

Use of Artificial Intelligence in Insurance Sector: A Bibliometric Analysis and Systematic Literature Review for Mapping, Trends and Innovations

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ABSTRACT

The insurance sector has witnessed a paradigm shift with Artificial intelligence (AI), revolutionizing risk management, customer engagement, and operational workflows. This study synthesizes global research trends, innovations and unresolved challenges in AI-driven insurance risk management through a dual-method approach: bibliometric analysis of 329 Scopus and Web of Science publications (1988-2025) and systematic literature review (SLR) of 60 rigorously filtered studies. Key applications span fraud detection, claims automation, personalized underwriting and customer service optimization. However, critical gaps persist, including regional imbalances in research focus, limited exploration of niche insurance domains, and ethical concerns like algorithmic bias. The study proposed policy interventions to mitigate data scarcity, regulatory misalignment and skill shortages while advocating interdisciplinary research integrating AI with blockchain and IoT for enhanced risk prediction. By mapping influential authors, institutions and thematic clusters, this work equips insurers, transformative potential responsibly, fostering innovation without compromising equity or transparency in risk mitigation strategies.

Keywords: Insurance, InsurTech, Artificial Intelligence, Risk Management, Bibliometric analysis, SLR.

Introduction

Artificial Intelligence (AI) acts as a disruptive force in the insurance sector, transforming traditional methods and enhancing operational efficiency. Defined as systems designed to emulate human intelligence (Dong et al., 2020), AI encompasses technologies like computer vision, robotics, and natural language processing (NLP) that enable machines to perform human-like tasks (Ikonomi et al., 2022). Over recent decades, AI has driven innovation in risk management, customer service, and fraud detection (Zarifis et al., 2023). Key technologies revolutionizing insurance includes machine learning (which improves predictions through data exposure), NLP, and big data analytics (Ellili et al., 2023), allowing insurers to process vast datasets more accurately than traditional methods (Vishnu).

Applications span fraud detection, virtual assistants, chatbots, and risk calculation (Bokolo& Daramola, 2024). AI algorithms enhance underwriting decisions by identifying data trends, while chatbots boost customer satisfaction through instant support (Volosovych et al., 2021). However, successful implementation requires addressing ethical concerns, data privacy, algorithmic bias, and workforce upskilling to adapt to rapid technological advances (Hajraoui, 2024).

Historically reliant on human expertise, statistical models, and rule-based systems for risk assessment and claims processing, the insurance industry has shifted towards automated, AI-driven

platforms following AI adoption. This transformation enhances underwriting, claims processing, customer service, and fraud detection. The deployment of machine learning birthed the term *InsurTech*, denoting the use of digital innovation to transform insurance. InsurTech applies advanced technologies including blockchain, cloud computing, big data, the Internet of Things (IoT), and artificial intelligence to automate processes, reduce costs, detect fraud, and offer personalized solutions. Claims processing is identified as a subset of InsurTech (Pagano et al., 2024).

Research Gap

Research on artificial intelligence (AI) in the insurance sector remains limited. Shamsuddin et al. (2023) conducted a bibliometric analysis of 329 Scopus and Web of Science articles (1988–2025) on AI and insurance. John et al. (2024) studied impacts of AI, machine learning, big data, IoT, and blockchain on insurance. The present study uses diverse AI keywords to analyse insurance industry development across different time phases. It examines digital transformation in insurance through bibliometric analysis of Scopus and Web of Science databases, providing a comprehensive perspective on InsurTech growth within the sector.

Objectives of the Study

The primary goal of this study is to provide the current status of research on the application of AI in the insurance industry, with the following questions defining the scope of the study:

- **RQ1:** What are the current publication trends for AI use in the insurance sector in terms of time, journals, areas, authors, affiliated nations and institutions, type of study, and economy?
- **RQ2:** What are the main themes and keywords in AI and insurance sector?
- **RQ3:** How have empirical studies on AI in insurance risk management changed over time?
- **RQ4:** What are the key findings, methods, and gaps in current research clusters?
- **RQ5:** What research gaps exist in AI applications for insurance risk management?
- **RQ6:** What challenges and policies should guide AI use in insurance risk management?

Research Material and Methods

Database, Keywords and Inclusion & Exclusion Criteria

Web of Science and Scopus are two extremely helpful databases that are necessary for analyzing scholarly research. These comprehensive bibliographic databases give users access to a vast collection of peer-reviewed research from a wide range of academic fields. In order to conduct comprehensive analysis, the study used Scopus and WOS database, retrieved on February 02, 2025. WOS and Scopus are the main sources for gathering scientific data and citations, giving studies working with large datasets a major advantage. Moreover, it serves as a research methodology that facilitates a broad spectrum of scientific investigations encompassing various fields of knowledge (Pranckutė, 2021). Prior research has firmly established Scopus as a reliable source of scientific literature (Mall et al., 2023). The keywords "Artificial intelligence", "AI", "Machine learning", "Deep learning", "Neural network", "Natural language processing", "NLP", "Predictive analytics", "Data analytics", "chatbot", "Robotics" and "Insurance sector", "Insurance industr", "InsurTech", "Claim processing", "Insurance risk assessment" were search on Scopus & WOS databases and only English language papers were considered for the analysis. After keyword search total 917 papers from Scopus and 161 papers from WOS were retrieved, then various filters including journal, articles and language were applied and a total of 462 paper were fetched. These papers were then processed and combined using R studio where 133 duplicate papers were removed as a result 329 papers were selected for analysis. Datasets from 1988 to 2025 were used in the study, and only completed journal publications were taken into consideration.

