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Validation of the Urban Management Policy Implementation Model Using Structural Equation Modeling

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Abstract

This study was conducted with the aim of validating the urban management policy implementation model. In terms of methodology, the present research is quantitative–descriptive, and in terms of purpose, it is applied research. The statistical population consisted of 500 managers, experts, and employees associated with urban management. Based on Cochran's formula, a sample size of 125 participants was selected using simple random sampling. The research instrument was a researcher-developed questionnaire, the validity of which was assessed using face validity, while its reliability was examined using Cronbach's alpha coefficient; the overall alpha values for all variables were found to be higher than 0.70. Data analysis was conducted using structural equation modeling with SmartPLS software. The results indicated that the path coefficients of strategies to outcomes (0.929), causal conditions to the core category (0.390), the core category to strategies (0.391), contextual conditions to the core category (0.118), intervening conditions to the core category (0.494), contextual conditions to strategies (0.385), and intervening conditions to strategies (0.838) were obtained. To evaluate the model, structural equation modeling was applied using SmartPLS software. All significance values were greater than 1.96, and the standardized coefficients were greater than 0.38, indicating that the model was confirmed. Given that the goodness-of-fit index was obtained as 0.965, the fit of the final model was confirmed. The findings indicate full confirmation of the model derived from the grounded theory approach. It can be concluded that the urban management policy implementation model is valid, and the results of this study can be of interest to authorities responsible for the development and growth of this society.

Keywords: Urban management, policy implementation, grounded theory

1. Introduction

The insurance industry is undergoing a profound transformation driven by the rapid diffusion of advanced digital technologies, particularly Artificial Intelligence (AI). Traditionally founded on actuarial reasoning, statistical risk modeling, and human expertise, contemporary insurance systems now confront unprecedented volumes of heterogeneous data generated through electronic platforms, interconnected devices, and real-time transactional ecosystems. This transformation is especially consequential in health insurance systems, where the growth of electronic medical records, digital prescriptions, and automated claims processing has simultaneously expanded service capabilities and intensified exposure to operational complexity and fraud risk. The integration of AI is increasingly recognized as a foundational mechanism for sustaining competitiveness, improving efficiency, and safeguarding financial resources across the insurance value chain (Kumar et al., 2023; Mikalef et al., 2023; Saadat et al., 2023).

Artificial Intelligence has evolved from a conceptual frontier into a practical infrastructure for organizational decision-making. Contemporary AI systems combine machine learning, deep learning, natural language processing, computer vision, and large-scale data analytics to replicate and augment cognitive processes such as perception, reasoning, learning, and prediction (Achak et al., 2022; Babaian et al., 2023). These capabilities allow organizations not only to automate routine functions but also to generate novel insights, anticipate emerging risks, and optimize strategic resource allocation. In knowledge-intensive industries such as insurance, AI competencies have emerged as critical organizational assets that influence performance, innovation capacity, and competitive differentiation (Karmipour, 2023; Mikalef et al., 2023).

The strategic relevance of AI is amplified within healthcare and health insurance ecosystems, where operational environments are characterized by extreme information asymmetry, high transaction volumes, regulatory complexity, and persistent vulnerability to fraud and abuse. Global evidence indicates that health systems lose billions annually to fraudulent activities, administrative errors, and inefficient claims processing. The increasing digitalization of healthcare services—especially electronic prescriptions and online claims—has exponentially increased both the detectability of fraud and the sophistication of fraudulent schemes (Alipour & Ghaemi, 2016; Duman & Sagıroglu, 2017; Insurance Research, 2020). Consequently, insurers are compelled to adopt intelligent systems capable of continuously learning, adapting, and detecting anomalous patterns within vast transactional datasets.

AI technologies offer precisely these capabilities. Machine learning algorithms can autonomously identify subtle correlations, classify suspicious claims, and predict fraudulent behavior with accuracy levels that far exceed traditional rule-based systems (Kempa & Peng, 2021; Zhang, 2024). Neural networks and ensemble learning methods, such as Random Forest and gradient-boosted models, have demonstrated superior performance in detecting complex fraud structures across diverse insurance datasets (Abutalebi & Lorestani, 2020; Kempa & Peng, 2021). The transition from static detection mechanisms toward dynamic, learning-based architectures has thus become a central imperative for modern insurers seeking to protect financial sustainability while improving service quality.

