

Modeling Enablers of AI in Insurance Sector Using Total ISM

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Abstract

This research paper will investigate the key enablers within the insurance industry that enable the implementation of AI and technology-enabled insurance solutions. The use of artificial intelligence and emerging technologies is needed for making sustainable corporate decisions. On the grounds of dynamic capabilities theory, this study is based on the rapid adaptation of AI in insurance. It utilizes the ISM-MICMAC model to analyze data and incorporates interviews with experts to confirm the results. With 13 significant enablers the study evolves into a systematic model, reflecting their interrelationship. The management of an organization is found the most pivotal factor in adopting AI, and sustainability is the most impacted enabler, as highlighted by 14 experts. MICMAC analysis classified these enablers into four groups, which are in accordance with the ISM framework results. This study contributes to the limited research in this field by proposing an organized model of AI adoption determinants. It puts forward practical information for insurance experts and decision-makers to create successful strategies. With analyzed outset of these important enablers in the insurance industry, insurance providers can incorporate AI with greater efficiency, improve their operations and use the study as a blueprint for future research and strategy formulation in digitally transforming the insurance industry.

Keywords: Artificial Intelligence, Enablers, Insurance, Interpretive Structural Modeling (ISM), Cross-impact Matrix Multiplication Applied to Classification (MICMAC), Structured Self-interaction Matrix (SSIM).

Introduction

The future of insurance is being transformed by emerging technologies. These technologies are becoming the norm in the insurance industry. The enhanced functionality, efficiency and benefits of these technologies have been good to the insurance industry. According to the Global Insurtech, the projected market growth was at a CAGR of 10.80% from 2019 to 2025, reaching a market size of USD 10.14 billion by 2025 (1). One of the major areas of application of Artificial Intelligence (AI) is in the insurance industry, which is a big field for AI to be applied (2, 3). More than 80% of insurance CEOs see AI as a critical component of their businesses or as a significant part of their businesses within the next three years (4). There is limited direct contact between insurers and consumers in much of the insurance business, which takes place through the intermediaries. As a result, brokers globally together make between \$4.5 billion and \$45 billion each year from insurers around the world (5). AI offers analytical tools, predictive modelling, and customer insight in real-time to satisfy these demands (6). It can analyze data sets to help make

pricing, risk and claims management decisions (7, 8). This will yield greater fraud prevention, better catering to customer requirements in product and contract creation, the ability to analyse legal documents, assistance from chatbots and virtual assistants, and office operations (9). However, the influence of AI is special to the insurance industry as it might differ from other industries on the grounds of pandemics, recessions and quick transformation (10). Previous literature reviews focused on the applications, future perspectives, and difficulties of AI in the insurance sector (11). Enablers covered in this study are accuracy and transparency, automation, blockchain technology, claims processing, digital transformation, fraud detection and prevention. Standardized mortality risk measures can also help to improve the transparency of underwriting in life insurance (12). With AI, automated interactions with consumers and stakeholders can be made using natural language processing (13). The embedding of blockchain technology in IoT devices and AI systems will help to increase the efficiency and the process of claiming. AI has also helped in the

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development of personalized insurance products, efficiency, customer engagement and satisfaction (14, 15). AI automation can enhance the strength of personalized insurance products and customer and stakeholder engagement (16). The AI adoption involves some important issues including the relationships between them and the growth of use of AI (17). AI governance, ethics and regulatory frameworks, decentralized tools and the regulation of autonomous AI are becoming more relevant (18).

The use of AI in insurance is significant. One important research gap is the identification of enablers to enable effective use of AI. These enablers should be identified, addressed and exploited for successful implementation. The critical enablers assist managers in developing future strategies (11).

The present investigation is driven by the given research questions:

RQ1: Which key enablers are affecting the insurance industry's AI adoption in India?

RQ2: How are these identified enablers interconnected and how can they be prioritized with ISM and MICMAC analysis?

RQ3: How can a structured framework be built to represent the connections between the contextual variables?

This study offers guidance on AI adoption and a blueprint. The literature review, multi-case analysis, and survey have been utilized in previous studies, but the ISM has not been utilized as the researchers could not find it beforehand (19).

The insurance industry is also a commoditized business, with narrow margins, and is challenged by technological advancements (20). With technology at the fingertips of consumers, their expectations are evolving and insurers will need to adapt (20, 21). The finance sector, particularly insurance, has been leading the digitization charge with AI (15). Digital technologies in insurance, as well as the role of AI as a financial assistant have been explored in research (22). But very few studies determine the extent of AI enablers in insurance, especially in the marketing of products

and reaching out to customers. Hence, this research involves a literature analysis and expert discussions to identify the enablers and demonstrate their relationships (23, 24).