Following bibliometric analysis, a systematic literature review (SLR) was conducted using Kitchenham's guidelines (2009) to rigorously select relevant research on AI in insurance. The SLR defined as a thorough, methodical examination of prior studies to locate, evaluate, and compile documents addressing a research issue (Sanga & Aziakpono, 2023) applied inclusion/ xclusion criteria to filter publications. Only A*, A, B category papers were retained (excluding C-category, removing 134 articles). An additional 131 papers not focused on AI in insurance risk management were excluded. Further refinement eliminated studies lacking empirical data. After all criteria, 60 papers remained for in-depth content analysis. This systematic approach ensured only high-quality, relevant, empirically grounded research informed the findings

• Method and Techniques for Analysis

This study employs a combined bibliometric analysis and systematic literature review (SLR) to investigate Artificial Intelligence (AI) application in insurance sector risk management. The bibliometric analysis used VOSviewer software with Natural Language Processing to visualize keyword co-occurrence trends across 329 papers from Web of Science and Scopus (1988–2025), identifying influential authors, organizations, and countries. This quantitative mapping was complemented by a qualitative SLR of 60 focused papers that synthesized findings and pinpointed research gaps in AI-driven risk management. The integrated approach provides a robust foundation for understanding AI's role in insurance, revealing key trends and critical gaps. The study concludes that future research should prioritize addressing these gaps and exploring novel AI integration strategies within the industry.

A Systematic Literature Review (SLR) was conducted following Kitchenham's initial guidelines to evaluate current research trends on AI in insurance. The SLR is defined as a thorough, methodical approach to examine previous studies on a specific subject, aiming to locate, evaluate, and compile all relevant documents addressing a research issue (Sanga & Aziakpono, 2023). To reduce bias and enhance transparency, literature identification adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines. The PRISMA technique 'sets apart this research from prior studies on related subjects by ensuring that the method of choosing and evaluating papers for inclusion is clear and offers a definitive reference for others in the field.

