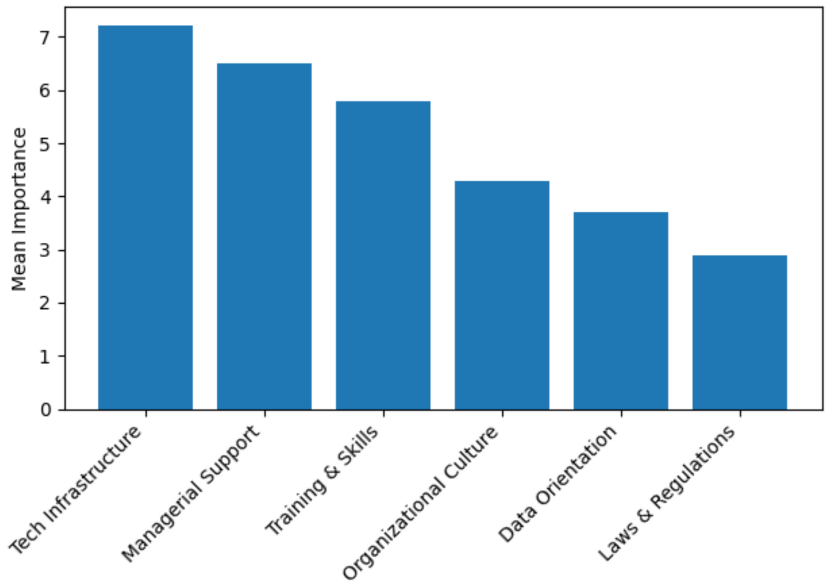

Figure 1. Prioritization of the research components

The descriptive statistical results for the study variables, based on data from 15 experts, reflect the relative distribution and key characteristics of each component and are presented in Table 6. The first component, technological infrastructure, with a mean of 7.22, indicates its high importance in InsurTech processes. The low standard deviation of 0.49 also reflects a relatively high convergence and agreement among experts in evaluating this component, such that none of the experts provided markedly different assessments in this domain. Regarding organizational culture, with a mean of 6.49 and a standard deviation of 0.65, the evaluations indicate the relative importance of this component. Although the mean is high, the somewhat larger standard deviation compared to technological infrastructure suggests greater diversity in experts' views on organizational culture. The minimum value of 5.24 and maximum value of 8.32 also reflect, to some extent, differences across expert perspectives. Managerial support, with a mean of 6.01 and a standard deviation of 0.77, appears next. This standard deviation, which is slightly higher than for the other components, indicates greater variability in experts' evaluations of the influence and importance of managerial support. The minimum value of 4.38 and maximum value of 7.95 also suggest some disagreement in its assessment. For training and skills, the mean of 5.47 and standard deviation of 0.60 indicate the relative importance of this component; however, the moderate standard deviation suggests that expert opinions in this area are not as convergent as for some other components. The minimum value of 3.94 and maximum value of 6.76 further illustrate variability in assessments. Laws and regulations, with a mean of 5.07, shows the lowest mean among the remaining components. Its standard deviation (0.51) is low, indicating that most experts hold similar views regarding laws and regulations; nevertheless, the lower mean indicates that this component is generally perceived as less important than the others. The minimum value of 3.77 and maximum value of 6.28 also reflect relatively limited differences in evaluations. Data orientation, with a mean of 4.83 and a standard deviation of 0.38, has the lowest mean, and its low standard deviation indicates stronger convergence among experts in this area. The minimum value of 4.00 and maximum value of 5.84 also reflect limited—though still meaningful—differences in evaluations of this dimension.

Table 6. Descriptive Statistics of the Study Variables Based on Data From 15 Experts

Component	Mean	Standard Deviation	Minimum	Maximum
Technological Infrastructure	7.22	0.49	5.91	8.38
Organizational Culture	6.49	0.65	5.24	8.32
Managerial Support	6.01	0.77	4.38	7.95
Training and Skills	5.47	0.60	3.94	6.76
Laws and Regulations	5.07	0.51	3.77	6.28
Data Orientation	4.83	0.38	4.00	5.84

The results of the Shapiro–Wilk test for examining the normality of the data across the different research components indicate that all datasets follow a normal distribution. For the technological infrastructure component, the W statistic is 0.972

and the p-value is 0.083, which is greater than the significance level of 0.05; therefore, the data for this component are normally distributed. Similarly, for organizational culture, the W statistic is 0.964 with a p-value of 0.065, which again exceeds 0.05, confirming normal distribution. For managerial support, the W statistic is 0.959 and the p-value is 0.073, indicating normality. Likewise, for training and skills, the W statistic equals 0.978 with a p-value of 0.12, also supporting normality. Regarding laws and regulations, the W statistic is 0.969 and the p-value is 0.088, again confirming a normal distribution. Finally, for data orientation, the W statistic is 0.975 and the p-value is 0.101, which likewise confirms normality. Since the p-values for all components exceed 0.05, it can be concluded that the data for all components are normally distributed (Table 7).