Blockchain can offer a non-tamperable, transparent platform for transactions, thereby mitigating fraud, enhancing claims transparency, lowering claims disputes, and allowing real-time sharing (14). It is immutable and safeguards claims data and minimizes forged claims. Decentralized governance can help to foster trust, participation and compliance in AI research. In a decentralized insurance scheme, damages can be covered from the insurance but lower premiums will incentivize risk minimization. It is estimated that AI-driven RPA can raise claims-processing accuracy by 45%, cut costs and cut premiums (25).

While the utilization of cross-business data and AI automation can enhance fraud detection, it may prove to be problematic (10). While Big Data and Predictive Analytics have potential in combating fraud, infrastructure and resources are limiting factors to adoption (26). For companies to achieve digital transformation, they must strike a balance between innovation and data security (27). Real-time analysis of datasets can be used for fraud prevention with AI-powered solutions and AI improves real-time threat detection (28, 29). AI can be used to assess the credit exposure, forecast market fluctuations, and reduce operational inefficiency in the context of risk management (30). Routine queries are managed by the Chatbots and Virtual Assistants, allowing agents to attend to more complicated cases. AI's role in customer experience is that of personalized offerings, which brings ethical and regulatory challenges (31, 32). To make AI work, therefore, the models need to guarantee compliance, security, and efficiency of operations as they also need to promote innovation (17).

Methodology

The methodology follows the specific experimental design for conducting this research study.

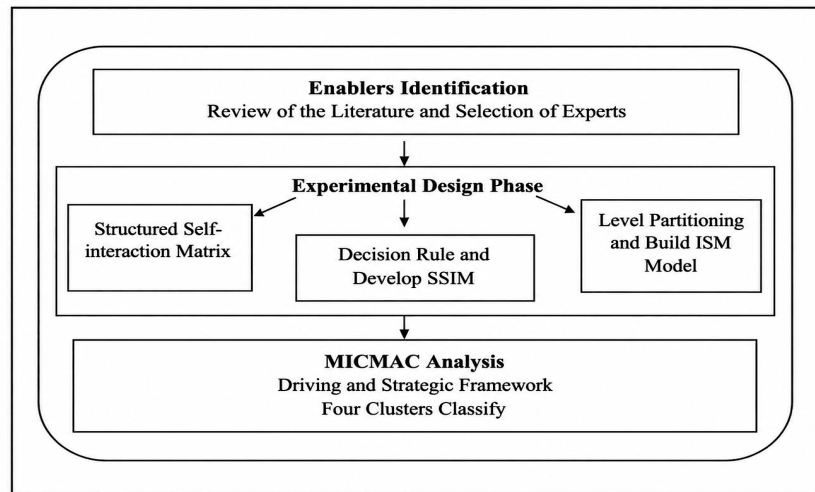


Figure 1: ISM Methodology

Figure 1 illustrates the ISM methodology adopted in this study, which begins with identifying the enablers, develops the SSIM, organizes the hierarchical levels of the structural framework and then applies dependency-driving analysis to classify the enablers into four clusters. The enablers were derived from a systematic review of scholarly literature and validated through expert insights. The results of the search in Web of Science, Scopus, and Google Scholar with the terms (Artificial Intelligence) AND (Insurance) AND

(Artificial Intelligence (AI)) with (Enablers) yielded 41 articles relevant to this study that adopted mixed-method designs were found in 32 articles. Findings from the review suggest that research into the enablers of AI in insurance is still emerging and requires more comprehensive investigation. Reading through the literature and listening to the experts, 13 enablers were identified and presented in Table 1 with definitions.

Table 1: List of Enablers to AI Insurance Sectors

Enablers	Meaning	References
Analytical Capability	AI is driven by big data in the insurance industry and it enhances risk evaluation, identifying fraudulent activities, improving customer support, and boosting operational efficiency. It leverages data to refine decision-making processes and streamline operations.	(26)
Transparent Framework	Block chain provides a secure, transparent platform for AI applications through its guarantee of an immutable and verifiable record of data. This supports data integrity and security, which are necessary for creating reliable AI models.	(8, 14, 33-37).
Digital transformation	Artificial Intelligence (AI) speeds up digital transformation through process automation, smarter decision-making and enhanced customer experience. AI drives efficiency, competitiveness, innovation, and data-driven insights throughout industries and AI-based solutions optimize operations, decrease costs, and allow businesses to responsive and adaptive to market dynamics.	(20, 38-40)
Fraud detection and prevention	Based on past claims analysis and pattern recognition, real-time surveillance, and biometric tools, AI increases accuracy and reliability in detecting fraud.	(28, 29, 41-46)
Decentralized control	AI agents demonstrate the power of decentralized tools and offer a solution to harmonize governance with international ethics. Decentralized platforms promote fairness, trust, and resilience in effective regulation of artificial intelligence.	(18, 47-49)
Claims Settlement	Artificial Intelligence (AI) improves claims settlement through automated processing, fraud reduction, and enhanced accuracy.	(14, 15, 50)