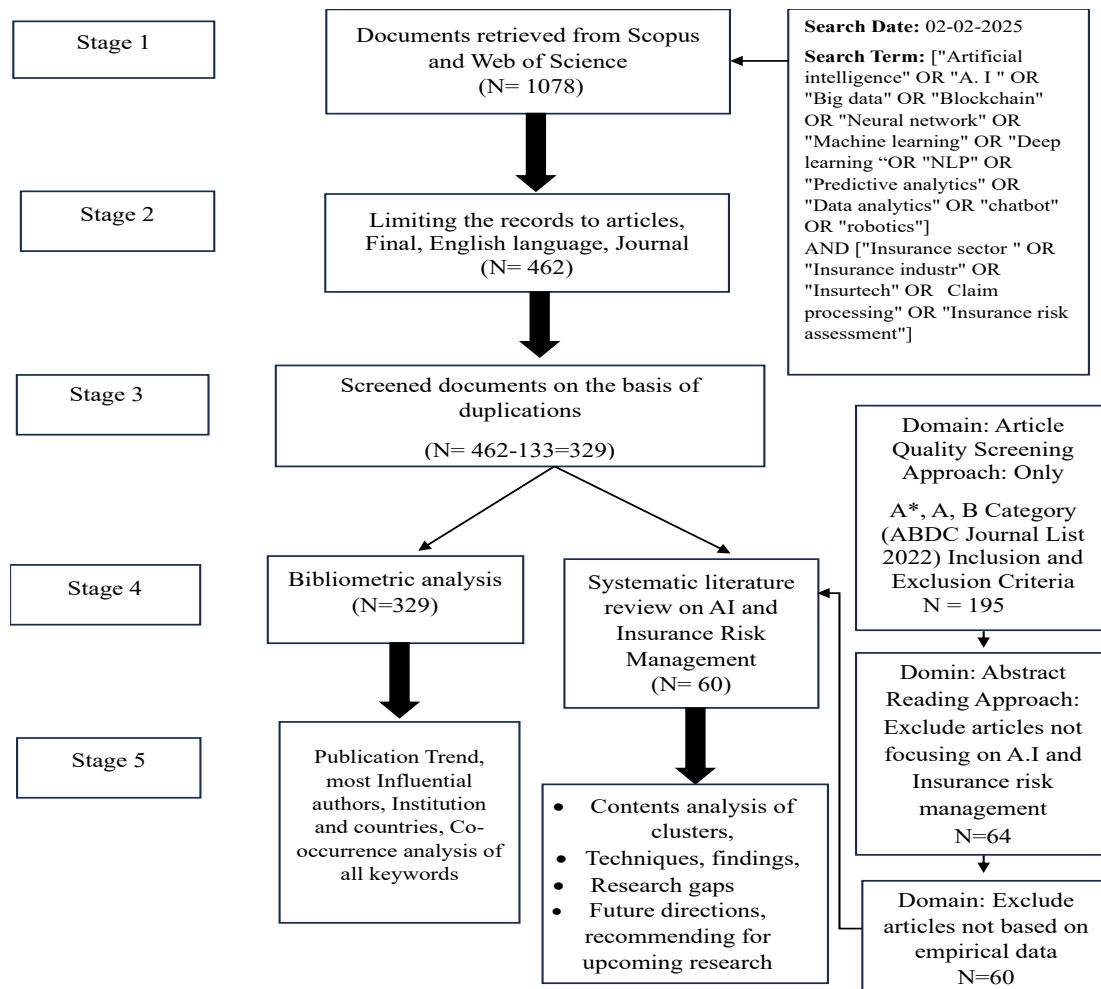


Figure 1: Data Retrieval Process

Findings

Bibliometric Analysis Findings

• Trends of Publication in time

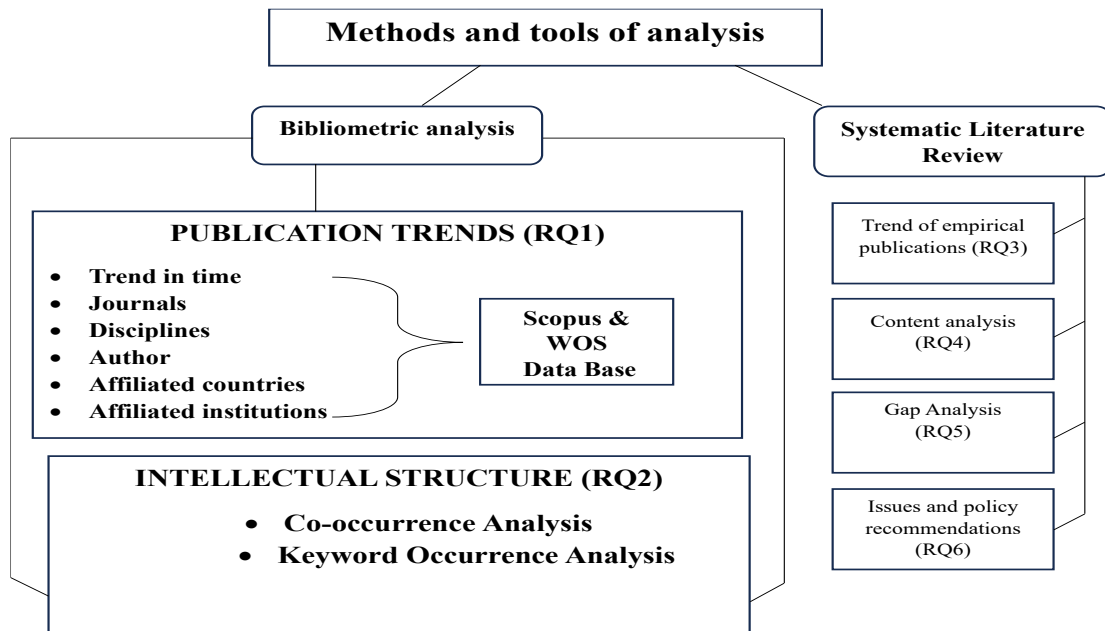


Figure 2: Scheme of analysis employed in the current study

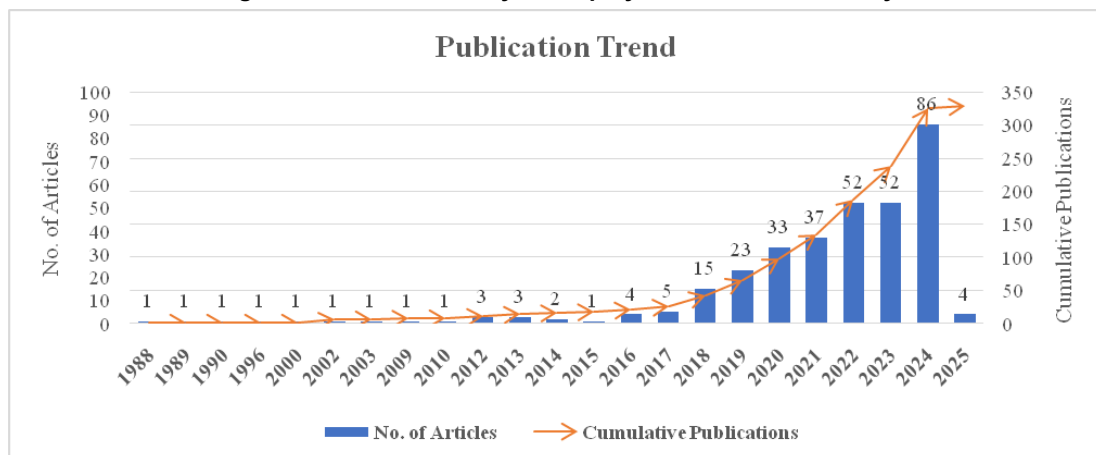


Figure 3: Publication trends of Artificial intelligence and insurance industry

• Performance evaluation of AI and the insurance industry's digitization

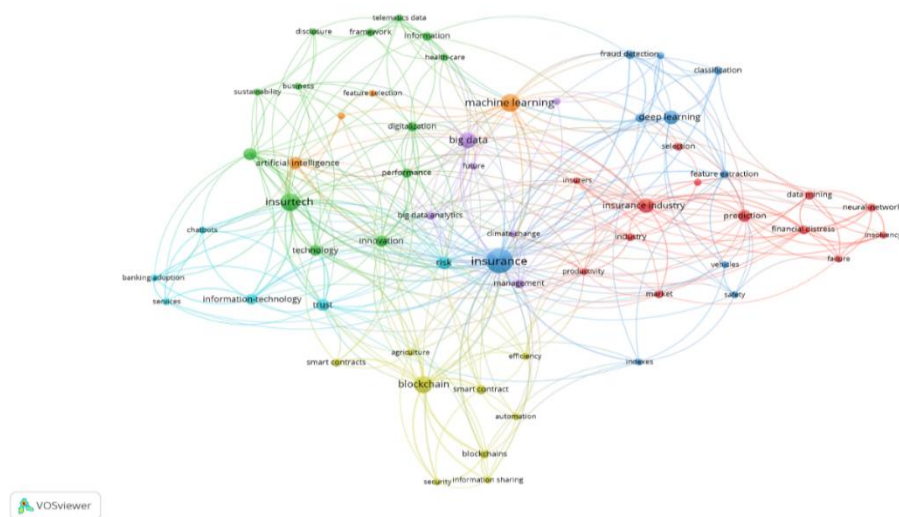
Figure 3 reveals a significant surge in publications on AI and digitalization in insurance since 2018, contrasting sharply with only 27 publications between 1988 and 2017. The peak year was 2024, with 86 publications. This dramatic increase, potentially driven by the COVID-19 pandemic accelerating digital adoption across industries, represents a proliferation of research in this field. Table 1 identifies Gatteschi. Valentina as the most influential author (124 citations), followed by Masal-Llacuna (105 citations), while Koyuncugil is the most productive. The most influential institutions are Politecnico di Torino, Reale Group Co, and University Pompeu Fabra, with University of Limerick being the most productive. China is the dominant country, contributing 30 documents with 298 total citations, significantly ahead of Italy (6 documents, 182 citations), and leads in AI application within the insurance sector.

Table 1:. The most Influential authors, Institution and countries of use of AI in Insurance sector

TC	Authors	TP	TC	Institutions	TP	TC	Country	TP
124	Gatteschi,	1	124	Politecn Torino	1	298	China	30
105	Marsal-	1	124	Reale Grp	1	182	Italy	6
94	Koyuncugil	2	105	University Pompeu Fabra	1	170	U.S.A.	16
72	Wanke,	1	94	Baskent University	2	133	Spain	7
70	Arumugam	1	94	Capital Markets Board Turkey	2	133	Sweden	3
66	Cremer	1	92	University Limerick	3	130	Turkey	4