Table 7. Normality Test Results (Shapiro–Wilk)

Component	W Statistic	p-value	Result
Technological Infrastructure	0.972	0.083	Normal
Organizational Culture	0.964	0.065	Normal
Managerial Support	0.959	0.073	Normal
Training and Skills	0.978	0.12	Normal
Laws and Regulations	0.969	0.088	Normal
Data Orientation	0.975	0.101	Normal

The results of the one-way ANOVA for comparing mean differences among the components indicate that statistically significant differences exist among the component means. In this analysis, the sum of squares for between-component variation is 78.42 with 5 degrees of freedom. The mean square equals 15.68, and the computed F statistic is 37.92. The p-value is 0.000, which is less than the significance level of 0.05; therefore, the null hypothesis stating no difference among the means is rejected. These results indicate that at least one component mean differs significantly from the others (Table 8).

Table 8. Mean Difference Test (One-Way ANOVA)

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F	p-value
Between Components	78.42	5	15.68	37.92	0.000**
Within Components	122.08	294	0.415		
Total	200.5	299			

The results of the Pearson correlation test reveal significant relationships among the various components. Specifically, managerial support exhibits a significant correlation of 0.62 with technological infrastructure and a weaker correlation of 0.29 with organizational culture. In addition, technological infrastructure shows weak correlations of 0.29 with both organizational culture and training and skills, with p-values below 0.05, indicating statistically significant relationships. Organizational culture has a correlation of 0.58 with training and skills and 0.54 with data orientation, both of which are statistically significant. Furthermore, training and skills demonstrate a strong correlation of 0.76 with laws and regulations, and data orientation also shows a significant correlation of 0.49 with laws and regulations. Overall, these findings indicate that meaningful relationships exist among the different InsurTech components, some of which are stronger than others—particularly the relationships between training and skills and laws and regulations, and between organizational culture and training and skills.

Table 9. Pearson Correlation Test Among Components

Components	Managerial Support	Technological Infrastructure	Organizational Culture	Training and Skills	Laws and Regulations	Data Orientation
Managerial Support	1	0.62	0.29	0.41	0.59	0.62
Sig. (2-tailed)	—	0.000	0.023	0.004	0.030	0.031
Technological Infrastructure	0.62	1	0.29	0.29	0.41	0.38
Sig. (2-tailed)	0.000	—	0.019	0.023	0.009	0.004
Organizational Culture	0.29	0.29	1	0.58	0.54	0.54
Sig. (2-tailed)	0.023	0.019	—	0.000	0.014	0.009
Training and Skills	0.41	0.29	0.58	1	0.76	0.38
Sig. (2-tailed)	0.004	0.023	0.000	—	0.000	0.078
Laws and Regulations	0.59	0.41	0.54	0.76	1	0.49
Sig. (2-tailed)	0.030	0.009	0.014	0.000	—	0.000
Data Orientation	0.62	0.38	0.54	0.38	0.49	1
Sig. (2-tailed)	0.031	0.004	0.009	0.078	0.000	—

4. Discussion and Conclusion

The present study set out to design and validate a customer value–based InsurTech model by identifying, structuring, and prioritizing the key components that drive successful digital transformation in the insurance industry. The empirical results provide strong evidence that technological infrastructure functions as the primary driving force of InsurTech implementation, followed by managerial support, training and skills, organizational culture, data orientation, and laws and regulations. This hierarchical structure is theoretically consistent with the emerging body of InsurTech scholarship that positions technology as the backbone of contemporary insurance transformation (Ahmad et al., 2025; Braun & Jia, 2025; Moloi & Mulaba-Bafubiandi, 2024). The dominance of technological infrastructure in the model underscores the fact that digital transformation in insurance is fundamentally constrained or enabled by the availability, quality, and integration of digital systems, platforms, and data architectures.

The quantitative prioritization results further reinforce this conclusion. Technological infrastructure obtained the highest mean importance score and occupied the top level in the ISM hierarchy, indicating that improvements in this dimension exert cascading effects on all other components of InsurTech implementation. This finding aligns with Braun and Jia's argument that InsurTech is not merely an add-on to existing operations but constitutes a reconfiguration of insurance production, distribution, and service processes around digital capabilities (Braun & Jia, 2025). Similarly, Moloi and Mulaba-Bafubiandi emphasize that digital infrastructure forms the foundation upon which long-term insurance processes are redesigned and optimized (Moloi & Mulaba-Bafubiandi, 2024). The current results therefore confirm that investments in core digital platforms, analytics systems, and automation tools represent the most critical leverage point for insurers seeking sustainable competitive advantage.