	Analytics driven by AI evaluate claims quicker, providing equitable assessments and faster payments. Machine learning and automation make documentation easier, reduce errors, and increase customer satisfaction, making the claims process faster, transparent, and cost-saving for insurers.	
Risk Management	Combining AI with blockchain creates opportunities to enhance regulatory compliance and strengthen risk management within financial services effectively.	(17, 51–54)
Governance and Trust	The evolving intelligence and AI governance landscape emphasizes compliance, trust and data privacy in modern organizations. Implementing robust governance frameworks enhances trust with users while enabling organizations to advance their AI capabilities responsibly and transparently	(55, 56)
Accuracy and Transparency	Access to large past data sets and machine learning advances provide the promise to improve the transparency and accuracy of claims processing in life insurance, applying standardized metrics to measure mortality risk appropriately.	(12, 14, 57)
Automation	AI and automation collaborate to create seamless "intelligent automation." Virtual assistants handle sales and claims, while AI-driven processes and data usage address regulatory challenges efficiently.	(10, 58, 59)
Data Analytics	AI-powered data analytics is transforming insurance by processing vast real-time data, uncovering patterns, and enabling precise, personalized pricing. It also streamlines claims processing, improving efficiency and decision-making in the industry.	(10, 15, 52, 60)
Customer Personalization	In the Insurance Industry, AI-driven personalization is leading to unprecedented changes by making it possible to address individual customer needs by providing customized products and services.	(32, 61, 62)
Financial Controlling	A detailed AI application overview in finance, financial controlling and insurance to cover major challenges and consider the connection between AI and the growth of these sectors.	(16)

Table 1 presents the enablers identified for AI adoption in the insurance sector. It clearly shows identification of variables for the study first through extensive literature review and later confirmed by experts. While the review of extant research facilitated the identification of variables, domain experts helped confirm them and establish relationships between these variables. The variables identified include analytical capability, which is an important aspect of technology driven analytical solutions as it enhances the organization's ability to serve its customers with precise solutions while enhancing the organization's operational efficiency. AI ensures a transparent framework, digital transformations, fraud detection and prevention, decentralized control, claim settlement, risk management, governance and trust, accuracy and transparency, automation, data analytics, customer personalization, financial controlling. Together these variables lead to higher adoption of AI in the insurance sector.

For conducting ISM, a minimum of two domain experts are required (63, 64). There should be eight experts for ISM methodology (65). The present study involved 14 domain experts from both government and private sectors, each possessing a minimum of fifteen years and, in some cases, over twenty years of experience. These experts were meticulously chosen based on their proficiency and extensive knowledge of AI in the Indian insurance sector. Their insights and informed perspectives played a crucial role in developing the ISM (Interpretive Structural Modeling) model and demonstrating relationships among the enablers. The inclusion of such highly experienced professionals enhances the credibility, accuracy and authenticity of the study. The experts are presented in Table 2. Upon completing the interviews, the experts were asked for their feedback, and these were consolidated to formulate the SSIM (Structural Self-Interaction Matrix). The sections provide an explanation of the ISM methodology and MICMAC analysis (66).

Table 2: Summary of Profile of Experts

Experts	Government/ Private Industry	Industry Name	Expert Profile (Role)	Total Experience (Years)	Qualification	Place
1	Government	General Insurance Corp. of India	Senior Vice President	>20	MBA, PhD	Noida
2	Private	Aditya Birla Life Insurance Company	Branch Manager	>17	MBA, PhD	Hyderabad
3	Private	Shriram Life Insurance	Senior Manager	>19	MBA, PhD	Noida
4	Government	New India Assurance Company Limited (NIA)	Chief Financial Officer	>20	M.Com, PhD	Pune
5	Private	Max Life Insurance	Vice President, Finance Dept., Banking	>15	MBA, PhD	Noida
6	Private	ICICI Prudential Life Insurance	Associate Professor AI and ML	>16	MBA	Bangalore
7	Government	Oriental Insurance Company Limited (OICL)	Operating Officer	>15	M.Com	Delhi
8	Government	LIC of India	Vice President	>17	M.Com, MBA	Delhi
9	Private	SIB Life Insurance	Senior Manager	>15	MBA	Jaipur
10	Private	Bajaj Allianz Life Insurance.	Senior Manager	>15	PGDM	Mumbai
11	Government	Agriculture Insurance Co. of India ltd.	Chief Operating Officer	>16	MBA	Delhi
12	Private	Aviva Life Insurance	Branch Manager	>20	PGDM	Gurgaon
13	Government	United India Insurance Co. Ltd.	Chief Financial Officer	>18	MBA	Chennai
14	Government	National Insurance Co. Ltd.	Chief Administrative Officer	>20	M.Com	Bangalore