Beyond fraud detection, AI is transforming the entire insurance lifecycle. From underwriting and pricing to claims management and customer interaction, intelligent systems are reshaping how insurers engage with clients and manage risk. In health insurance, AI-enabled diagnostic support systems, predictive analytics, and automated claim adjudication have already demonstrated substantial reductions in processing time, administrative cost, and human error (Alsuliman et al., 2020; Ellahham et al., 2020; Shafii, 2022). AI-driven decision support tools assist managers in forecasting healthcare expenditures, optimizing provider networks, and designing personalized insurance packages that align premiums with individualized risk profiles.

The technological foundations of this transformation are embedded within broader digital infrastructures such as the Internet of Things (IoT), blockchain, cloud computing, and big data platforms. IoT devices enable continuous health monitoring, generating real-time physiological and behavioral data that inform personalized insurance models and early risk intervention strategies (Gubbi et al., 2013; Qarakhani & Porhashmi, 2022). Blockchain infrastructures provide secure, transparent, and tamper-resistant ledgers for medical and insurance transactions, enhancing trust, data integrity, and regulatory compliance (Anvari & Safaei, 2022). Cloud computing facilitates scalable data storage and distributed AI computation, allowing insurers to deploy sophisticated analytics across geographically dispersed operations (Oksana et al., 2019). Together, these technologies form the structural backbone of contemporary Insurtech ecosystems, in which AI functions as the central intelligence layer.

The emergence of Insurtech reflects a fundamental reconfiguration of insurance business models. Insurtech firms leverage AI, advanced analytics, and digital platforms to redesign customer experiences, streamline operations, and generate new forms of value creation. Rather than incremental process improvement, Insurtech represents systemic innovation that challenges traditional organizational structures and regulatory paradigms (Kelnar, 2017; Young et al., 2022). Within this ecosystem, AI competencies become decisive organizational capabilities that determine whether insurers can successfully adapt to technological disruption and competitive pressures (Karmipour, 2023; Mikalef et al., 2023).

In the Iranian context, these transformations are particularly significant. The national implementation of electronic prescription and digital health services has created unprecedented data environments for basic health insurers. While these systems improve transparency and accessibility, they also expose insurers to increased risks of fraud, misuse, and operational inefficiency if intelligent detection mechanisms are not deployed. Empirical evidence from Iran's insurance sector indicates that between 20% and 30% of declared health insurance claims contain inaccuracies or fraudulent elements, largely due to non-systematic document processing and insufficient analytical capacity (Insurance Research, 2020). This vulnerability underscores the urgency of deploying AI-based detection frameworks tailored to the structural conditions of Iran's healthcare and insurance institutions.

Historical research on insurance fraud detection in Iran has primarily relied on classical data mining techniques such as logistic regression, decision trees, Naïve Bayes classifiers, neural networks, and support vector machines (Alipour & Ghaemi, 2016; Firoozi et al., 2011; Hosseini Nasab et al., 2008; Hosseini Nasab & Rezaei, 2018). While these methods have yielded valuable insights, the rapid evolution of fraud tactics and the explosion of high-dimensional data necessitate more advanced AI architectures capable of continuous learning and adaptive reasoning. Recent studies confirm that hybrid AI models combining multiple machine learning approaches significantly outperform conventional statistical methods in detecting fraudulent insurance behavior (Kempa & Peng, 2021; Zhang, 2024).

At the organizational level, the development of AI competencies has become an essential driver of sustained performance. AI competency encompasses not only technical infrastructure but also organizational processes, human capital, governance frameworks, and strategic alignment mechanisms that enable effective AI deployment (Karmipour, 2023; Mikalef et al., 2023). Organizations that cultivate such competencies gain superior capacity for innovation, operational efficiency, and market responsiveness. Conversely, firms lacking coordinated AI capabilities risk technological obsolescence and competitive erosion.

The healthcare sector further magnifies both the opportunities and challenges of AI integration. AI applications in medical diagnosis, clinical decision support, patient monitoring, and health system management have demonstrated remarkable potential to enhance care quality, reduce costs, and expand access to services (Aung et al., 2021; Ellahham et al., 2020; Mak & Pichika, 2019). However, these benefits are accompanied by ethical, legal, and governance concerns related to privacy, data security, accountability, and algorithmic bias (Achak et al., 2022; Takhshid, 2021). Addressing these challenges requires robust regulatory frameworks and interdisciplinary collaboration among technologists, policymakers, healthcare professionals, and insurance executives.