The second most influential factor, managerial support, plays a pivotal mediating role between technological investments and organizational outcomes. The strong statistical relationships observed between managerial support and technological infrastructure indicate that leadership commitment is essential for translating digital resources into operational performance and customer value. This finding is strongly supported by prior research emphasizing the strategic role of leadership in steering digital transformation, coordinating innovation initiatives, and mitigating resistance to change (Shahroodi et al., 2024; Valimi et al., 2021). Shahroodi et al. demonstrate that insurers with strong managerial engagement achieve superior retention and performance outcomes by aligning digital strategies with organizational goals (Shahroodi et al., 2024). In the present study, managerial support occupies an upper-mid position in the ISM hierarchy, confirming its function as an accelerator of transformation rather than an independent driver.

Training and skills emerged as the third most influential component, reflecting the growing recognition that digital transformation is as much a human challenge as it is a technological one. The significant correlations between training and technological infrastructure, organizational culture, and regulatory compliance highlight the systemic role of human capital development in InsurTech success. These findings are consistent with Rana et al.'s observation that emerging technologies in insurance demand new skill sets in analytics, AI management, cybersecurity, and customer experience design (Rana et al., 2022). Similarly, Nguyen's work shows that organizational customers' perceptions of value are strongly shaped by employees' technological competence and service delivery capabilities (Nguyen, 2023). Without continuous upskilling, even the most advanced InsurTech systems fail to generate meaningful performance improvements.

The role of organizational culture in the model is particularly noteworthy. Although ranked below training and managerial support, organizational culture occupies a high structural level in the ISM hierarchy and exhibits strong correlations with both training and data orientation. This indicates that culture serves as a contextual amplifier of InsurTech effectiveness. These findings corroborate Lindlar's assertion that innovative technologies deliver their full value only within consumer-centric organizational cultures that promote learning, experimentation, and customer focus (Lindlar, 2021). Gilsing et al. likewise emphasize that service-dominant business models in insurance depend on cultural alignment across organizational subsystems (Gilsing et al., 2021). The present study extends this literature by demonstrating empirically that organizational culture interacts with both human capital and data capabilities to shape customer value creation.

Data orientation, while ranking lower in relative importance, nonetheless exhibits significant relationships with training, culture, and regulatory factors. This suggests that data-driven decision-making constitutes an enabling capability whose effectiveness depends on complementary organizational conditions. Prior studies consistently highlight the centrality of data analytics in modern insurance operations, including underwriting accuracy, fraud detection, customer segmentation, and personalized service delivery (Nicoletti, 2020; Rana et al., 2022). However, as the present findings indicate, data orientation alone does not guarantee performance gains unless supported by skilled personnel and a culture of evidence-based management.

Finally, laws and regulations appear at the base of the hierarchy with the lowest relative importance. Although regulatory frameworks provide essential boundaries for InsurTech operations, their limited influence on day-to-day implementation suggests that legal compliance functions primarily as a structural constraint rather than a performance driver. This finding resonates with Mullins et al.'s argument that ethical and regulatory guidelines in AI-driven insurance primarily protect stakeholder trust and legitimacy rather than directly enhancing operational efficiency (Mullins et al., 2021). Similarly, Ricky's study on InsurTech adoption highlights that regulatory clarity facilitates innovation but does not substitute for internal technological and organizational capabilities (Ricky, 2025).

Taken together, the results of this study provide robust empirical support for a systemic, customer value–based view of InsurTech transformation. The structural relationships identified through ISM demonstrate that successful InsurTech implementation is not achieved through isolated investments but through coordinated development of technological, managerial, human, cultural, data, and regulatory components. This integrated perspective is strongly consistent with prior theoretical frameworks emphasizing service-dominant logic and customer-centric business model innovation in insurance (Baranauskas & Raišienė, 2021; Ebrahimi et al., 2024; Nayak et al., 2022). Moreover, the prioritization results offer actionable guidance for executives seeking to sequence their transformation initiatives effectively.

This study has several limitations that should be acknowledged. First, the empirical analysis was conducted within a specific organizational and industrial context, which may restrict the generalizability of the findings to other insurance markets or geographic regions. Second, the reliance on expert judgments, although methodologically appropriate for structural modeling, may introduce subjective bias. Third, the cross-sectional design limits the ability to capture dynamic changes in InsurTech maturity over time.

Future studies could extend this research by testing the proposed model across different types of insurance firms and national contexts to assess its robustness and generalizability. Longitudinal designs may provide deeper insights into how InsurTech components evolve and interact over time. Additionally, future research could integrate objective performance indicators to complement perceptual measures and further validate the causal relationships identified in this study.

Insurance executives should prioritize investments in digital infrastructure while simultaneously strengthening leadership commitment, workforce capabilities, and organizational culture. Managers are encouraged to adopt an integrated transformation roadmap rather than fragmented technology initiatives. Continuous employee training, data-driven decision systems, and proactive regulatory engagement should be embedded into the organization's strategic planning processes to ensure sustained customer value creation and competitive advantage.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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