The methodology employed in this paper is Interpretive Structural Modeling (ISM), proposed by Warfield in 1974 (67, 68). ISM functions as an interactive analytical method that is used to select and consolidate relationships between variables (Enablers). It is especially effective in problem definition and problem structuring difficult problems (69). The methodology depends on independent professionals' input to determine enablers' relationships (70). ISM's most prominent strength is its ability to deal with loosely organized and scattered variables (Enablers) to facilitate decision-making about their relationships in a system. ISM has an important function of structuring complicated groups of elements into an organized pattern and is essentially driven by knowledgeable views.

The process of ISM comprises of the following steps, as expressed in Warfield framework (68):

- a) Development of an initial Self-Interaction Matrix (SSIM) that reveals the direction of logical relationships between uncovered enablers. To represent and establish the relationship between two enablers, both Government and private sector experts were consulted.
- b) Building the early reachability matrix based on the binary coding system and then including indirect relationships to create the FRM (Final Reachability Matrix)
- c) Dividing the enablers into various hierarchical levels on the basis FRM (final Reachability Matrix).
- d) Developing a Digraph.
- e) Developing ISM model from the Digraph.

f) Evaluating ISM model for logical coherence and implementing the essential adjustments to improve its framework (71).

Data Analysis

The ISM is a useful instrument for decision-making and issue-solving. This method facilitates careful

consideration of intricate interdependencies between variables.

Step 1: Development of SSIM Matrix

The SSIM table shown in Table 3 uses the notations V, A, X, and O. These symbols carefully record the directional and non-directional connections between the items being examined.

Table 3: Structural Self-interaction Matrix (SSIM)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1		V	A	X	X	A	A	O	A	O	V	O	V
2			A	A	A	O	A	V	A	A	V	O	V
3				V	V	V	V	V	V	V	V	O	V
4					X	O	A	O	A	O	V	O	O
5						A	A	O	A	A	V	O	O
6							X	V	X	X	V	O	O
7								V	X	X	V	O	V
8									O	O	V	O	X
9										X	O	V	V
10											V	O	V
11												O	O
12													O
13													

Note: V = *i* influence *j*, A = *j* influence *i*, X = *i* and *j* influence each other, O = *i* and *j* are unrelated.

Step 2: Development of Initial Reachability Matrix (IRM)

Table 4 presents the Initial Reachability Matrix, which marks the beginning of the process for deriving the Final Reachability Matrix (FRM). The Initial Reachability Matrix (IRM) is derived from the SSIM matrix by applying the following rules:

- If symbol V is entered then (i,j) and (j,i) becomes 1 and 0 respectively.
- If symbol A is entered then (i,j) and (j,i) becomes 0 and 1 respectively.
- If symbol X is entered then (i,j) and (j,i) becomes 1.
- If symbol O is entered then (i,j) and (j,i) becomes 0.

Table 4: Initial Reachability Matrix (IRM)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	Driving Power
1	1	1	0	1	1	0	0	0	0	0	1	0	1	6
2	0	1	0	0	0	0	0	1	0	0	1	0	1	4
3	1	1	1	1	1	1	1	1	1	1	1	0	1	12
4	1	1	0	1	1	0	0	0	0	0	1	0	0	5
5	1	1	0	1	1	0	0	0	0	0	1	0	0	5
6	1	0	0	0	1	1	1	1	1	1	1	0	0	8
7	1	1	0	1	1	1	1	1	1	1	1	0	1	11
8	0	0	0	0	0	0	0	1	0	0	1	0	1	3
9	1	1	0	1	1	1	1	0	1	1	0	1	1	10
10	0	1	0	0	1	1	1	0	1	1	1	0	1	8
11	0	0	0	0	0	0	0	0	0	0	1	0	0	1
12	0	0	0	0	0	0	0	0	0	0	0	1	0	1
13	0	0	0	0	0	0	0	1	0	0	0	0	1	2
Driving Force	7	8	1	6	8	5	5	6	5	5	10	2	8	