Recent policy-oriented research emphasizes that AI not only transforms organizational operations but also reshapes public policy processes by enhancing evidence-based decision-making, regulatory oversight, and service delivery effectiveness (Babaian et al., 2023). In insurance governance, AI enables regulators and insurers to monitor compliance, detect systemic risks, and design adaptive regulatory responses that evolve alongside technological change. Such governance innovations are particularly relevant for emerging economies, where institutional modernization and technological development must progress in tandem.

Despite the growing body of international research on AI in insurance and healthcare, significant empirical gaps remain in understanding how AI-based mechanisms can be systematically implemented within Iran's basic health insurance sector. Existing studies have largely examined isolated applications of data mining or specific machine learning models, without constructing integrated frameworks that align technological capabilities with organizational processes and regulatory constraints (Alipour & Ghaemi, 2016; Hosseini Nasab & Rezaei, 2018; Kempa & Peng, 2021). Furthermore, few studies have employed structured expert consensus methods to identify the most effective AI components for fraud detection and operational optimization under localized institutional conditions.

Addressing these gaps is essential for advancing both academic understanding and practical implementation of AI-driven insurance systems in Iran. The convergence of AI, IoT, blockchain, and digital health infrastructures offers unprecedented potential to redesign insurance governance, improve financial sustainability, and enhance public trust in health insurance institutions (Anvari & Safaei, 2022; Qarakhani & Porhashmi, 2022; Saadat et al., 2023). However, realizing this potential requires rigorous identification of priority AI mechanisms, strategic alignment with organizational competencies, and continuous adaptation to evolving technological and regulatory environments.

Therefore, the aim of this study is to identify and prioritize the most effective artificial intelligence mechanisms for detecting insurance fraud and enhancing operational performance in Iran's basic health insurance sector using a structured Delphi-based expert consensus framework.

2. Methods and Materials

The present article is based on a "qualitative" approach, conducted using the Delphi technique, and has been applied research in terms of its purpose and descriptive in terms of data collection.

In this research, the statistical sample is equal to the statistical population. This research used purposive sampling to select the sample, with the sample size determined to be 14 people. The members include experts who hold executive positions in the implementation of the electronic prescription and dispensing plan of basic health insurers and simultaneously have over 10 years of experience in controlling current costs and insurance violations.

The characteristics of the experts are provided in Table 1.

Table 1: Job Characteristics of the Experts

Position	Work Experience (Years)	Specialization Domain
Head of Medical Documents Office, Health Insurance	26	Treatment Guidelines and Processes
Head of Supervision and Evaluation Office, Health Insurance	21	Supervision Guidelines and Processes
Manager of Statistics, IT Group, Health Insurance	16	Electronic Guidelines and Processes
Expert, Supervision and Evaluation Office, Health Insurance	19	Supervision Guidelines and Processes
Senior Manager, Armed Forces Medical Services Insurance	25	Treatment Guidelines and Processes
Manager of Specialized Evaluation and Supervision, Armed Forces Medical Services Insurance	14	Supervision Guidelines and Processes
Manager of Medical Documents, Armed Forces Medical Services Insurance	11	Treatment Guidelines and Processes
Technical Expert, Armed Forces Medical Services Insurance	13	Supervision Guidelines and Processes
Technical Expert, Armed Forces Medical Services Insurance	11	Treatment Guidelines and Processes
IT Manager, Armed Forces Medical Services Insurance	13	Electronic Guidelines and Processes
Deputy of Treatment Services, Social Security Organization	26	Treatment Guidelines and Processes
Head of Inspection and Supervision Office, Social Security Organization	18	Supervision Guidelines and Processes
Expert, Inspection and Supervision Office, Social Security Organization	14	Supervision Guidelines and Processes
Head of Statistics and IT Office, Social Security Organization	18	Electronic Guidelines and Processes

The research tool in the qualitative part of this study was the use of a "structured questionnaire" in the first stage, which was closed and open-ended based on items extracted from the "theoretical literature" and was used with a five-point Likert scale, with the options: completely unimportant, unimportant, medium importance, important, very important, to determine the most important applications of artificial intelligence in identifying types of insurance fraud. In the following stages of the research, another "researcher-made questionnaire" was completed and designed with the help of experts' opinions and the addition of their desired items in a "closed" form, with a five-point Likert scale with the options: very much, much, medium, very little, little to identify the most effective factors.

Initially, theoretical literature in this regard was extracted through "library studies" which included the study of similar theses in this field, as well as reputable domestic and foreign articles, both electronic and non-electronic, presented at reputable scientific conferences and fields, and the use of electronic and non-electronic books. "32 items" were extracted, which are listed in Table 2, broken down by items and scientific sources. Then, through the Delphi method, a researcher-made questionnaire was prepared and distributed among 14 insurance industry experts in the field of basic health insurance to determine the roles of artificial intelligence in identifying types of insurance fraud.

