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Proposing a Smartization Model in the Insurance Industry Based on Financial Technology

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ABSTRACT

Digital transformation and the development of financial technologies have created new opportunities for the insurance industry that can lead to improved efficiency, increased customer satisfaction, and reduced operational risks. The primary objective of this study is to propose a comprehensive model for smartizing the insurance industry based on financial technologies; a model that, through the integration of insurance processes, facilitates more accurate decision-making, enhances efficiency, and reduces uncertainty in insurance operations. This study adopts a mixed-methods approach. In the qualitative phase, using the grounded theory method, data were collected and analyzed through semi-structured interviews with 10 managers and experts from the insurance industry in order to extract the dimensions and components of smartization. In the quantitative phase, data were collected through researcher-designed questionnaires from a statistical population of 384 insurance customers, managers, and experts, and analyzed using structural equation modeling. The qualitative findings indicate that components such as data security, technological innovation, human skills, governance, and leadership play a key role in the success of smartization, while environmental factors and the digital ecosystem provide the context for achieving these outcomes. The quantitative findings also demonstrate that variables including data security, ease of use, perceived usefulness, and customer trust have a significant impact on the adoption of financial technologies and the utilization of smart insurance services. The proposed model can assist insurance companies in designing smartization strategies, optimizing processes, reducing risks, and delivering personalized services to customers. In addition to providing a practical and applicable framework, this study offers recommendations to policymakers and regulatory bodies for formulating supportive and supervisory policies aimed at the development of financial technology and the smartization of the national insurance industry. The results indicate that the use of modern insurance technologies not only contributes to increased productivity and cost reduction, but also leads to the creation of a sustainable competitive advantage in the insurance industry.

Keywords: Smartization, insurance industry, financial technology, productivity, digital transformation

Introduction

The insurance industry is undergoing profound transformation as digital technologies reshape value creation, service delivery, and competitive dynamics across financial markets. Rapid advances in financial technology (FinTech), data analytics, artificial intelligence, cloud computing, and platform-based business models have

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fundamentally altered customer expectations, operational processes, and regulatory interactions within insurance ecosystems. In this context, traditional insurance models—characterized by paper-based processes, fragmented data systems, and limited customer engagement—are increasingly challenged by digitally enabled competitors and insurtech startups that emphasize speed, personalization, transparency, and cost efficiency (1, 2). As a result, insurers face mounting pressure to redesign their organizational structures, technological infrastructures, and strategic orientations in order to remain relevant in an increasingly digital financial landscape.

Digital transformation in insurance is not merely a technological upgrade but a multidimensional organizational change process that integrates digital tools with strategic, cultural, and governance reforms. Recent studies emphasize that successful digital transformation requires alignment between technology adoption, human capital development, process reengineering, and leadership commitment (3, 4). In insurance markets, this transformation has been accelerated by the diffusion of FinTech solutions that enable automated underwriting, digital claims management, personalized pricing, and real-time risk assessment. Such innovations have expanded insurers' capacity to leverage big data and business intelligence for improved decision-making and operational efficiency (5, 6). Consequently, FinTech has emerged as a central driver of smart insurance systems that aim to enhance productivity, reduce transaction costs, and improve customer experience.

Trust has been consistently identified as a critical determinant of FinTech adoption in insurance contexts. Unlike conventional financial services, insurance products are intangible, long-term, and risk-oriented, which amplifies customers' reliance on trust in digital platforms, algorithms, and data governance mechanisms. Empirical evidence suggests that perceived trustworthiness of digital systems significantly influences adoption intentions, particularly in emerging and regulated markets (7, 8). Moreover, the integration of automated decision-making tools such as robo-advisory services and algorithmic underwriting raises concerns regarding transparency, fairness, and data security, which further reinforce the importance of trust as a foundational element of digital insurance ecosystems (9, 10). Addressing trust-related barriers therefore represents a strategic imperative for insurers seeking to scale FinTech-based services.

From a theoretical perspective, technology adoption in insurance has been extensively examined through behavioral and acceptance models such as TAM, TAM2, UTAUT, and UTAUT2. These frameworks highlight the roles of perceived usefulness, ease of use, subjective norms, and facilitating conditions in shaping user acceptance of digital innovations. Recent extensions of these models emphasize the mediating and moderating roles of trust, perceived risk, and regulatory assurance in financial services adoption (11, 12). In insurance-specific contexts, these factors interact with institutional constraints, risk perceptions, and socio-cultural norms, resulting in complex adoption dynamics that cannot be fully explained by technological attributes alone (13, 14). This complexity underscores the need for integrative models that combine technological, organizational, and environmental dimensions.

In emerging economies, digital transformation in insurance is further shaped by structural and institutional characteristics such as regulatory maturity, infrastructure readiness, and market concentration. Studies conducted in developing and transitional markets indicate that while FinTech offers substantial opportunities for financial inclusion and operational efficiency, its diffusion is often constrained by regulatory ambiguity, limited digital literacy, and organizational resistance to change (10, 15). In the Iranian insurance industry, these challenges are particularly salient due to centralized regulatory structures, legacy systems, and uneven technological capabilities across firms.

Nonetheless, recent empirical research highlights growing momentum toward digital insurance models driven by policy support, competitive pressures, and increasing customer demand for digital services (3, 4).

Several studies have attempted to conceptualize digital insurance and FinTech integration within the Iranian context. Research on digital transformation maturity frameworks demonstrates that insurers progress through distinct stages ranging from basic digitization to advanced data-driven and intelligent operations (3). Similarly, data-driven models of digital insurance emphasize the role of analytics, interoperability, and ecosystem partnerships in enhancing service innovation (6, 16). These contributions provide valuable insights into technological capabilities but often focus on isolated dimensions such as infrastructure or analytics, rather than offering a holistic smartization model that integrates causal drivers, contextual conditions, strategic actions, and performance outcomes.