Table 5: Final Reachability Matrix (FRM)

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	Driving Force
1	1	1	0	1	1	0	0	1*	0	0	1	0	1	7

2	0	1	0	0	0	0	0	1	0	0	1	0	1	4
3	1	1	1	1	1	1	1	1	1	1	1	1*	1	13
4	1	1	0	1	1	0	0	1*	0	0	1	0	1*	7
5	1	1	0	1	1	0	0	1*	0	0	1	0	1*	7
6	1	1*	0	1*	1	1	1	1	1	1	1	1*	1*	12
7	1	1	0	1	1	1	1	1	1	1	1	1*	1	12
8	0	0	0	0	0	0	0	1	0	0	1	0	1	3
9	1	1	0	1	1	1	1	1*	1	1	1*	1	1	12
10	1*	1	0	1*	1	1	1	1*	1	1	1	1*	1	12
11	0	0	0	0	0	0	0	0	0	0	1	0	0	1
12	0	0	0	0	0	0	0	0	0	0	0	1	0	1
13	0	0	0	0	0	0	0	1	0	0	1*	0	1	3
Driving force	8	9	1	8	8	5	5	11	5	5	12	6	11	

Step 3: Table 5 Present the Final reachability matrix (FRM) shown is obtained from Initial Reachability Matrix (IRM) by following the Transitivity Rule (TR) (72). As per this rule all variables are connected to each other in sequencing.

Step 4: Level Partitioning

Factors are shifted according to their respective levels (73). The Final Reachability Matrix (FRM) led to the creation of the Level Partitioning, as shown in Table 6. The Final Reachability Matrix (FRM) is utilized during the commencing run to partition to regulate the level relationship between the elements. Segregation is done for thirteen elements. It was found that "Data Analytics" and "Customer Personalization" were the top level. As these are on the top level, these do not influence any other elements but may influence factors at the same level. In ISM (Interpretive Structural Modeling), factors of increased level cannot affect factors placed on decreased levels. In the second cycle, the reachability set pointed to elements 8

and 13, constituting "Governance and Trust" and "Financial controlling" respectively. These factors regulate the second-highest level of the model. In the third run, accessibility set recognized only one factor "Financial Controlling" placed at Level 3. In the fourth run, the reachability set contained "Analytical Capability", "Fraud Detection and Prevention", and "Decentralized Control", together constituting Level 4 of the model. In the fifth run, the highest number of factors was recognized. The fifth-level factors were "Claims Settlement," "Risk Management," "Accuracy and Transparency," and "Automation." These constituted the second-lowest tier of the hierarchy. Lastly, in the final iteration, "Digital Transformation" was removed and placed at the base level of the model. This means that all other factors were directly or indirectly affected by Digital Transformation, which thus became the anchor of the model. Upon the elimination of transitive links, the simplified conical matrix appears in the following Table.

Table 6: Level Partitioning

Enablers	Reachability Set	Antecedent Set	Intersection Set	Level
1	1, 4, 5,	1, 3, 4, 5, 6, 7, 9, 10,	1, 4, 5,	4
2	2,	1, 2, 3, 4, 5, 6, 7, 9, 10,	2,	3
3	3,	3,	3,	6
4	1, 4, 5,	1, 3, 4, 5, 6, 7, 9, 10,	1, 4, 5,	4
5	1, 4, 5,	1, 3, 4, 5, 6, 7, 9, 10,	1, 4, 5,	4
6	6, 7, 9, 10,	3, 6, 7, 9, 10,	6, 7, 9, 10,	5
7	6, 7, 9, 10,	3, 6, 7, 9, 10,	6, 7, 9, 10,	5
8	8, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13,	8, 13,	2
9	6, 7, 9, 10,	3, 6, 7, 9, 10,	6, 7, 9, 10,	5
10	6, 7, 9, 10,	3, 6, 7, 9, 10,	6, 7, 9, 10,	5
11	11,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13,	11,	1
12	12,	3, 6, 7, 9, 10, 12,	12,	1
13	8, 13,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13,	8, 13,	2

Table 7: Conical Matrix (CM)