3. Findings and Results

In the first stage, using the experts' opinions, 4 items were deleted and based on their opinions in the open section of the first questionnaire, 3 items suggested by the experts were added. The results are listed in Table 3. Finally, 31 items were extracted and used in the next package of questionnaires sent to the experts to score and identify the final items according to Table 2.

Table 2: Items identified from theoretical literature for the roles of artificial intelligence in identifying types of insurance fraud

Row	Suggested Items	Source
1	Machine Learning	Bakhshayesh (2018)
2	Decision Tree, Neural Networks, Clustering, Hybrid Methods, Linear & Nonlinear Regression, Bayesian Belief Networks	Alipour & Ghaemi (2016)
3	Computer Vision, Speech Processing, Natural Language Processing	Achak et al. (2022)
4	Machine Learning, Artificial Neural Networks, Deep Learning, Computer Vision/Machine Vision, Evolutionary Computation (Genetic Algorithms, Evolutionary Strategies, Genetic Programming), Fuzzy Logic, Natural Language Processing, Expert Systems, Data Mining, Robotics, Agent-Based Modeling	Babaian et al. (2023)
5	Blockchain	Anvari & Safaei (2022)
6	Internet of Things (IoT)	Qarakhani & Porhashmi (2022)
7	SVM Algorithm, Artificial Neural Networks	Abutalebi & Lorestani (2020)
8	Anomaly Detection in Data, Genetic Algorithm, Transition State Analysis, Rule-Based Approach, Statistical Methods, Data Mining, Model-Based Reasoning	Insurance Research Institute (2020a)
9	Decision Tree, Support Vector Machine (SVM), Neural Network, Naive Bayes, Random Forest, K-Nearest Neighbors (K-NN), Regression, Linear Regression, Logistic Regression, Prediction, Neural Network, Logistic Model, Clustering, K-Means, G-Means, Naive Bayes, Neural Network, Outlier Detection, Isolation Forest, Smart Sifter, Apriori Algorithm, Hybrid Methods	Rahim Khani (2021)
10	Apriori Algorithm, OWA Method	Hosseini Nasab et al. (2008)
11	Naive Bayes, Decision Tree, Logistic Regression	Firoozi et al. (2021)
12	Decision Tree, Artificial Neural Networks, K-Nearest Neighbors (K-NN)	Hosseini Nasab & Rezaei (2018)
13	Machine Learning, Internet of Things (IoT)	Young et al. (2022)
14	ChatGPT	Peres et al. (2023)
15	Machine Learning, Random Forest, Standard Logistic Regression, Deep Belief Networks	Kempa & Peng (2021)
16	Machine Learning	Alsuliman et al. (2020)
17	Machine Learning	Ellahham et al. (2020)
18	Machine Learning, Deep Learning, Cloud Computing, Blockchain	Oksana et al. (2019)

The emergence of complex issues with insufficient information has led to the development of consensus or agreement methods. Among consensus methods, the nominal group technique and the Delphi method can be named. The goal of this method is to achieve the most reliable group agreement of experts on a specific subject using questionnaires and polling experts repeatedly, considering the feedback from them. In fact, this method is a complete examination of the opinions of expert panel members, with three main features: anonymous response to questions (questionnaires), repetition of sending questions (questionnaire) rounds and receiving feedback from them, and statistical analysis of group responses to questions. In the Delphi method, the mental data of expert individuals are converted into nearly objective data using statistical analyses. This method leads to consensus in decision-making. The Delphi method has been used in numerous fields of forecasting and decision-making.

In this research, first, the methods suggested by various studies mentioned in the theoretical literature for identifying insurance fraud based on AI competencies were collected. In 3 stages, in the form of a questionnaire and in person, they were distributed among experts so that by selecting the options (Very Effective, Effective, Somewhat Effective, Low Impact, Very Low Impact) representing numbers 5 to 1, they could evaluate the factors. For this purpose, in the first stage, using the Geometric Mean, methods with a score less than 3 were removed from the options, and factors that scored equal to or greater than 3 were recorded for the second and third stages of the questionnaire.