Insurtech startups have played a catalytic role in reshaping insurance markets by introducing agile, customer-centric solutions that challenge incumbent insurers' traditional value chains. Peer-to-peer insurance platforms, usage-based insurance, and embedded insurance services exemplify how digital ecosystems blur industry boundaries and redefine risk-sharing mechanisms (2, 11). Empirical studies indicate that collaboration between insurers and insurtech firms can enhance innovation capacity, reduce time-to-market, and foster organizational learning, provided that governance structures and strategic alignment are effectively managed (4, 17). However, resistance from internal stakeholders and misalignment between legacy systems and digital platforms often impede such collaborations.

Beyond technological and organizational considerations, digital insurance transformation has significant implications for social inclusion and accessibility. Research on vulnerable and underserved populations demonstrates that digital insurance solutions can improve access and affordability, but adoption is contingent upon cognitive, affective, and normative factors that shape individuals' digital engagement (15). These findings suggest that smart insurance models must account for heterogeneity in user capabilities, trust perceptions, and digital readiness, particularly in diverse socio-economic contexts. Failure to address these dimensions may exacerbate digital divides and undermine the inclusiveness of insurance innovation.

Another critical dimension of FinTech-enabled insurance is its alignment with broader sustainability and governance objectives. Emerging evidence indicates that digital insurance platforms can support ESG integration through enhanced transparency, data-driven risk assessment, and automated advisory services (9). Such capabilities position smart insurance systems not only as efficiency-enhancing tools but also as mechanisms for responsible risk management and sustainable financial practices. This perspective expands the strategic relevance of FinTech adoption beyond operational performance to encompass long-term value creation and societal impact.

Despite the growing body of literature on digital transformation and FinTech adoption in insurance, several research gaps remain. First, existing studies often adopt either a technology-centric or behavior-centric lens, overlooking the interdependencies between environmental drivers, organizational contexts, strategic responses, and performance consequences. Second, empirical research in emerging markets tends to focus on adoption intentions rather than on comprehensive smartization processes that explain how digital transformation unfolds within insurance organizations over time (14, 18). Third, there is limited integration of qualitative insights and quantitative validation in developing context-specific models that reflect the realities of national insurance systems.

Addressing these gaps requires a holistic analytical framework that captures the complexity of smart insurance transformation as a dynamic and systemic phenomenon. Grounded and mixed-method approaches are particularly suited for this purpose, as they enable theory building from empirical data while allowing for statistical validation of proposed relationships. By integrating causal conditions such as market competition and technological change with contextual factors like organizational culture and regulation, and linking them to strategic actions and measurable outcomes, such models can offer actionable insights for both practitioners and policymakers (1, 17).

In the Iranian insurance industry, developing a comprehensive smartization model based on FinTech is especially timely given ongoing policy reforms, increasing digital penetration, and the strategic necessity of enhancing competitiveness in regional and global markets. A structured and empirically grounded model can support insurers in prioritizing investments, managing transformation risks, and aligning digital initiatives with organizational capabilities and customer expectations (3, 4). Moreover, such a model can inform regulators in designing supportive frameworks that balance innovation with consumer protection and systemic stability.

Accordingly, the aim of this study is to develop and validate a comprehensive smartization model for the insurance industry based on financial technologies, integrating causal, contextual, intervening, strategic, and outcome dimensions to explain and enhance digital transformation in insurance organizations.

Methods and Materials

This study was designed as a cross-sectional investigation, and data were collected and analyzed within a specific time frame in order to identify the current status and the relationships among variables. Focusing on the present time allows for an examination of the needs, challenges, and capacities of Iran's insurance industry, particularly in the area of smartization based on financial technology. Although the study is cross-sectional, its findings can serve as a foundation for future longitudinal research and enable the testing and updating of the proposed model in response to technological advancements or market changes.

Data collection was conducted in two qualitative and quantitative phases. In the qualitative phase, semi-structured interviews were conducted with insurance industry experts, financial technology managers, university faculty members, and innovation specialists to identify the key dimensions and indicators of smartization, and sampling continued until theoretical saturation was achieved. The data were analyzed using open, axial, and selective coding. In the quantitative phase, a researcher-developed questionnaire based on the qualitative findings was designed and distributed among a sample of customers and stakeholders in the insurance industry. The validity and reliability of the questionnaire were confirmed through expert judgment, Cronbach's alpha test, and composite reliability. The collected data were analyzed using statistical software and structural equation modeling techniques to evaluate and validate the final research model.

Findings and Results

The qualitative phase of this study was conducted with the aim of identifying and explaining the components, dimensions, and conditions affecting smartization in the insurance industry based on financial technologies. Given the innovative and dynamic nature of the topic under investigation, the use of a grounded theory approach to extract a model and theory from empirical and field data was considered the most appropriate option for developing an indigenous framework grounded in the realities of Iran's insurance industry. In this section, data were collected through semi-structured interviews with specialists, senior managers in the insurance industry, and financial technology experts. These data were then analyzed using a three-stage coding process (open, axial, and selective). The analysis process systematically led to the identification of key concepts, the relationships among them, and ultimately the formation of an initial conceptual model of smartization in the insurance industry.

In the continuation of this section, in addition to presenting the coding process and tables of extracted concepts and categories, the theoretical model derived from the qualitative analysis will also be explained.