Variables	11	12	8	13	2	1	4	5	6	7	9	10	3	Driving Force	Level
11	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
12	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1
8	1	0	1	1	0	0	0	0	0	0	0	0	0	3	2
13	1*	0	1	1	0	0	0	0	0	0	0	0	0	3	2
2	1	0	1	1	1	0	0	0	0	0	0	0	0	4	3
1	1	0	1*	1	1	1	1	1	0	0	0	0	0	7	4
4	1	0	1*	1*	1	1	1	1	0	0	0	0	0	7	4
5	1	0	1*	1*	1	1	1	1	0	0	0	0	0	7	4
6	1	1*	1	1*	1*	1	1*	1	1	1	1	1	0	12	5
7	1	1*	1	1	1	1	1	1	1	1	1	1	0	12	5
9	1*	1	1*	1	1	1	1	1	1	1	1	1	0	12	5
10	1	1*	1*	1	1	1*	1*	1	1	1	1	1	0	12	5
3	1	1*	1	1	1	1	1	1	1	1	1	1	1	13	6
Dependence Force	12	6	11	11	9	8	8	8	5	5	5	5	1		
Level	1	1	2	2	3	4	4	4	5	5	5	5	6		

Step 5: Construction of the Conical Matrix

Table 7 displays the Conical Matrix that was developed from the Final Reachability Matrix by rearranging the rows and columns according to the levels established during level partitioning.

Step 6: Construction of the Reduced Conical Matrix

Table 8 shows the Reduced Conical Matrix that was constructed after removing the transitive and

redundant links from the Conical Matrix. This matrix is used to construct the final ISM model.

Step 7: ISM Model

The ISM-based model is built based on the Final Reachability Matrix (FRM) and levels determined through iterations (74). The enablers are positioned at different levels based on their hierarchical structure. Figure 2 exhibits the ISM Model which highlights the levels of enablers and their interrelationships.

Table 8: Reduced Conical Matrix (CM)

Variables	11	12	8	13	2	1	4	5	6	7	9	10	3	Driving Force	Level
Data Analytics	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Customer Personalization	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1
Governance and Trust	1	0	1	1	0	0	0	0	0	0	0	0	0	3	2
Financial Controlling	1*	0	1	1	0	0	0	0	0	0	0	0	0	3	2
Transparent Framework	0	0	1	1	1	0	0	0	0	0	0	0	0	4	3
Analytical capability	0	0	0	0	1	1	1	1	0	0	0	0	0	7	4
Fraud detection and prevention	0	0	0	0	1	1	1	1	0	0	0	0	0	7	4
Decentralized control	0	0	0	0	1	1	1	1	0	0	0	0	0	7	4
Claims Settlement	0	1*	0	0	0	1	1*	1	1	1	1	1	0	12	5
Risk management	0	1*	0	0	0	1	1	1	1	1	1	1	0	12	5
Accuracy and Transparency	0	1	0	0	0	1	1	1	1	1	1	1	0	12	5
Automation	0	1*	0	0	0	1*	1*	1	1	1	1	1	0	12	5
Digital transformation	0	0	0	0	0	0	0	0	1	1	1	1	1	13	6
Dependence Force	12	6	11	11	9	8	8	8	5	5	5	5	1		
Level	1	1	2	2	3	4	4	4	5	5	5	5	6		

