ARTIFICIAL INTELLIGENCE APPLICATION IN INSURANCE: A SYSTEMATIC LITERATURE REVIEW AND LESSONS FOR THE INSURANCE INDUSTRY IN UGANDA

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ABSTRACT

This paper presents a framework-based systematic review of existing research on the application of artificial intelligence (AI) in insurance and lessons for the emerging insurance industry in Uganda. Through a systematic literature review, we identify key findings and their implications for insurers in Uganda. Our study findings through the ADO framework identify the Antecedents, decisions, and outcomes of AI Application in Insurance and highlights the transformative role of AI in risk management, customer service, and claims processing. While the TCM framework is adopted to provide an organized review of the theory, context and methods used in the articles under review. The review aggregates 9 unique antecedents derived from 37 relevant articles and classifies them into three broad categories. The review identifies the research gaps in the extant insurance literature and provides future research directions include investigating the long-term impacts of AI on customer behavior, addressing ethical considerations, and the impact of collaboration among insurers, regulators, and technology providers in the insurance sector.

K E Y WO R D
Artificial intelligence, Insurance Industry, Responsible AI Adoption, Innovation

1.0 INTRODUCTION

The integration of artificial intelligence (AI) technologies into various industries has garnered significant attention in recent years. Sectors such as construction, manufacturing, healthcare, finance, transportation, logistics and several others have embraced AI to streamline operations, enhance decision-making processes, and improve overall efficiency (Vishnu & Kira, 2020; Baxter & Xu, 2019; Rayda & Mohsen, 2021; John et al., 2021; Bharadiya, 2023). In the insurance industry, considerable research has highlighted AI's potential to transform traditional practices and address enduring challenges faced by the industry. Indeed, AI is already being used in fraud detection (Eckert, Neunsinger, & Osterrieder, 2022), as virtual assistants (Benedek, Ciumas, & Nagy, 2022) and in calculating insurance risk (Zarifis, Holland &Milne, 2023)

While numerous studies have examined AI's application across various industries (Popkova, & Sergi, 2020; Peres, Jia, Lee, Sun, Colombo, & Barata, 2020; Zeba, Dabić, Čičak, Daim, & Yalcin, 2021; and Jan, Ahamed, Mayer, Patel, Grossmann, Stumptner, & Kuusk, 2023), a considerable extant literature focuses on how AI has been applied in insurance (Kose, Gokturk, & Kilic, 2015; Kelley et al., 2018; Ekin, 2020; Park, Park & Choi, 2021; Kotb & Ming, 2021; Aslam et al., 2022; and Arumugam & Bhargavi, 2023).

As such, several scholars have highlighted the effect of Machine learning (ML) and Deep learning (DL) (as elements of artificial intelligence) on insurance processes. These technologies have fundamentally reshaped how insurers assess risk, process claims, interact with customers, and manage their operations (Zarifis, Holland, & Milne, 2023). However, it is notable that adoption of AI in the insurance industry is not without its challenges and considerations. While these technologies offer significant opportunities for insurers to enhance their processes, they also present several complexities and concerns like regulatory compliance, integration & scalability and data quality & privacy that must be addressed.

These become even more complicated when considering the evolving regulatory landscape, stiff competition, and increasing customer expectations. Despite these challenges, it is agreed that by strategically embracing AI insurers can unlock new opportunities for growth, differentiation, and innovation.

This gap is particularly relevant in the emerging market context of Uganda, where insurers face unique challenges including limited access to data, inadequate technological infrastructure, and low insurance penetration. Indeed, with agriculture sustaining nearly 80% of Uganda's population, significant steps have been taken to incorporate AI into Agri-insurance practices.

Initiatives like the agro-consortium which unites multiple insurance firms, backed by government support, are already making insurance more accessible and affordable for farmers. This collaborative approach is currently alleviating financial pressures and strengthening the agricultural sector's resilience. One notable advancement is the utilization of AI-driven satellite data for weather pattern analysis and predictions (Uganda Insurance Regulatory Authority, 2022). By leveraging satellite technology, insurance companies can swiftly assess crop damages caused by events like droughts or floods, enabling them to process legitimate claims without the need for on-the-ground assessments.

In operations, AI is transforming how insurance companies integrate data internally. Through the implementation of smart solutions, authorized staff can access certain data anywhere in the world at the comfort of their laptops, granting staff instant access to critical data. This not only enhances operational efficiency but also bolsters business continuity plans, as demonstrated during crises like the COVID-19 pandemic. Companies embracing AI and digitalization in their operations are better positioned to navigate disruptions, ensuring uninterrupted service delivery, and staying ahead in the market.