In line with developing a smartization model in the insurance industry based on financial technologies, this research was conducted using a qualitative approach through semi-structured interviews with 10 senior managers and experts in Iran's insurance industry, as theoretical saturation was achieved with this number. The purpose of these interviews was to identify the key dimensions, requirements, challenges, success factors, and outcomes associated with the application of financial technologies (FinTech) in the process of smartizing the insurance industry. The interview questions were purposefully designed to comprehensively extract the experiences, perspectives, and specialized analyses of these managers regarding the implementation of modern technologies in the insurance sector. The data analysis process was carried out based on the initial coding approach of grounded theory; accordingly, rich instances of the interviewees' statements were first extracted, and then the initial key concepts for each response were identified. The results of this stage were compiled in the form of tables containing question items, descriptive instances, and initial concepts. This process laid the groundwork for the subsequent stage of thematic analysis and theory development. To facilitate a better understanding of the professional background of the participants, their demographic characteristics are also presented in the table below.

Table 1. Demographic Characteristics of the Research Participants

No.	Age (Years)	Years of Experience in the Insurance Industry	Education Level	Field of Study
1	45	20	PhD	Insurance Management
2	39	14	Master's Degree	Industrial Engineering
3	52	27	PhD	Financial Management
4	41	16	Master's Degree	Information Technology
5	36	10	Master's Degree	Insurance Management
6	48	22	PhD	Economics
7	43	18	Master's Degree	Executive Management
8	37	12	PhD	Innovation Management
9	50	25	PhD	Insurance Law
10	40	15	PhD	Information Technology Engineering

In the following, illustrative interview excerpts are presented separately for each research interviewee in the form of a table:

Table 2. Interview Excerpts by Interviewee

Interviewee	Interview Excerpts	No.
Interviewee 1	We launched several joint projects with insurtech startups, including online claims assessment, personalized insurance offers, and facilitation of the insurance purchase process. In one project, customers could upload photos of damages through an application, and the system would automatically estimate the amount of damage and the approximate payment time. This process significantly increased customer satisfaction due to the speed and accuracy of services and also resulted in cost savings.	1
Interviewee 1	One of the key success factors in implementing financial technologies was our focus on employee training and strengthening the digital culture within the organization. Initially, we did not believe this transformation was essential, but with the entry of startups and changes in customer needs, we realized that transformation had to be applied at all organizational levels, including technical teams, sales, and executive management. This process required substantial time and resources, but its outcomes were clearly reflected in improved productivity and customer satisfaction.	2
Interviewee 1	The most significant challenge we faced was internal organizational resistance and a lack of acceptance of change. Many managers with long experience in traditional methods perceived this transformation as a threat to their positions and resisted adopting new approaches. This mindset slowed the pace of change initially and led to complete توقف of some projects.	3
Interviewee 2	Experience in implementing financial technologies in the insurance industry showed that investment in infrastructure and human resource training is essential for success. By establishing appropriate infrastructure and enhancing organizational culture, we were able to smartize insurance processes, reduce request processing time, and increase data accuracy; however, in projects where interdepartmental coordination was insufficient, problems and failures also occurred.	4

Interviewee 2	The implementation of smartization systems faced legal and infrastructural constraints. Some units were not prepared to accept change, and the lack of transparency in legal processes and coordination among departments caused delays or project suspension. Experience demonstrated that precise management, a receptive organizational culture, and workforce training are essential for success.	5
Interviewee 3	Our organization initiated a digital transformation program in 2019 that included online policy issuance systems, digital case management, and smart customer interaction through mobile applications. Establishing a digital transformation unit and recruiting fintech specialists facilitated the smartization path and generated innovative experiences in delivering insurance services.	6
Interviewee 3	Collaboration with insurtech startups in automobile damage image analysis reduced claim processing time by up to 70%. The new system automatically processed customer information and proposed personalized policies, reducing errors and accelerating processes.	7
Interviewee 4	We started with digitizing forms and support systems and then moved toward data analytics, damage pattern identification, and risk management. This gradual transformation enabled employees to adapt to new technologies, and innovative projects progressed with executive management support.	8
Interviewee 4	Successful projects included the development of an installment-based premium payment system via an internal digital wallet, implemented in collaboration with a fintech partner, which attracted more than 50,000 active users. This project increased customer satisfaction through simplicity and payment security and served as an example of fintech's impact on insurance.	9
Interviewee 5	Online issuance of motor insurance policies initially faced resistance from agents, but through training sessions, explanation of benefits, and offering higher commissions, gradual technology adoption was achieved. Experience showed that training and motivating employees are vital for project success.	10
Interviewee 5	The information technology team, equipped with specialized personnel familiar with insurance, was able to accurately define and communicate requirements, thereby reducing implementation risk and enabling processes to proceed with greater speed and accuracy.	11
Interviewee 6	Collaboration with an insurtech startup for vehicle damage assessment based on images was a successful experience that initially involved skepticism. After evaluating system performance across 50 pilot cases, gradual trust was established and the system became part of the assessment process.	12
Interviewee 6	Transparency of objectives and roles was critical to the success of technological projects; once responsibilities and expectations were clarified, different teams avoided conflict and blame-shifting, leading to improved performance.	13
Interviewee 7	Using an installment premium payment system with a domestic fintech enabled customers to pay installments without in-person visits, increased policy renewal rates by 20%, and reduced insurance leakage.	14
Interviewee 7	Project success required the support of middle and senior managers who, through participation in meetings and clarification of needs, enhanced coordination between technology and operations units and enabled integrated team performance.	15
Interviewee 8	Utilizing insurtech platforms for health risk assessment in life insurance enabled personalized premium rates and increased customer satisfaction. Collaboration with startups and machine learning algorithms enhanced analytical accuracy and speed.	16
Interviewee 8	Smartizing processes is impossible without clean and comprehensive data. By integrating data from different branches, we developed decision-support dashboards that improved managerial decision-making and enhanced customer experience.	17
Interviewee 9	The use of insurtech in issuing motor insurance allowed customers to upload vehicle photos via an application, enabling the system to automatically assess risk; issuance processes that previously took several days are now completed within minutes.	18
Interviewee 9	Coordination between technical teams and insurance experts made technological products more effective, ensuring that the terminology and requirements of both sides were accurately reflected in projects; experience showed that cross-functional interaction is vital for success.	19
Interviewee 10	Implementing a supplementary health insurance platform using machine learning algorithms enabled analysis of medical costs and prediction of claim patterns. The system classified policyholder behavior and provided precise pricing, which reduced company losses and increased customer satisfaction.	20