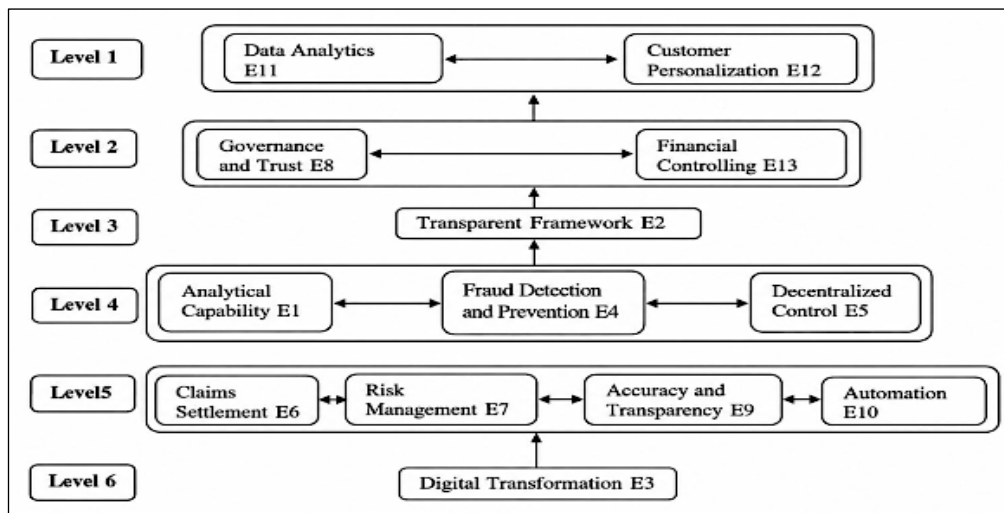


Figure 2: ISM Model

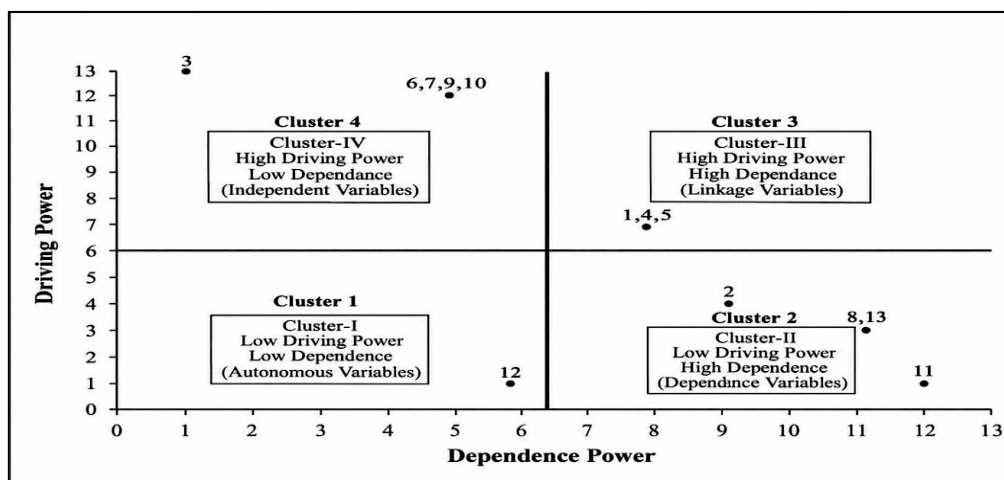


Figure 3: MICMAC Analysis

Step 8: MICMAC Analysis

Figure 3 illustrates the results of the MICMAC analysis of the identified enablers. The enablers are plotted onto a driving power vs. dependence power matrix and grouped into four clusters of autonomous, dependent, linkage and independent variables. Each cluster shows the relative influence and dependence of each enabler within the system.

Results and Discussion

MICMAC analysis categorizes variables into four clusters:

- Autonomous Enablers
- Dependent Enablers
- Linkage Enablers
- Independent Enablers

The classification of enablers is based on their Driving force and dependency, which are derived from the final reachability metrics. The MICMAC diagram visually represents these relationships,

with Driving force on the vertical axis and dependency on the horizontal axis.

Cluster-I: Autonomous Region

This category includes enablers with low Driving force and low dependency. These enablers are less influential and do not actively engage with the system. In this study, only one enabler was identified in Cluster-I. However, Customer Personalization falls into this category. Since it does not significantly impact motivation among stagnant business owners, it should not be a priority (33, 75). With involvement of AI which can analyze huge data can suggest features and help customers modify the product as per their needs. With some standard specific features to be mandatorily present with product it can provide options to buyers to add or remove additional features. This can not only help buyers get features that is needed by them but also modify the premium paid.

Cluster-II: Dependent Region

Enablers in this category have low Driving force but high dependency, meaning they are largely influenced by other enablers. The identified enablers in this cluster include Transparent Framework like disruptions brought by Blockchain technology, involvement of Governance and Trust in the insurance sector, Data Analytics required for analyzing huge data of insurance customers and providers, and the required Financial Controlling to handle such efforts. Prior studies have highlighted the role of Blockchain disruptions in Transparent Framework (14, 34, 36). These enablers appear at the top of the Interpretive Structural Modeling (ISM) framework.

Cluster-III: Linkage Region

This cluster consists of enablers with both high Driving force and high dependency. These enablers are crucial as they influence other enablers while also being influenced by them. Cluster III act as a bridge between independent enablers (Cluster IV) and dependent enablers (Cluster II). In this study, the enablers Analytical Capability available with existing service providers, Fraud Detection and Prevention, which are required by both the insurance providers and customers and Decentralized Control.

Cluster-IV: Independent Region

Independent enablers possess high Driving force but low dependency, making them fundamental to the system's transformation. These enablers significantly impact other variables and can alter the system's dynamics. The key enablers identified in this category are Claims Settlement forming the basis of customer satisfaction, Risk Management which is essential to manage the risks associated with financial transactions involved in insurance, Accuracy and Transparency, and Automation providing a great work-frame, forming the foundation of the ISM model. Given their influence, they require careful management and strategic prioritization.

Implications of the Study

The impacts of the study are not just for the insurance industry, academic researchers but also for those involved in designing and applying AI-based solutions in the industry. The most significant academic implications include.