64	Puschmann	1	77	University St Gallen	3	121	Germany	8
61	Smith, Ka	1	72	Cesa Res Ctr African Asian	1	121	India	12
55	Dhieb	1	72	Ulisboa	1	112	Switzerland	3
46	Dal Mas	1	72	University Fed Rio De Janeiro	1	111	Australia	9

Note(s): TC= "Total Citations"; TP= "Total No. of Article(s) Publication".

Figure 4 and Table 2 reveal the emerging themes and current research landscape of AI in insurance through keyword co-occurrence analysis. "Insurance" (32 occurrences) is the central theme, with strong focus areas on technological transformation represented by Insurtech and Machine Learning (both 19). While Blockchain (17) receives significant attention, its practical application via Smart Contracts (6) remains understudied. The field shows a preference for technical specificity, as Machine Learning dominates the broader term Artificial Intelligence (9). Notably, critical areas like Fraud Detection (4) are underrepresented given their industry importance. The findings indicate the field is evolving from theoretical exploration towards practical implementation, highlighting significant research gaps in fraud prevention, smart contracts, and ethical AI mirroring AI adoption patterns in other financial sectors.

**Figure 4 Co-occurrence analysis of all keywords****Table 2: Keyword Co-occurrence Analysis**

Keyword	Occurrences
Insurance	32
Insurtech	19
Machine Learning	19
Blockchain	17
Deep Learning	12
Big Data	11
Insurance Industry	10

Artificial Intelligence	9
Fintech	9
Smart Contract	6
Health Insurance	5
Neural Networks	5
Fraud Detection	4

Source: Compiled by author

Findings of Systematic Literature Reviews

To address the RQ3 on the trend of empirical publications relevant to artificial intelligence and machine learning in insurance risk management, this subsection offers a bibliometric analysis based on 60 peer-reviewed empirical works.