Selective coding is conducted with a focus on identifying the relationships among concepts and forming core categories. At this stage, the researcher seeks to organize the initial concepts around a "core category" and to link other codes to it as causal conditions, contextual conditions, intervening conditions, strategies, and consequences. This structure ultimately leads to the development of a paradigmatic model. Therefore, the objective of this stage is to move beyond the descriptive level toward theoretical explanation, through which a deeper understanding of the central phenomenon and the factors influencing it is achieved.

Table 3. Classification of Codes

No.	Variables	Main Concepts	Sub-Concepts
1	Causal Conditions	Need to accelerate insurance processes	Reduction in customer response time, improvement of online services

2		Increased customer demand for digital services	Growth in demand for online services, faster access to insurance information
3		Emergence of new financial technologies	Entry of fintech firms, use of advanced technologies in risk assessment
4		Reduction of operational costs in insurance	Reduction in customer acquisition costs, reduction in administrative costs
5		Competition with insurance technology startups (insurtechs)	Creation of competition in providing innovative services, necessity of updating legacy systems
6	Contextual Conditions	Traditional organizational culture in insurance companies	Resistance to change, reluctance to adopt new technologies
7		Centralized and hierarchical structure of the insurance industry	Concentration of power at top management levels, slow decision-making
8		Weak digital infrastructure	Lack of appropriate infrastructure for technology implementation, limitations in connectivity to global networks
9		Shortage of specialized human resources in technology	Need to recruit specialists in fintech and information technology
10		Lack of up-to-date regulations regarding fintech	Legal gaps in fintech utilization, incompatibility with international regulations
11	Intervening Conditions	Role of regulatory institutions such as the Central Insurance Authority	Supportive policies, standardization of digital activities
12		Government support for insurance startups	Creation of supportive conditions for innovative firms, encouragement of investment in technology
13		Managers' adaptability to technological change	Retraining and empowerment of managers, acceptance of technological change at managerial levels
14		National economic stability and exchange rate	Effects of economic fluctuations on costs and technology investment
15		Level of digital literacy among insurance employees	Digital training of employees, improvement of IT knowledge in the insurance industry
16	Strategies	Development of digital insurance platforms	Creation of online platforms for insurance assessment and service delivery
17		Collaboration with fintech startups	Launch of joint projects with startups, use of new business models
18		Training and retraining employees in digital skills	Technical training courses for employees, strengthening digital capabilities
19		Reengineering traditional processes	Revision of legacy processes, optimization of operations for technology use
20		Investment in cloud technology and artificial intelligence	Use of cloud infrastructure, implementation of AI in risk analysis
21	Consequences	Increased customer satisfaction and user experience	Ease of access to insurance services, improvement of online purchasing experience
22		Increased accuracy in risk assessment	Use of big data for more accurate risk evaluation, reduction of human error
23		Reduction of fraud and human error	Use of AI algorithms to detect fraud
24		Increased productivity and profitability of insurance companies	Cost reduction, increased sales, access to new markets
25		Alignment with global insurance standards	Improved competitive position in global markets, compliance with international regulations

The selective coding table presented, based on grounded theory, provides a detailed representation of the qualitative analysis process concerning "smartization of the insurance industry based on financial technologies." This table consists of five main sections: causal conditions, contextual conditions, intervening conditions, strategies, and consequences, each of which analyzes different dimensions of the phenomenon under study and clarifies the complex relationships among them.

Causal conditions refer to the factors that initiate or facilitate smartization processes in the insurance industry. In this section, the need to accelerate insurance processes, increased customer demand for digital services, the emergence of new financial technologies, reduction of operational costs, and competition with insurance technology startups (insurtechs) are identified as the most significant driving forces. These factors reflect rapid changes in the external environment as well as the insurance industry's need for innovation and updating existing systems in order to keep pace with technological developments.

The contextual conditions section examines factors that influence the capabilities and challenges of implementing financial technologies within the internal and structural environment of the insurance industry. Traditional organizational culture, centralized and hierarchical structures, weak digital infrastructure, shortages of specialized technological human resources, and the lack of up-to-date regulations in dealing with fintechs are among the barriers that slow the digital transformation process in the insurance industry. These factors mainly relate to internal and contextual characteristics of insurance companies and institutions that must be addressed in order to remove obstacles.

Intervening conditions refer to factors that may strengthen or weaken the implementation process of financial technologies. In this section, the role of regulatory institutions such as the Central Insurance Authority, government support for insurance startups, managers' adaptability to technological change, national economic stability, and the level of digital literacy among insurance employees are identified as intervening factors. These factors directly influence the pace of digital transformation in the insurance industry and can either accelerate or slow down the process of change.

The strategies section introduces the proposed actions and strategies for implementing smartization in the insurance industry through financial technologies. The development of digital insurance platforms, collaboration with fintech startups, employee training and retraining, reengineering of traditional processes, and investment in cloud technologies and artificial intelligence are among the strategies widely proposed in the insurance industry to achieve smartization. These actions can facilitate the adoption of new technologies in insurance service delivery and contribute to improved productivity.