Table 3: Recorded Scores Based on Geometric Mean for Proposed Methods

Row	Suggested Items	Geometric Mean	Result
1	Machine Learning	4.8	Accept
2	Decision Tree	4.2	Accept
3	Neural Networks	4.6	Accept
4	Hybrid Methods	4.9	Accept
5	Linear & Nonlinear Regression	4.3	Accept
6	Bayesian Belief Networks	3.2	Accept
7	Blockchain	4.1	Accept
8	Computer Vision	4.6	Accept
9	Speech Processing	4.6	Accept
10	Natural Language Processing (NLP)	4.6	Accept
11	Evolutionary Computation (Genetic Algorithms)	4.3	Accept
12	Fuzzy Logic	3.7	Accept
13	Data Mining	4.8	Accept
14	Robotics	2.9	Reject
15	Agent-Based Modeling	4.5	Accept
16	Internet of Things (IoT)	4.3	Accept
17	SVM Algorithm	4.1	Accept
18	Anomaly Detection in Data	4.8	Accept
19	Model-Based Reasoning	4.7	Accept
20	Naive Bayes	3.1	Accept
21	Random Forest	3.3	Accept
22	K-Nearest Neighbors (K-NN)	3.7	Accept
23	Apriori Algorithm	3.9	Accept
24	OWA Method	4.8	Accept
25	Deep Belief Networks	1.9	Reject
26	Standard Logistic Regression	2.8	Reject
27	Cloud Computing	3.8	Accept
28	Clustering	4.2	Accept
29	Expert Systems	4.8	Accept
30	ChatGPT	5.0	Accept
31	Evolutionary Strategies & Genetic Programming	4.2	Accept
32	Smart Sifter	2.2	Reject
33	Cost Alerting	(Proposed by Experts)	Accept
34	Sampling	(Proposed by Experts)	Accept
35	Prediction	(Proposed by Experts)	Accept

After implementing the first stage of assessing and evaluating the panel experts' views on the factors raised from the theoretical foundations, the 28 methods that had a geometric mean equal to or higher than 3, along with the 3 methods that experts had also pointed out in the open section of the questionnaire, were included in this round's questionnaire and provided again to the panel members to determine the importance level of each method using the Likert scale. In this stage, only methods rated by experts as "Effective" and "Very Effective" with a geometric mean above 3 were accepted. The results obtained for the 31 methods are shown in the table below:

Table 4: Recorded Scores Based on Geometric Mean for Proposed Methods (Stage 2)

Row	Suggested Items	Geometric Mean	Result
1	Machine Learning	4.8	Accept
2	Decision Tree	4.3	Accept
3	Neural Networks	4.6	Accept
4	Hybrid Methods	4.9	Accept
5	Linear & Nonlinear Regression	4.3	Accept
6	Bayesian Belief Networks	2.9	Reject
7	Blockchain	4.3	Accept
8	Computer Vision	4.5	Accept
9	Speech Processing	4.6	Accept
10	Natural Language Processing (NLP)	4.4	Accept
11	Evolutionary Computation (Genetic Algorithms)	4.4	Accept
12	Fuzzy Logic	3.4	Accept
13	Data Mining	4.8	Accept
14	Agent-Based Modeling	4.5	Accept
15	Internet of Things (IoT)	4.2	Accept
16	SVM Algorithm	3.8	Accept
17	Anomaly Detection in Data	4.6	Accept
18	Model-Based Reasoning	4.7	Accept
19	Naive Bayes	2.9	Reject
20	Random Forest	3.5	Accept
21	K-Nearest Neighbors (K-NN)	3.9	Accept
22	Apriori Algorithm	3.8	Accept
23	OWA Method	4.5	Accept
24	Cloud Computing	3.9	Accept
25	Clustering	4.2	Accept
26	Expert Systems	4.8	Accept
27	ChatGPT	4.9	Accept
28	Evolutionary Strategies & Genetic Programming	3.9	Accept
29	Cost Alerting	4.7	Accept
30	Sampling	2.8	Reject
31	Prediction	3.7	Accept

Kendall's W coefficient for members' responses regarding the results of methods that were "Effective" and "Very Effective" in this round was 0.841.

In the third stage, considering the removal of the 3 methods that did not obtain the necessary score from the experts, a new questionnaire with the 28 identified factors that were considered "Effective" and "Very Effective" by the experts (mean above 3) along with the previous scores was provided to the panel members, who had to specify their opinion regarding the importance level of each method.

The results of the third stage are shown in Table 5. Furthermore, Kendall's W coefficient for members' responses regarding the results of methods that were "Effective" and "Very Effective" in this round was 0.899.