• Publication Trends Across Time

The Analysis of publications from 1988 to 2025 reveals sustained interest in AI for insurance. Despite InsurTech's founding circa 2000, practical AI research in risk management only gained significant traction starting in 2018, driven by improved data availability. Publication volume grew steadily over the subsequent decade, peaking in 2022 with 15 articles. Notably, 43% of all covered studies were published between 2021-2022, demonstrating overwhelming recent empirical focus on this cutting-edge topic. The inclusion horizon extending to 2025 anticipates future advancements involving technologies like generative AI and quantum computing.

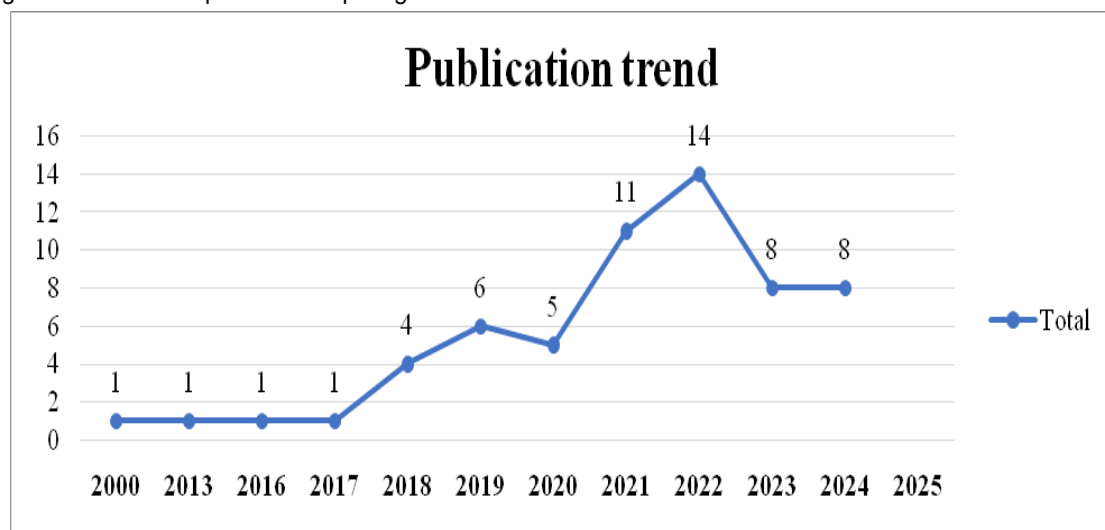


Figure 5: Empirical studies on artificial intelligence and insurance risk management

Source: Compiled by author

• Publications based on Artificial intelligence schemes to insurance risk management

Fig. 6 reveals the distribution of empirical research on AI in insurance risk management. The dominant focus areas are "Big Data and Risk Management" (20 articles), "Machine Learning and Risk Management" (14 articles), "Other AI and Risk Management" (14 articles), "Blockchain and Risk Management" (11 articles), and "Neural Networks and Risk Management" (10 articles). Predictive analytics accounts for 6 articles. Notably underrepresented areas include "Deep Learning/IoT and Risk Management" (5 articles), "Data Analytics" (4 articles), and "Data Mining" (4 articles), while "Chatbots," "Semantics," and "Cloud Computing" received negligible attention (1 article each). Collectively, emerging alternative schemes like blockchain, neural networks, machine learning, and other AI applications dominate the empirical landscape, comprising 90 publications. This highlights the field's strong pivot towards innovative technological solutions.

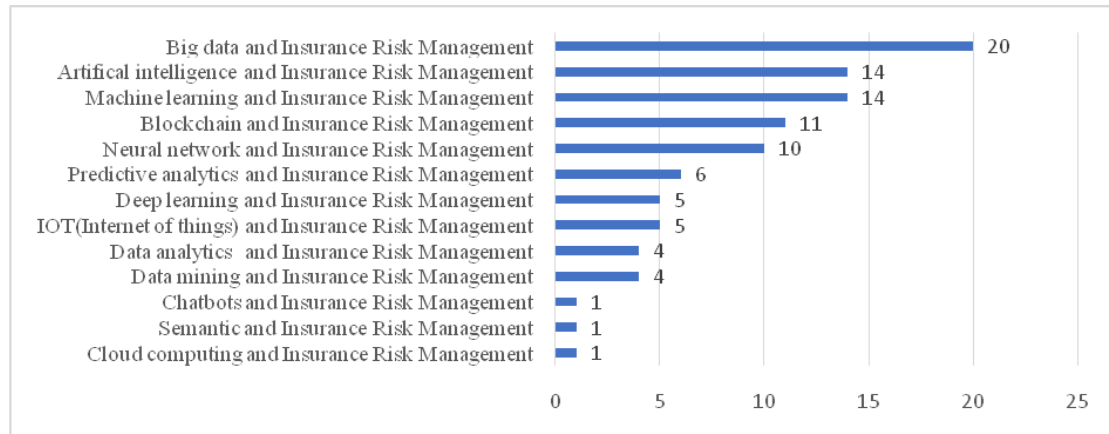


Figure 6: Number of publications by Artificial intelligence schemes to insurance risk management