The consequences section addresses the outcomes and effects resulting from the implementation of financial technologies in the insurance industry. Positive consequences include increased customer satisfaction and user experience, improved accuracy in risk assessment, reduction of fraud and human error, increased productivity and profitability of insurance companies, and alignment with global insurance standards. These outcomes demonstrate the benefits and positive impacts that smartization of the insurance industry through financial technologies can generate for insurance companies and their customers. Overall, this table serves as a useful tool for structuring and comprehensively analyzing the factors influencing digital transformation in the insurance industry and provides a solid foundation for designing effective implementation strategies.

In the quantitative section, 12 individuals in the sample held managerial positions, 92 held deputy positions, 164 served as advisors, and 116 were experts. Moreover, the majority of the sample (42.7%) reported their organizational position as expert. A total of 123 respondents had 1–10 years of work experience, 123 had 11–20 years of work experience, and 138 had 21–30 years of work experience. The majority of the sample (35.9%) had 21–30 years of work experience. Regarding age groups, 127 respondents were in the 30–40 age group, 150 were in the 41–50 age group, and 107 were in the 51–60 age group. The majority of the sample (39.1%) belonged to the 41–50 age group. In order to gain a better understanding of the research population and to become more familiar with the study variables, it is necessary to describe the data prior to conducting statistical analyses. Therefore, before testing the research hypotheses, descriptive statistics of the variables used in the study were examined. The mean, as one of the central tendency parameters, represents the center of gravity of the population and indicates that if the mean were substituted for all observations in the population, the total sum of the data would remain unchanged. In addition, the maximum represents the highest value of a variable in the statistical population, while the minimum represents the lowest value. The results of the descriptive statistics are presented in the table below.

Table 4. Mean and Standard Deviation of the Model Variables

Factor	Causal Conditions	Intervening Conditions	Contextual Conditions	Strategies	Consequences	Core Category
Mean	4.0147	3.9779	4.1289	4.5071	4.1632	3.6632
Standard Deviation	0.63850	0.79731	0.81808	0.56049	0.70450	0.93366
Minimum	1.14	1.00	1.00	1.00	1.00	1.00
Maximum	5.00	5.00	5.00	5.00	5.00	5.00
Kurtosis	1.454	0.309	0.620	6.018	1.839	-0.625
Skewness	-0.828	-0.761	-1.069	-2.064	-1.219	-0.262
Variance	4.0147	3.9779	4.1289	4.5071	4.1632	3.6632
Median	0.63850	0.79731	0.81808	0.56049	0.70450	0.93366

The table presented contains statistical information on the study model variables, including the mean, standard deviation, minimum and maximum values, kurtosis, skewness, variance, and median for each factor. The means indicate the overall level of each variable in the examined sample. For example, strategies have the highest mean value (4.5071), indicating the high importance of this factor in the model. Standard deviations represent the dispersion of the data; for instance, the core category, with a standard deviation of 0.93366, shows the greatest dispersion. Kurtosis and skewness indicate the shape of the data distribution and its asymmetry, respectively. The high kurtosis value of 6.018 for strategies indicates a highly peaked distribution, while the negative skewness for most variables suggests a left-skewed distribution. These statistical indicators can contribute to more precise analysis and a better understanding of the behavior of variables within the model.

To apply statistical methods, calculate appropriate test statistics, and make logical inferences about the research hypotheses, the most important step prior to any analysis is selecting the appropriate statistical method. For this purpose, knowledge of the data distribution is of fundamental importance. Accordingly, the Kolmogorov–Smirnov test was used in this study to examine the assumption of normality of the research data. Based on the following hypotheses, the normality of the data was assessed:

H0: The data follow a normal distribution.

H1: The data do not follow a normal distribution.

According to the Kolmogorov–Smirnov test table, if the significance level for all independent and dependent variables is greater than the 5% error level, the null hypothesis (H0) is accepted, indicating that the data distribution is normal.

Table 5. Normality Test of the Examined Variables

Variable	Test Statistic	Significance Level	Result
Causal Conditions	0.079	0.000c	Not normal
Intervening Conditions	0.118	0.000c	Not normal
Contextual Conditions	0.159	0.000c	Not normal
Strategies	0.192	0.000c	Not normal
Consequences	0.118	0.000c	Not normal
Core Category	0.136	0.000c	Not normal

Based on the values presented in the above table, where the significance level of the test for all variables is less than 0.05, the null hypothesis (H0) is rejected and the alternative hypothesis (H1) is accepted. Therefore, the distributions of the variables do not follow a normal distribution. Accordingly, nonparametric methods were used to examine the relationships among the research variables and to test the hypotheses.

To test correlations, given the nonparametric distribution of the data, Spearman's correlation test was used to examine the relationships among the main variables.

H0: There is no significant relationship between the two variables.

H1: There is a significant relationship between the two variables.

Table 6. Correlations Among the Research Model Variables

	Causal Conditions	Intervening Conditions	Contextual Conditions	Strategies	Consequences	Core Category
Causal Conditions	1.000	0.515**	0.551**	0.517**	0.542**	0.339**
Intervening Conditions	0.515**	1.000	0.697**	0.427**	0.505**	0.458**
Contextual Conditions	0.551**	0.697**	1.000	0.460**	0.502**	0.389**
Strategies	0.517**	0.427**	0.460**	1.000	0.693**	0.238**
Consequences	0.542**	0.505**	0.502**	0.693**	1.000	0.364**
Core Category	0.339**	0.458**	0.389**	0.238**	0.364**	1.000

In the above table, * indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

The results of Spearman's correlation analysis among the main research variables are presented in the above table. As shown, all correlation coefficients fall between zero and one, and the significance levels of the correlation coefficients are less than 5%. Therefore, the null hypothesis is rejected and the alternative hypothesis is accepted, indicating that there are significant correlations among all research variables. Consequently, it is feasible to test the hypotheses using structural equation modeling.