Over 50% of members had evaluated the 28 final identified factors in the second and third rounds as an effective or very effective method with a mean above 3. Kendall's W coefficient for members' responses regarding the ranking of factors in the third round was 0.899. Given that the number of panel members was more than ten, this level of Kendall's W is considered quite significant (Meshki et al., 2004). Moreover, Kendall's W coefficient for the ranking of effective methods in the research increased by only 0.058, indicating that this coefficient or the level of consensus among panel members between two consecutive rounds does not show significant growth.

In this research, through an extensive review of theoretical foundations, the main types of methods that AI can use in the insurance industry and in the domain of basic health insurers to detect violations in health insurance were extracted. After implementing the Delphi technique and analyzing the results of the three-stage survey of panel experts, these methods were modified and adjusted, and ultimately the final model of the most effective factors is presented in Figure 1. Figure 2 also depicts the position of AI in the interaction of insurance organizations with the insured and medical centers through a diagram.

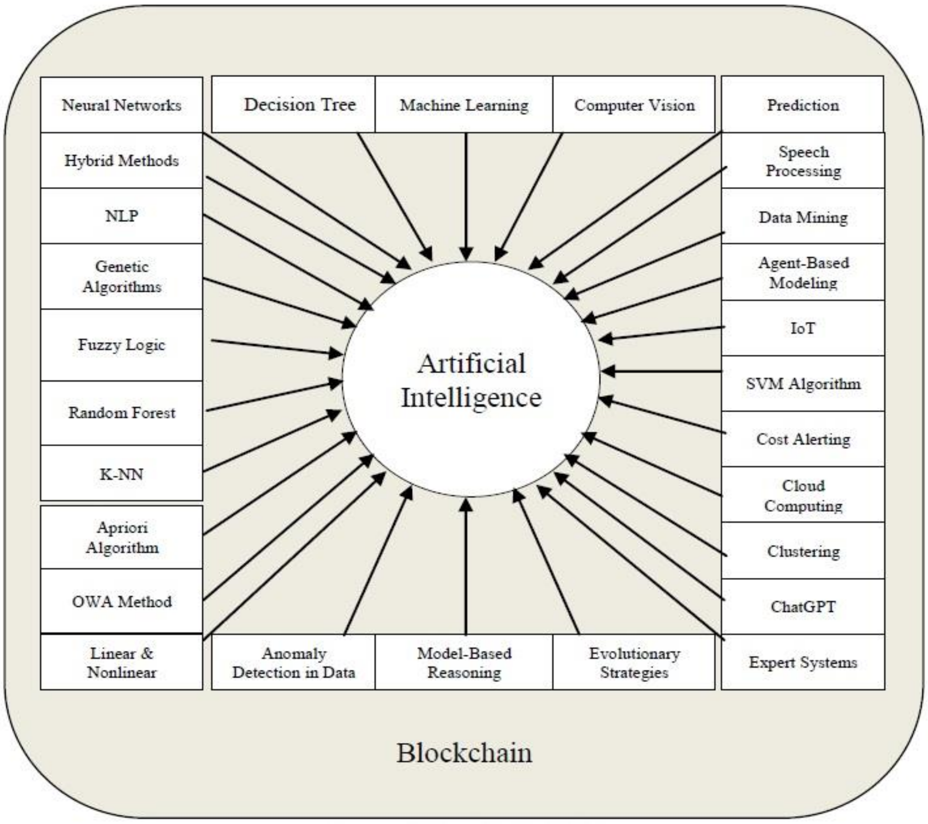

Figure 1: Final Research Model

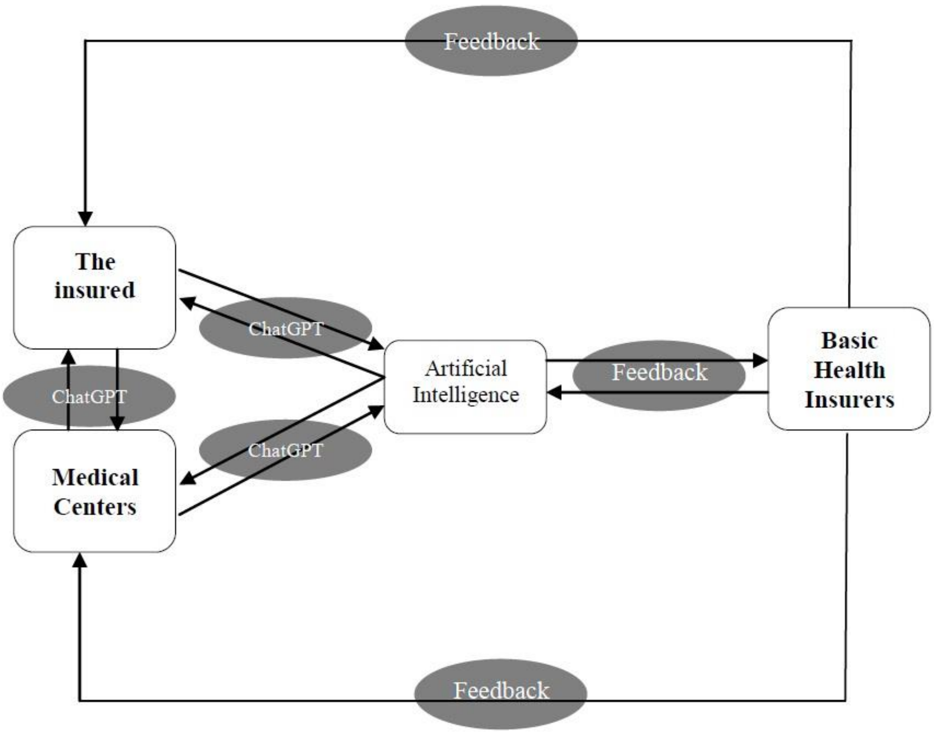

Figure 2: Diagram illustrating the position of AI in the interaction between basic health insurers, medical centers, and the insured

4. Discussion and Conclusion

The present study sought to identify and prioritize the most effective artificial intelligence mechanisms for detecting insurance fraud and enhancing operational performance in Iran's basic health insurance sector using a structured Delphi-based expert consensus framework. The results of the three-round Delphi process revealed a high level of expert agreement, as reflected by Kendall's W values exceeding 0.84 in the second round and 0.89 in the third round, indicating strong convergence of expert opinions. The final model consisted of twenty-eight AI-related mechanisms that experts consistently evaluated as "effective" or "very effective," with ChatGPT, hybrid analytical methods, machine learning, expert systems, data mining, anomaly detection, model-based reasoning, blockchain, and advanced predictive tools occupying the highest ranks. These findings empirically demonstrate the multidimensional nature of AI's contribution to insurance transformation, confirming that effective fraud detection and operational optimization require a synergistic configuration of multiple AI technologies rather than reliance on isolated algorithms.