Implications for Research

The study aims to create a method by using integrated ISM and MICMAC approach for identifying adoption enablers' complexities in dynamic settings in different sectors. The results are helpful for researchers and insurers particularly to implement AI in insurance and other sectors.

The model can be used as the foundation for further research to adopt emerging technologies in insurance sector. The findings can be used to understand challenges and approaches in technology implementation in other domains which will help in digital transformation, innovation and effective management in insurance sector.

Implications for Practitioners in the Insurance Sector

The consequences of AI adoption are investigated in this research. The study of arrayed structure of enablers and their relation through analyzing ISM and MICMAC techniques provides us strategic directions for arriving at decision making and intervention arranging. The important findings of the study are outlined below.

The research is majorly used to identify the critical enablers for AI implementation in insurance sector, like claims settlement, risk management, governance and trust, accuracy and transparency, the requirement for multilingual support and to understand the limitation of AI's impact.

The research helps to analyze by ranking the enablers identified and providing a structured framework which will help the insurance sector and financial institutions to create better strategies for overcoming challenges in AI adoption.

Based on priority, the enablers are ranked hierarchically into six levels. It identifies digital transformation (Level 6) as the most important enabler of AI adoption is the insurance industry that makes it a key area for insurance firms and policymakers, especially in India.

Furthermore, the research identifies key enablers like data analysis, customer individualization, financial management, and the creation of an open AI framework. These research inferences can help insurance firms in focusing on critical action areas and forming targeted strategies for overcoming barriers to AI adoption. Policymakers too can use these insights to understand systemic short-

comings to AI adoption and facilitate better policies and regulations.

Overall, the study helps the stakeholders to address the issues in AI adoption in the insurance sector, with the aim to improve customer experiences and increase operational efficiency.

Conclusion

This research aims to identify major enablers that affect execution of AI within the insurance sector. Considering specialist judgements and information from previous literature, ISM methodology is used to generate a formal blueprint that investigates the relationships between these enablers. In addition, MICMAC analysis is used to classify the enablers according to their driving and subordination power. The research identifies and explores 13 essential enablers linked with implementation of AI within the insurance industry.

Out of the six levels that are developed by the ISM Model, Digital transformation was found to be the bottom level enabler with the highest independence power. This indicates that their enablers are more influential than those that come after claim settlement, risk management, accuracy and transparency, and automation, which provide independent regions.

The hierarchy model places enablers like "Data Analysis and "Customer personalization at the top as they have the lowest Driving force and the highest dependence power.

Limitations

The primary limitation of this research lies in its reliance on a cause-and-effect diagram that was formulated using expert opinions in a specific industrial setting, which may add subjectivity to the outcome. Moreover, it may be difficult to identify and rank the enablers. Due to the nature of the industry, certain enablers may be critical when applied to a developing nation like India now, but as the insurance industry develops and adopts more sustainable practices, their impact may diminish. On the other hand, as the sector advances towards a more mature and a higher level of sustainability, enablers that are currently viewed as less important might become more decisive. The results also indicate that some of the key enablers are preventing AI adoption, such as lack of an open framework, constraints in its reach and analytical powers, difficulties in fraud detection and

prevention, inabilities in claims settlement, decentralized control problem, automation obstacles, governance and trust issues, data analytics limitation, and challenges in customer personalization.

Future Research Prospects

The proposed ISM- MICMAC framework can be verified with larger and more diverse samples of experts and quantitative techniques in future studies. Comparative and longitudinal studies can analyze the evolution of AI-enablers over time and from country to country. Additional studies might also explore new technologies, legal and ethical concerns, cyber security, and the effects of AI implementation on efficiency, customer satisfaction, fraud prevention, and profitability.

Abbreviations

AI: Artificial Intelligence, CAGR: Compounded Annual Growth Rate, FRM: Final Reachability Matrix, IRM: Initial Reachability Matrix, ISM: Interpretive Structural Modeling, RQ: Research questions, SSIM: Structured Self-interaction Matrix, TR: Transitivity Rule.

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Author Contributions

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Conflict of Interest

The authors have no Conflict of Interest regarding this article's publication.

Data Availability

The data supporting the analysis and the findings are derived from the opinion of the Experts in the

domain industry and publicly available journal articles. All analyzed sources are cited in the reference section. The processed data can be made available from the corresponding author on a reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the manuscript. All content generated through AI was critically reviewed, edited and verified by the authors to ensure accuracy, originality and compliance with academic standards. The authors take full responsibility for the integrity and validity of the manuscript

Ethics Approval

No human or animal participants were involved thus ethical approval is not required.

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