Before conducting factor analysis, it is first necessary to ensure whether the available data are adequate for factor analysis. For this purpose, the KMO index and Bartlett's test are used. Based on the significance level, it can be concluded that the data are suitable for sampling adequacy. The KMO test indicates whether the sample size is appropriate for factor analysis. The value of this index ranges between zero and one. If the index value is close to one (at least 0.60), the data are suitable for factor analysis; otherwise (typically below 0.60), factor analysis results are not appropriate for the given data. Given the obtained index (KMO = 0.924), it is indicated that the number of observations is adequate for factor analysis.

The significance level of the test was 0.000, which means that the null hypothesis is rejected and there is a statistically significant relationship among the variables.

Model fit refers to the extent to which a model is consistent with and in agreement with the relevant data. Accordingly, this section evaluates the fit of the hypothesized research model to ensure its compatibility with the study data and, ultimately, to infer answers to the research questions. The evaluation of the fit of the research conceptual model was conducted in two stages: first, assessment of the measurement model fit, and second, assessment of the structural model fit, each of which is discussed in detail below.

Table 7. Coefficient of Determination and Adjusted Coefficient of Determination for the Research Variables

	Coefficient of Determination (R^2)	Adjusted Coefficient of Determination (Adjusted R^2)
Strategic Factors	0.365	0.360
Outcome Factors	0.499	0.497
Core Phenomenon	0.125	0.123

This table presents the values of the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2) for different variables in the model. Strategic factors: an R^2 of 0.365 indicates that 36.5% of the variance in the dependent variable is explained by these factors. The adjusted R^2 of 0.360 also indicates that, considering the number of variables in the model, the explanatory power remains acceptable. Outcome factors: with an R^2 of 0.499, nearly half of the variance in the dependent variable is attributable to these factors, indicating a substantial influence of these factors on outcomes. The adjusted R^2 of 0.497 emphasizes that these results remain valid and reliable even after accounting for the number of variables in the model. Core phenomenon: an R^2 of 0.125 indicates that only 12.5% of the variance in the dependent variable is explained by this phenomenon. This relatively low value suggests a weaker effect, potentially due to the presence of other variables that influence this phenomenon. The adjusted R^2 of 0.123 similarly indicates that, even after accounting for the number of variables, the explanatory power of this phenomenon remains low. These values show how each factor contributes to explaining and predicting outcomes within the model and clarify their importance in the overall research structure. Overall, understanding these coefficients can help optimize the model and identify strengths and weaknesses in the analysis.

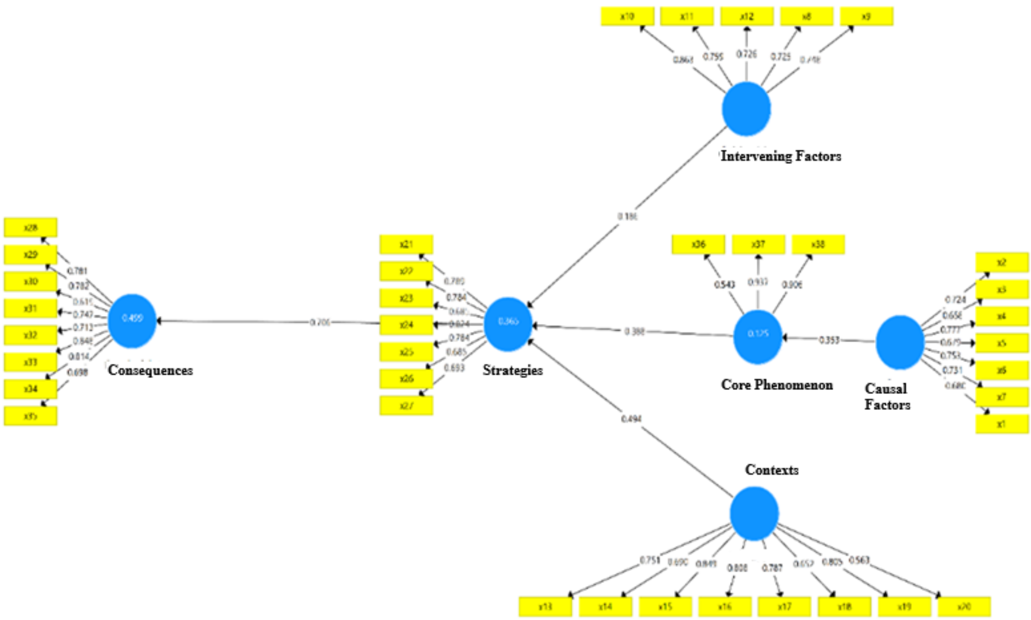

Figure 1. Standardized Regression Coefficients of the Research Model

In SmartPLS software, factor loadings are used to assess the extent to which observed variables (indicators) influence latent variables (constructs). A factor loading indicates the extent to which each indicator can explain changes in its corresponding latent variable. In general, factor loadings should be greater than 0.40 to indicate a statistically meaningful and acceptable effect on the latent variable. This enables the determination of whether the indicators effectively represent the intended concept and construct. Based on the presented figure, it is observed that all factor loadings exceed 0.40, and some even reach higher values, indicating that all indicators have a meaningful effect on the latent variables. Consequently, these significant factor loadings provide assurance that the measurement instrument used in this study performed adequately and can yield reliable results. This analysis suggests that the collected data appropriately explain the study concepts and that the model results can be used for decision-making and strategy formulation.