The dominance of machine learning and hybrid methods in the final model is highly consistent with contemporary theoretical and empirical research. Machine learning's ability to autonomously learn from evolving data patterns and continuously recalibrate detection mechanisms explains why experts considered it foundational for modern insurance systems. This finding aligns directly with prior evidence demonstrating the superior predictive performance of machine learning architectures in fraud identification, particularly when compared with traditional statistical approaches such as logistic regression and linear models (Kempa & Peng, 2021; Zhang, 2024). The experts' strong endorsement of hybrid methods further reflects the growing recognition that combining multiple analytical paradigms—such as neural networks, decision trees, clustering, and evolutionary computation—produces more robust and resilient detection frameworks capable of capturing both structured and unstructured fraud patterns (Abutalebi & Lorestani, 2020; Duman & Sagıroglu, 2017).

Another central result of the study is the prominent role assigned to data mining, anomaly detection, model-based reasoning, and predictive analytics. These mechanisms collectively enable insurers to transition from reactive, retrospective fraud control toward proactive, real-time monitoring and intervention. This shift mirrors global trends in healthcare insurance, where advanced analytics increasingly serve as early-warning systems that flag abnormal claim behavior before financial losses escalate (Alipour & Ghaemi, 2016; Hosseini Nasab & Rezaei, 2018). The experts' prioritization of anomaly detection confirms that fraud in health insurance rarely conforms to fixed templates; instead, it evolves dynamically, requiring detection systems that can identify subtle deviations from normative patterns across massive datasets. These results reinforce earlier conclusions that static rule-based detection frameworks are insufficient for modern insurance environments (Firoozi et al., 2011; Insurance Research, 2020).

The exceptionally high ranking of ChatGPT and natural language processing tools represents one of the most novel contributions of this study. Experts emphasized that generative AI systems and advanced NLP significantly enhance the quality of interaction among insurers, medical centers, and policyholders by automating inquiry resolution, document processing, fraud explanation, and compliance guidance. This finding extends earlier research on AI-enabled service automation in insurance by demonstrating that conversational AI is not merely a customer-service convenience but a strategic governance instrument capable of strengthening transparency, compliance, and trust across the insurance ecosystem (Babaian et al., 2023; Young et al., 2022). The result also aligns with emerging evidence that generative AI fundamentally reshapes organizational knowledge management and decision-making processes by transforming how information is accessed, interpreted, and operationalized (Kumar et al., 2023; Saadat et al., 2023).