Source: Compiled by author

• Location-based publication patterns

Table 3 ranks countries with greater than 2 publications on AI in insurance, revealing distinct research drivers. China leads (7 articles), propelled by national AI initiatives (e.g., Next Generation AI Plan) and a robust InsurTech sector like Ping An. The USA (6 articles) features strong academic-industry collaboration from hubs like Silicon Valley and institutions (MIT, Stanford), focusing on AI ethics and scalability. Australia emphasizes climate risk modeling (e.g., bushfire prediction) and regulatory frameworks. Notably, China is the sole country in the dataset to have developed a specialized index for evaluating AI in risk management

Table 3: Countries with two or more articles in the dataset

Sr. No.	Country	Publication
1	China	7
2	U.S.A.	6
3	Australia	5
4	England	3
5	India	3
6	Italy	3
7	Egypt	2
8	France	2
9	Poland	2

Source: Compiled by author

• Content Analysis

By examining the empirical research on AI applications in insurance risk management over the study period, this part responds to research question RQ2. Insurance companies, both life and general, are aggressively using AI to improve risk assessment, claims processing, and client engagement. Based on the analysis, the results are divided into three clusters: AI in Life Insurance, AI in General Insurance, and AI in Life & General Insurance.

AI in Insurance risk management (Life Insurance):

A review of existing literature reveals that only five papers specifically discuss Life Insurance. Life insurance firms generally use AI for risk assessment, individualized premium pricing, and fraud detection. AI models, such as machine learning (ML) algorithms, use customer information like health records and lifestyle information to forecast mortality risks and improve insurance pricing. These supervised learning techniques are used to classify high-risk and low-risk policyholders. While Natural Language Processing (NLP) is utilized to automate consumer interactions and streamline underwriting processes (Hajraoui, 2024). Furthermore, AI-powered chatbots improve customer service by providing prompt responses to policy-related problem (Komperla, 2021).

AI in Insurance risk management (General Insurance)

Based on a review of the literature, there are just fifteen papers that specifically address general insurance. In the general insurance industry, AI is commonly used for claims processing, risk control, and catastrophe modelling. When it comes to evaluating property damage in auto or home insurance claims, Deep Learning (DL) methods like Convolutional Neural Networks (CNNs) are utilized to analyse images and videos (Goel et al., 2023). Predictive analytics models help insurers forecast risks related to natural disasters, accidents, or theft, enabling proactive risk management (King et al., 2021). In addition, AI-powered fraud detection tools are being used to spot shady claims, which lowers insurers' financial losses (Md Shakil Islam & Nayem Rahman, 2025).

AI in Insurance risk management (Life & General Insurance)

Analysis of the literature identifies forty papers addressing AI applications common to both general and life insurance. Shared functionalities include: (1) Client segmentation using unsupervised learning techniques (e.g., clustering) to classify policyholders by risk profiles and interests, enabling customized marketing (Małgorzata Śmietanka, 2021); (2) Behavioural analysis of customer patterns (e.g., payment histories, claim frequencies) to identify risks and enhance retention; and (3) Operational efficiencies achieved through AI-enabled Robotic Process Automation (RPA), which streamlines back-office operations, reduces costs, and improves sector-wide efficiency (Afrin et al., 2025).