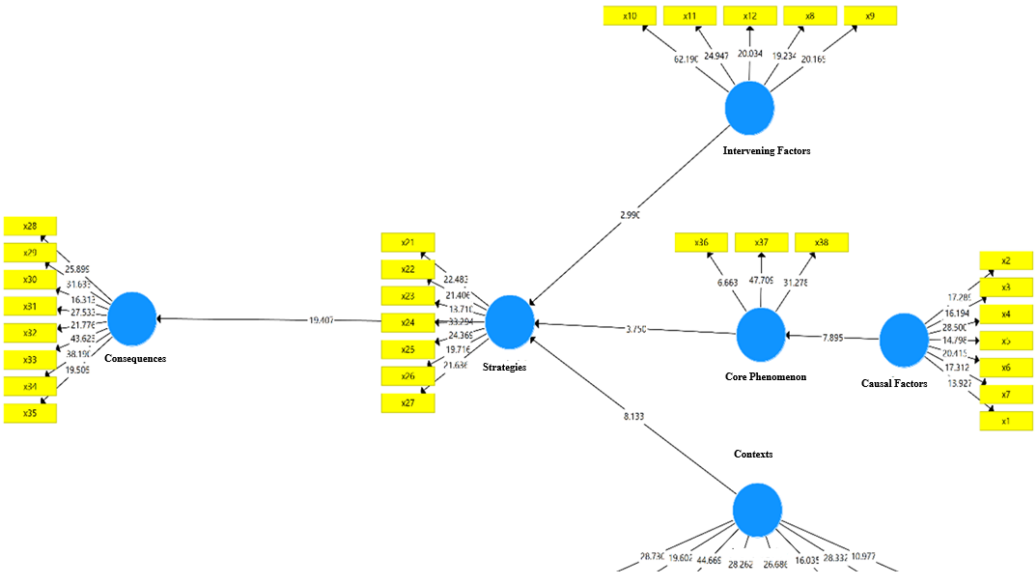

Figure 2. T-Values of the Research Model

Given that SmartPLS uses the t-statistic to examine the significance of relationships, and the critical value for a 5% error level is 1.96, significance is assessed by comparing the t-values of the relationships with 1.96. Specifically, if the t-value exceeds 1.96, the indicated relationship is significant. Based on the above figure, all t-values exceed 1.96; therefore, all model relationships are statistically significant.

Table 8. Results of Cronbach's Alpha, Composite Reliability, and Convergent Validity

Variables	Cronbach's Alpha (Alpha > 0.70)	Composite Reliability (CR > 0.70)	Average Variance Extracted (AVE > 0.50)
Strategic Factors	0.871	0.900	0.564
Contextual (Enabling) Factors	0.884	0.907	0.553
Causal Factors	0.845	0.880	0.512
Intervening Factors	0.823	0.876	0.587
Outcome Factors	0.889	0.912	0.567
Core Phenomenon	0.723	0.850	0.665

a) Since Cronbach's alpha, composite reliability (internal consistency), and AVE are all within their acceptable ranges, the adequacy of the reliability and convergent validity of the research model can be confirmed.

b) In addition, the factor loadings of each measurement item were reported in the following table (Table 4-15) to assess reliability and construct validity. As shown, all factor loadings exceed 0.40; therefore, the reliability and construct validity of the model measures can also be confirmed.

The Fornell–Larcker criterion assesses the strength of the relationship between a construct and its indicators compared with the relationship between that construct and other constructs. Acceptable discriminant validity indicates that a construct interacts more strongly with its own indicators than with other constructs. Discriminant validity is acceptable when the AVE of each construct is greater than the shared variance between that construct and other constructs in the model. In simpler terms, a model has acceptable discriminant validity when the values on the main diagonal are greater than the off-diagonal values below them. According to this criterion, a latent variable should exhibit greater variance among its own observed indicators than among other latent variables, indicating strong discriminant validity.

To compute the Fornell–Larcker criterion, the square roots of the AVE values for the latent variables were calculated from the AVE table.

Table 9 Fornell–Larcker Matrix

	Strategic Factors	Contextual (Enabling) Factors	Causal Factors	Intervening Factors	Outcome Factors	Core Phenomenon
Strategic Factors	0.751					
Contextual (Enabling) Factors	0.590	0.744				
Causal Factors	0.541	0.597	0.716			
Intervening Factors	0.497	0.715	0.517	0.766		
Outcome Factors	0.706	0.560	0.569	0.517	0.753	
Core Phenomenon	0.211	0.426	0.353	0.475	0.363	0.815

Discussion and Conclusion

The findings of the present study provide robust empirical support for the proposed smartization model of the insurance industry based on financial technologies, demonstrating that digital transformation in insurance is a multidimensional phenomenon shaped by the interaction of causal, contextual, intervening, strategic, and outcome-related factors. The results of the structural equation modeling confirm that strategic factors play a pivotal mediating role between environmental and organizational conditions and the ultimate performance outcomes of smart insurance initiatives. This finding is consistent with prior research emphasizing that digital transformation does not automatically translate into value creation unless it is operationalized through coherent strategies such as platform development, process reengineering, and human capital upskilling (1, 4). The high explanatory power of strategic factors suggests that insurers' deliberate choices in structuring and sequencing digital initiatives are more decisive than mere technological availability.