Blockchain technology emerged as another critical pillar in the final model. Experts recognized blockchain's capacity to secure medical and insurance records, prevent data tampering, and establish immutable audit trails for claims processing. This confirms previous findings that blockchain infrastructures substantially reduce information asymmetry, enhance data integrity, and strengthen institutional trust in healthcare and insurance transactions (Anvari & Safaei, 2022; Oksana et al., 2019). The integration of blockchain with AI further enables automated compliance verification and decentralized fraud detection, creating a resilient digital governance architecture for health insurance systems.

The strong emphasis on the Internet of Things reflects the growing importance of real-time data streams in insurance risk management. Experts highlighted IoT's capacity to continuously monitor health indicators, service delivery processes, and spatial relationships among prescribers, providers, and policyholders. These capabilities significantly expand insurers' situational awareness and allow early identification of suspicious patterns that would remain invisible in conventional data environments. This result corroborates prior research demonstrating that IoT adoption dramatically reduces operational costs, accelerates claims processing, and improves fraud prevention across insurance operations (Gubbi et al., 2013; Qarakhani & Porhashmi, 2022). It also supports broader evidence that IoT-driven data ecosystems form the technological substrate upon which AI-based decision systems achieve maximum effectiveness (Aung et al., 2021; Ellahham et al., 2020).

From an organizational perspective, the study's findings strongly reinforce the centrality of AI competencies as strategic assets. The breadth of mechanisms endorsed by experts indicates that AI effectiveness is not limited to algorithmic performance but depends on integrated organizational capabilities encompassing infrastructure, governance, human expertise, and adaptive learning systems. This conclusion directly supports the AI competency framework proposed in recent management literature, which posits that sustainable competitive advantage emerges from coordinated deployment of AI resources across organizational boundaries rather than from isolated technological investments (Karmipour, 2023; Mikalef et al., 2023). The Iranian insurance context, characterized by rapid digitalization and regulatory transformation, magnifies the importance of such coordinated AI capability development.

The findings also have profound implications for healthcare system governance. By enabling precise fraud detection, predictive modeling of healthcare expenditures, and automated regulatory compliance, AI becomes a core instrument of financial sustainability and public trust. This aligns with prior research emphasizing AI's capacity to improve healthcare quality, reduce administrative burden, and expand system-wide efficiency while simultaneously introducing new governance challenges related to accountability, transparency, and legal responsibility (Achak et al., 2022; Shafii, 2022; Takhshid, 2021). The expert consensus achieved in this study suggests that Iranian basic health insurers are institutionally prepared to embrace this transformation, provided that appropriate infrastructural and regulatory frameworks are established.

Finally, the exceptionally high consensus levels achieved through the Delphi process demonstrate that the identified model reflects a stable and reliable representation of expert judgment within the Iranian insurance sector. The convergence of expert opinion across successive rounds indicates that the prioritized mechanisms are not merely theoretical preferences but reflect practical, operational knowledge grounded in long-term professional experience. This strengthens the external validity of the model and enhances its applicability for policy formulation, organizational planning, and technological investment decisions.

Despite the robustness of the findings, the study is subject to several limitations. The reliance on expert judgment, while valuable for capturing tacit knowledge, may limit generalizability beyond the institutional context of Iran's basic health insurers. Additionally, the qualitative Delphi design does not permit direct measurement of the causal impact of specific AI mechanisms on fraud reduction or operational performance. Finally, infrastructural constraints, data accessibility limitations, and cybersecurity concerns within certain insurance institutions may influence the feasibility of large-scale AI deployment.

Future studies should incorporate quantitative validation of the proposed model using real insurance transaction datasets and advanced statistical techniques such as structural equation modeling and machine learning performance benchmarking. Longitudinal research designs would enable assessment of how AI adoption affects fraud rates, cost efficiency, and service quality over time. Comparative cross-national studies could further clarify how institutional, regulatory, and cultural factors mediate AI effectiveness in insurance systems.

Insurance executives should prioritize the development of integrated AI strategies that align technological investment with organizational restructuring, workforce training, and governance reform. Policymakers must establish adaptive regulatory frameworks that balance innovation with ethical safeguards, data protection, and accountability. Collaborative ecosystems involving insurers, healthcare providers, technology firms, and regulators should be cultivated to accelerate knowledge transfer and ensure sustainable digital transformation across the insurance sector.

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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