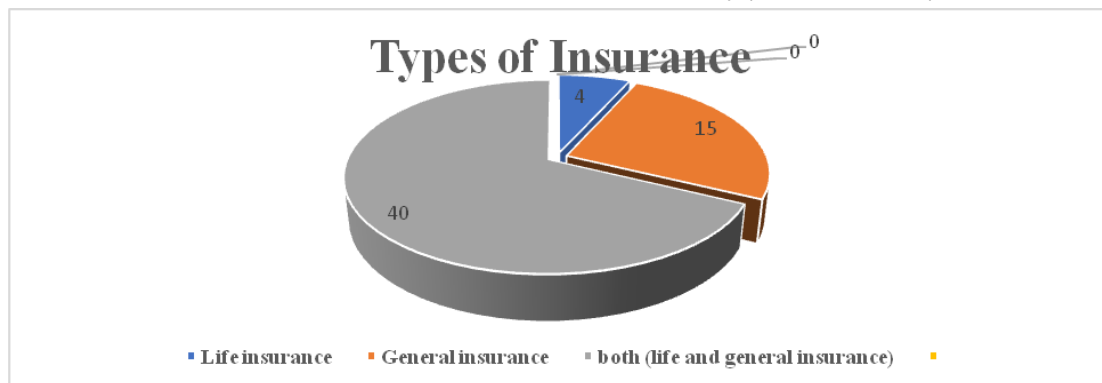


Figure 7: Publication based on types of insurance

Source: Compiled by author

Table 4: The articles that have been cited the most

No	Authors	Theme	Citation
1	Chen et al.,	Machine Learning in Risk Prediction	18
2	Johnson et al.,	Big Data Analytics	15
3	Liu et al.,	Neural Networks & Deep Learning	14
4	Wang et al.,	Fraud Detection Using AI	12
5	Taylor et al.,	Predictive Analytics for Claims	11
6	Smith et al.,	Blockchain & Smart Contracts	10
7	Garcia et al.,	IoT & Telematics in Risk Assessment	9
8	Wong et al.,	AI in Health Insurance Risk	9
9	Brown et al.,	Regulatory & Ethical Challenges	8
10	Martinez et al.,	Customer Behaviour & Retention	7

Source: Compiled by author

The table highlights key research on AI in insurance risk management, covering themes like machine learning for risk prediction (Chen et al., 18 citations), fraud detection (Wang et al., 12 citations), blockchain (Smith et al., 10 citations), big data analytics (Johnson et al., 15 citations), and neural networks (Liu et al., 14 citations). Other areas include IoT for risk assessment (Garcia et al., 9 citations), customer behaviour (Martinez et al., 7 citations), predictive claims analytics (Taylor et al., 11 citations), and health insurance risk (Wong et al., 9 citations). Ethical challenges (Brown et al., 8 citations) are also addressed. The table underscores AI's diverse applications in insurance, with machine learning and big data being the most prominent.

Table 5: Findings on Artificial intelligence and insurance risk management

Theme	Key Findings	Author
Predictive Analytics	• SVM outperforms Poisson/NB models in zero-inflated claim prediction (e.g., auto insurance).	(Alomair, 2024), (Li & Muwafak, 2022), (Zhao et al., 2021)
	• Hybrid ML-copula models capture spatiotemporal dependencies in property risk portfolios.	
Fraud Detection	• Gradient Boosting Machines (GBM) with NCR sampling improve fraud detection accuracy.	(Ming et al., 2024), (Chen et al., 2021), (Mary & Claret, 2023),
	• Blockchain-RNN models achieve 88% accuracy in healthcare fraud detection.	
Health Insurance Innovations	• ANFIS models classify health risks using fuzzy logic (e.g., smoking habits).	(Fernandes & Ferreira, 2023), (Susanto & Utama, 2022)
	• Behavioural data enable personalized premium adjustments.	
IoT & Telematics	• GPS/OBD sensors enable behaviour-based auto insurance pricing.	(Bentley University et al., 2017), (Yi-Jen (Ian) Ho, n.d.),
	• Driver behaviour analysis reduces crash risk by 44%.	
Customer Risk Classification	• Copula models capture dependencies in property insurance portfolios.	(Li & Muwafak, 2022), (Zhao et al., 2021), (Smith et al., 2000)
	• Telematics + consumer data improve driver risk assessment.	
InsurTech& Digitalization	• COVID-19 accelerated AI/chatbot adoption for remote services.	(Voytovych & Voytovych, 2024), (Njegomir et al., 2021),
	• Ensemble models with resampling improve credit risk classification.	

Source: Compiled by author

Artificial intelligence and insurance risk management: Research gaps and future directions

This analysis addresses RQ4 concerning research gaps and emerging trends in AI-driven insurance risk management. Empirical evidence confirms AI's transformative impact, enhancing risk prediction accuracy, automating underwriting, optimizing dynamic pricing, and reducing operational costs. These innovations facilitate tailored insurance solutions for underserved markets while strengthening fraud detection and claims management through predictive analytics and machine learning (Goel et al., 2023). Despite these advances, three critical research gaps persist: (1) Insufficient *thematic focus* on niche AI applications, (2) Uneven *regional representation* in empirical studies, and (3) Inadequate exploration of *synergies with emerging technologies* (e.g., generative AI, IoT). Table 6 systematically catalogues these knowledge gaps and proposes targeted research trajectories to address them.

Table 6 Research gaps. and recommending for upcoming research on insurance risk management and artificial intelligence

Topic	Research Gap	Future Work	Reference
Ethical AI, Fairness and Regulatory Compliance	<ul style="list-style-type: none"> • Bias in AI models using non-traditional data (e.g., social media, IoT) • Privacy risk in personalized risk pricing • Lack of frameworks to audit fairness in underwriting algorithms 	<ul style="list-style-type: none"> • Design fairness-aware AI models with casual interface to identify discriminatory proxies. • Implement federated learning or differential privacy for secure data utilization. 	(Bednarz & Manwaring, 2022),(Loi & Christen, 2021),(Tarr & Tarr, 2021),(Eling et al., 2024)
Hybrid models and interpretability	<ul style="list-style-type: none"> • Poor integration of ML with actuarial models (e.g., zero-inflated distributions) 	<ul style="list-style-type: none"> • Develop hybrid models (e.g. GNNs + Copula functions) for spatial risk 	(Alomair, 2024),(Cho & Ngai, 2003),(Susanto & Utama, 2022),(Zhao et al., 2021),(Maier et