However, despite these advancements, challenges such as regulatory compliance, integration complexities, and data privacy concerns persist, hindering the widespread adoption of AI in the Ugandan insurance industry (Uganda Insurance Regulatory Authority, 2022).

Therefore, this study aims to comprehensively review the application of AI in insurance. Indeed, a significant amount of research has been devoted to understanding how AI has been applied in insurance. In other words, studies on the application of AI in insurance are extensive and varied, highlighting its potential to revolutionize various aspects of the insurance value chain (Kose, Gokturk, & Kilic, 2015; Kelley et al., 2018; Ekin, 2020; Park, Park & Choi, 2021; Kotb & Ming, 2021; Aslam et al., 2022; and Arumugam & Bhargavi, 2023).

Notwithstanding the considerable progress made in the AI in insurance field. Research on this topic is still fragmented and lacks comprehensive synthesis. Existing research on AI application in insurance may be viewed to focus on two overarching domains of investigation. One focusing on antecedents of artificial intelligence in insurance and the other on its intermediaries. Studies on antecedents have examined factors such as technological capabilities, data availability, regulatory frameworks, and organizational readiness for AI adoption.

Conversely, research on AI's intermediaries explores into the mechanisms through which AI is operationalized within insurance organizations, encompassing aspects such as algorithmic decision-making processes, human-AI interactions, and the integration of AI technologies into existing workflows.

Despite the richness of insights offered by these two strands of literature, a comprehensive synthesis that bridges the gap between antecedents and intermediaries of AI in insurance is conspicuously absent (Kenett & Luciano, 2023). While several empirical studies have provided valuable insights into specific applications of AI in insurance, there is a notable absence of cohesive frameworks or overarching theoretical models that integrate these findings into a unified understanding.

Up until now, a concise review of AI application in insurance is provided in the work of Cattaneo, Kenett and Luciano (2023) and a generalized review of artificial intelligence in banking, financial services, and insurance in the work of Herrmann and Masawi (2022). As a result, there exists a gap in the academic literature wherein the broader implications and interconnections of AI applications across different facets of the insurance industry remain underexplored (Herrmann & Masawi (2022). As such, we find it prudent in this study to identify, categorize, and analyze relevant studies and provide an understanding of the current state of artificial intelligence application in the insurance sector.

To this end, the objective of this study is to comprehensively review both conceptual and empirical studies on artificial intelligence application in insurance published in academic journals from the year 1980 to 2023. In line with the recommendations by Ekin (2020), and Hamdoun (2021), and the work of Imam, Soliman, & Abdel-Atty (2023).

The present review will take a framework-based approach using the antecedents, decisions, and outcomes (ADO) and theories, contexts, and methods (TCM) frameworks by Paul & Benito (2018) to answer the following research questions:

1. What antecedents, decisions and outcomes characterize the application of artificial intelligence in insurance?
2. What are the theories, contexts, and methods used to study artificial intelligence in insurance?
3. What are the directions for future research and its implications within the field of artificial intelligence in insurance?

The rest of this paper is structured as follows: section 2 provides a summary outlining the developing field of artificial intelligence in insurance, covering its core concepts and influential studies. Section 3 describes in detail the methodology used to systematically select studies for analysis. Section 4 presents the findings of the primary studies selected covering the antecedents, decisions, and outcomes of artificial intelligence application in insurance and the theories, contexts, and methods employed by past studies to develop those findings. Section 5 concludes the research and offers suggestions for future research on insurance artificial intelligence.

2.0 THEORETICAL BACKGROUND

2.1. Artificial intelligence

The field of Artificial Intelligence (AI) has a rich history dating back to the mid-20th century, with foundational concepts emerging in the 1940s and 1950s through the pioneering work of Alan Turing, John McCarthy, Marvin Minsky, and others (Kelley, Fontanetta, Heintzman, & Pereira, 2018). AI, as defined by various scholars, encompasses the ability of machines or computer programs to learn, reason, and solve problems (Zhang & Lu, 2021). Moreover, AI is viewed as a specialized branch of computer science dedicated to developing systems capable of executing tasks traditionally reserved for human intelligence (Su et al., 2021). These perspectives collectively underscore the complexity and transformative potential of AI across diverse domains.