The significant relationships identified between causal conditions and strategic actions highlight the role of external pressures—such as increased customer demand for digital services, competition from insurtech startups, and the emergence of advanced FinTech solutions—as primary triggers of smartization. This aligns with evidence showing that market-driven forces and competitive dynamics often act as catalysts for digital innovation in insurance, compelling incumbents to adopt agile and customer-centric technologies to preserve market share (2, 11). The findings also resonate with studies conducted in emerging markets, which indicate that perceived market turbulence and technological opportunity jointly motivate firms to invest in digital transformation, even in the presence of regulatory and infrastructural constraints (14, 15).

Contextual conditions, including organizational culture, structural rigidity, and digital infrastructure readiness, were found to exert a significant indirect effect on smartization outcomes through their influence on strategic implementation. The negative skewness observed in contextual variables suggests that while many insurers acknowledge the importance of digital transformation, traditional hierarchical cultures and legacy systems remain substantial barriers. This result corroborates earlier findings in the Iranian insurance sector, which identified centralized decision-making and resistance to change as major impediments to effective digital transformation (3, 16). Similar patterns have been observed in other regulated insurance markets, where institutional inertia slows the translation of digital intent into operational change (13).

Intervening conditions—particularly regulatory support, managerial adaptability, and workforce digital literacy—were shown to significantly moderate the relationship between strategies and outcomes. The strong loading of these factors underscores the importance of governance and human agency in shaping digital transformation trajectories. The role of regulatory institutions as both facilitators and gatekeepers of FinTech adoption is well documented in the literature, with supportive policies and standard-setting mechanisms shown to reduce uncertainty and enhance organizational confidence in digital investments (7, 17). The present findings reinforce this view by demonstrating that regulatory clarity and policy alignment amplify the effectiveness of smartization strategies.

Trust-related dimensions embedded within intervening and outcome factors also emerged as critical determinants of successful smart insurance adoption. The significant associations between strategic initiatives and outcomes such as customer satisfaction, reduced fraud, and improved risk assessment accuracy suggest that FinTech-enabled systems can enhance both operational performance and relational value. These results are consistent with prior empirical studies highlighting trust as a central mechanism through which digital insurance services gain legitimacy among users (8, 10). In particular, the integration of automated underwriting, digital claims assessment, and data-driven pricing appears to strengthen perceived transparency and reliability when supported by robust data governance frameworks.

The relatively lower coefficient of determination for the core phenomenon, compared to strategic and outcome factors, warrants careful interpretation. While the core category captures the conceptual essence of smartization, its weaker explanatory power suggests that smart insurance transformation is not driven by a single dominant construct but rather emerges from the dynamic interplay of multiple factors. This finding aligns with systems-based perspectives on digital transformation, which argue that value creation arises from complementarities among technology, organization, and environment rather than from isolated innovations (5, 6). It also supports the argument that smartization should be viewed as an evolving capability rather than a static state.

The strong impact of outcome factors on organizational performance indicators such as productivity, profitability, and alignment with global standards underscores the strategic significance of FinTech-based smartization. The results indicate that insurers that successfully implement digital strategies are better positioned to achieve operational efficiency and competitive differentiation. This finding is in line with international evidence demonstrating that digital insurance platforms enable scalability, cost reduction, and enhanced analytics, thereby improving insurers' ability to compete in both domestic and international markets (9, 15). Moreover, the alignment with global insurance standards observed in the model reflects the role of digital transformation in facilitating regulatory harmonization and cross-border competitiveness.

From a theoretical standpoint, the study extends existing technology adoption models by embedding behavioral constructs such as trust and perceived usefulness within a broader organizational and strategic framework. While prior research has predominantly focused on individual-level adoption intentions using models such as TAM2 and UTAUT2 (11, 12), the present study demonstrates that organizational-level smartization requires simultaneous attention to strategy formulation, governance structures, and ecosystem relationships. This integrative perspective contributes to the literature by bridging micro-level adoption theories with macro-level digital transformation frameworks.

The findings also have important implications for understanding digital transformation in emerging economies. The Iranian insurance context illustrates how FinTech-driven smartization can progress despite structural constraints when supported by coherent strategies and adaptive governance. This supports comparative studies suggesting that while emerging markets face unique challenges, they also possess opportunities for leapfrogging through targeted digital investments and ecosystem partnerships (14, 18). The study thus provides empirical validation for context-sensitive models of digital insurance transformation.

Overall, the results confirm that smartization in the insurance industry is a strategic and systemic process rather than a purely technological upgrade. The proposed model captures this complexity by integrating multiple dimensions and empirically validating their interrelationships. By aligning qualitative insights with quantitative evidence, the study offers a comprehensive explanation of how FinTech-enabled smart insurance systems can be designed, implemented, and leveraged to achieve sustainable performance outcomes.

Despite its contributions, this study has several limitations that should be acknowledged. First, the cross-sectional design limits the ability to capture the dynamic and evolutionary nature of digital transformation over time. Second, although the sample size was adequate for structural equation modeling, the study relied on self-reported data, which may be subject to response bias. Third, the focus on the Iranian insurance industry may constrain the generalizability of the findings to other institutional and regulatory contexts with different market structures and levels of digital maturity.

Future research could adopt longitudinal designs to examine how smartization capabilities evolve and how strategic interventions influence outcomes over time. Comparative studies across different countries or insurance markets would also enhance understanding of contextual variations in FinTech-driven transformation. Additionally, future studies could incorporate objective performance indicators and advanced analytics techniques to complement perceptual measures and further validate the proposed model.

Insurance executives should prioritize the alignment of digital strategies with organizational culture and governance structures to maximize the benefits of FinTech adoption. Policymakers and regulators can support smartization by providing clear regulatory frameworks and incentives that encourage innovation while safeguarding consumer trust. Practitioners should also invest in continuous workforce upskilling and ecosystem partnerships to ensure that digital transformation efforts translate into sustainable competitive advantage.

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Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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