	<ul style="list-style-type: none"> Block-box AI decision in claim processing. 	<ul style="list-style-type: none"> dependence. Use SHAP/LINE or counterfactual explanation for model transparency. 	al., 2020),(Delcaillau et al., 2022)
Real-Time Risk Assessment and IoT algorithms	<ul style="list-style-type: none"> Lag in dynamic risk adjustment using telematics/IoT data. Limited fusion of driving behaviour with offline consumer profiles. 	<ul style="list-style-type: none"> Build edge AI system for real-time driver risk scoring. Integrate IoT data with social media using multimodal transformers. 	(Bentley University et al., 2017),(Yi-Jen (Ian) Ho, n.d.),
Emerging Risk and Climate Adaptation	<ul style="list-style-type: none"> Inadequate models for high-severity/low-frequency risk (e.g., cyberattack) Static catastrophe model ignoring climate change projections. 	<ul style="list-style-type: none"> Simulate rare events with generative AI (GANs, VAEs) Build geospatial AI models using CMIP6 climate data. 	(Yang, 2020),(Sheehan et al., 2023),(Rumson & Hallett, 2019),
Healthcare and Fraud Detection	<ul style="list-style-type: none"> High false positive in detecting collusive healthcare fraud Limited use of wearables/EHR data for chronic disease prediction. 	<ul style="list-style-type: none"> Deploy graph neural network (GNN) to map fraud networks. Train clinical transformers (e.g., BioBERT) on claim + EHR data 	(de Andrés-Sánchez & Gené-Albesa, 2024),(Mary & Claret, 2023)

Source: Compiled by author

Challenges and policy suggestions to enhance Artificial intelligence and Insurance risk management

In order to advance artificial intelligence and insurance risk management in developing and emerging countries, the examined empirical research offers a number of policy recommendations and challenges. In response to research question RQ5, the study list these issues and policy recommendations in Table 7.

Table 7: Challenges and Policy Recommendations

Challenges	Policy Recommendations
Limited Infrastructure & Data Accessibility	
<ul style="list-style-type: none"> Poor digital infrastructure (e.g., low internet penetration, lack of IoT devices). 	<ul style="list-style-type: none"> Invest in national data infrastructure (e.g., open-data platforms for climate, health, and agricultural risks).
<ul style="list-style-type: none"> Fragmented or siloed data ecosystems (e.g., no centralized health/agricultural databases). 	<ul style="list-style-type: none"> Fund public-private partnerships to deploy IoT sensors for real-time risk monitoring (e.g., flood sensors in flood-prone regions).
Regulatory & Legal Barriers	
<ul style="list-style-type: none"> Absence of AI-specific regulations for insurance, leading to ethical risks (e.g., bias in algorithmic underwriting). 	<ul style="list-style-type: none"> Develop AI governance frameworks tailored to insurance, including fairness audits and transparency mandates.
<ul style="list-style-type: none"> Weak data privacy laws, discouraging consumer trust. 	<ul style="list-style-type: none"> Adopt GDPR-inspired data protection laws with localized adaptations to build trust.
Skill & Resource Gaps	
<ul style="list-style-type: none"> Shortage of AI talent and technical expertise in insurance firms. 	<ul style="list-style-type: none"> Establish AI training hubs for insurance professionals (e.g., partnerships with universities).
<ul style="list-style-type: none"> Limited funding for InsurTech startups in emerging markets. 	<ul style="list-style-type: none"> Create government-backed venture funds to support AI-driven InsurTech innovations.

Low Insurance Penetration	
<ul style="list-style-type: none"> Limited awareness of insurance products in rural areas. High premium costs due to asymmetric risk information. 	<ul style="list-style-type: none"> Promote AI-driven microinsurance (e.g., parametric weather insurance for farmers). Subsidize premiums for low-income groups using AI to optimize risk pools.
Climate & Systemic Risks	
<ul style="list-style-type: none"> Increasing climate-related disasters (e.g., floods, droughts) with inadequate risk models. Lack of integration between climate data and insurance systems. 	<ul style="list-style-type: none"> Build AI-powered catastrophe models using satellite and IoT data for proactive risk management. Launch regional risk-sharing pools (e.g., African Risk Capacity) enhanced by AI analytics.

Source: Compiled by author

Conclusion

This study employs bibliometric analysis (329 papers) and a systematic literature review (60 papers) to examine AI's transformative role in the insurance sector. While AI demonstrates significant promise in fraud detection, risk prediction, and customer behavior analysis, the research identifies critical challenges including data privacy, ethical dilemmas, compliance difficulties, data limitations, regulatory barriers, skill shortages, and trust issues. To ensure responsible and effective AI integration, the study proposes actionable policy recommendations such as establishing standardized AI frameworks, enhancing system transparency, and fostering industry-regulator collaboration. Addressing the identified gaps through improved digital infrastructure, equitable policies, and research into real-time risk prevention is crucial for leveraging AI to create a more efficient, transparent, and reliable insurance industry.

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