Furthermore, the theoretical framework of AI has laid the groundwork for the development of various models, such as Neural Networks, Decision Trees, and Support Vector Machines (France et al., 2016). Neural Networks, mimicking the structure and function of the human brain, excel in learning complex patterns from data. Decision Trees offer transparent models for decision-making, while Support Vector Machines excel in classifying data points into distinct categories (Kose, Gokturk, & Kilic, 2015). These models exemplify the multifaceted approaches within AI, each tailored to address specific tasks and challenges.

Moreover, AI is characterized by several dimensions, including technical, ethical, legal, economic, and interdisciplinary considerations (Maillart, 2021). While the technical dimension focuses on the development and refinement of AI methodologies, the ethical and societal dimension delves into the moral and societal implications of AI integration (Su et al., 2021). Additionally, the legal and regulatory dimension addresses governance frameworks governing AI, while the economic dimension explores the profound shifts catalyzed by AI in industries and labor dynamics. Lastly, the interdisciplinary dimension highlights AI's expansive nature, transcending the confines of computer science (Lim, Rasul, Kumar, & Ala, 2022).

2.2 Artificial Intelligence and Insurance

The application of artificial intelligence in the insurance industry has evolved and as such it is portrayed as the use of computational algorithms to analyze data for decision-making, risk assessment, fraud detection, and personalized healthcare services (Russell & Norvig, 2016). Indeed, AI's impact on insurance spans diverse areas, including claims processing, underwriting, customer service, customized medicine insurance (Chen et al., 2019; Lohr, 2020).

Moreover, the integration of AI in insurance systems marks a paradigm shift in the industry, reshaping and reimaging several insurance processes. While AI-powered interventions offer immense potential for improving operational efficiency, fraud detection capabilities, customer satisfaction, and premium pricing strategies, they also necessitate a reevaluation of existing practices and frameworks (Azzone, Barucci, Moncayo, & Marazzina, 2022). To address challenges arising from data limitations, inadequate skills in AI, and the industry's historical aversion to risk and tradition. As insurers navigate this transformative journey, collaboration among insurers, regulators and technology providers becomes essential for driving innovation and ensuring the responsible adoption of AI in the insurance sector.

3.0 METHODOLOGY

3.1 Review Method

This study utilizes a systematic literature review methodology for its reproducible, transparent, unbiased, rigorous, and scientific approach (Palmatier et al., 2018). It involves identifying, screening, and synthesizing existing research studies relevant to a particular research question (Depraetere, Vandeviver, & Keygnaert, 2021). Lim, Kumar, and Ali (2022) outline four categories under which a systematic review can be broadly classified, these are theory-based review (Gilal et al., 2019, 2021; Lim, 2020; Lim & Weissmann, 2021; Paul & Rosado-Serrano, 2019), Meta-analytical review (Rana & Paul, 2020; Schmid & Morschett, 2020; Tang & Buckley, 2020), Method-based review (Ji et al., 2019) and the Domain-based review.

Moreover, the domain-based review is further classified into five subtypes. Indeed, these are the structured review that synthesizes theories, constructs, contexts, and methods in literature related to specific research themes (Canabal & White, 2008; Hao et al., 2019; Kahiya, 2018; Paul & Feliciano-Cestero, 2020; Paul & Singh, 2017; Rosado-Serrano et al., 2018); the bibliometric review that focuses on publication statistic (Donthu et al., 2020; Vallaster et al., 2019); a hybrid review that integrates different tenets of domain-based reviews (Kumar et al., 2020); reviews aiming for theory development that focus on creating theoretical models, hypotheses, or propositions for future testing (Paul & Mas, 2020; Sharma et al., 2021) and a framework-based reviewwhich utilizes existing organizing frameworks like ADO or TCCM to structure the review. Alternatively, authors may choose to develop their framework, as illustrated by previous studies (Paul & Benito, 2018; Paul & Mas, 2020).

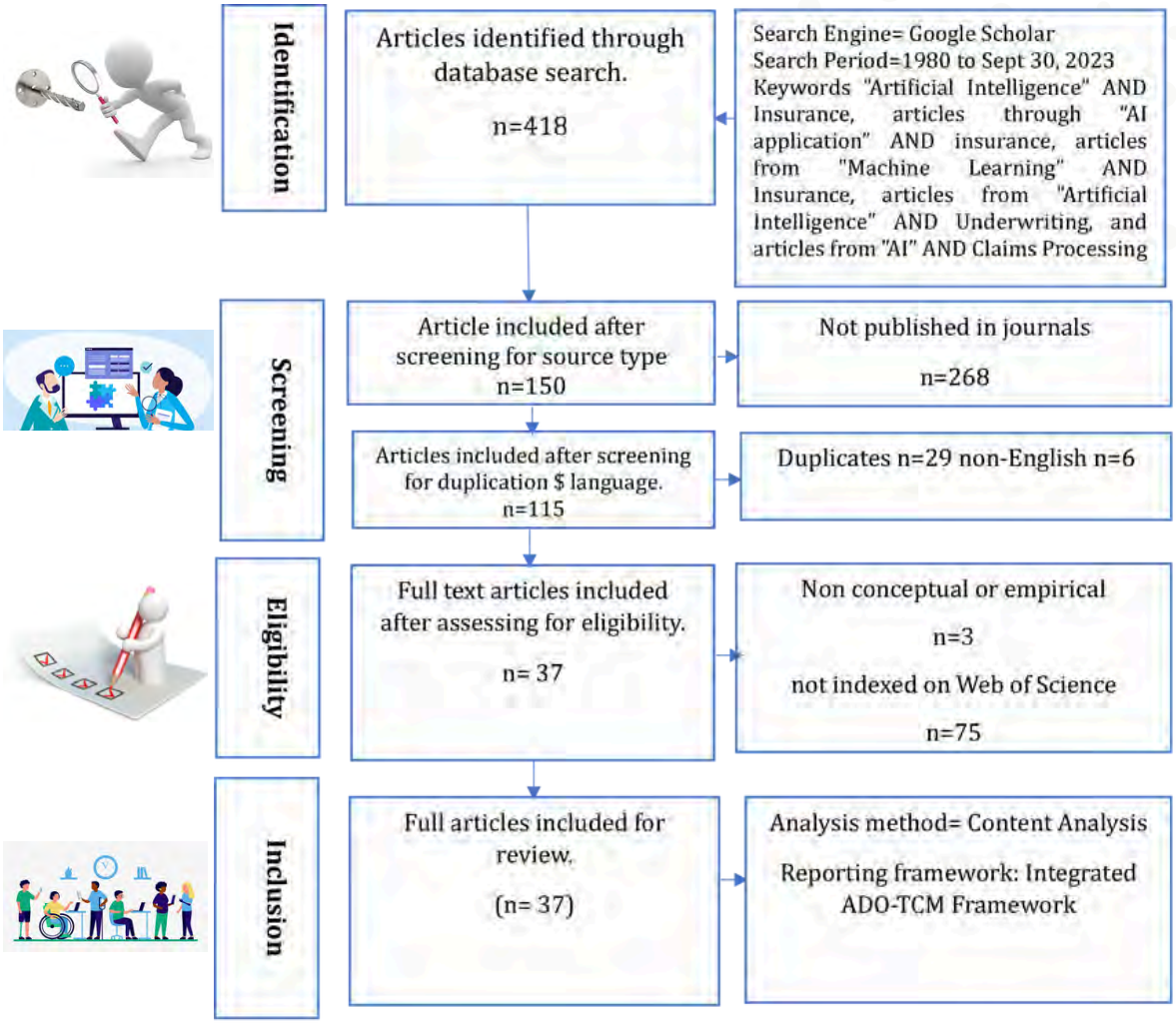
Considering this study's focus on artificial intelligence application in insurance we adopt an integrated organizing framework-based review approach that aligns with the work of Lim, Yap, and Makkar's approach (2021). we merge two pivotal frameworks typically utilized in systematic reviews: the ADO framework (Paul & Benito, 2018), that captures the antecedents, decisions, and outcomes pertinent to artificial intelligence in insurance, and the TCM framework (Paul et al., 2017), shaping the examination of theories, contexts, and methodologies employed in understanding the application of artificial intelligence in insurance. lessons derived from this review, guided by these frameworks, aim to illuminate existing gaps and future research direction in the field of insurance artificial intelligence.

3.2 Review Procedure

This review follows the widely accepted PRISMA reporting protocol for systematic literature reviews (Moher et al., 2009). Although the PRISMA protocol was first adopted in healthcare systematic literature eview research, it has been demonstrated that reviews in other fields, such as

insurance studies, can benefit just as much from the methodology (Huurne et al., 2017; Lim, Yap, & Makkar, 2021). The protocol suggests four steps to creating a thorough scientific review. These are Identification, screening, eligibility, and inclusion. In the next sections we provide an explanation of the action we performed in each of these steps, along with their rationale. The flow diagram, illustrating the details of each phase, is presented in Figure 1.

Figure 1. Review procedure based on the PRISMA protocol.



3.2.1 Identification

In the identification stage, we conducted a thorough search for articles from 1980 to 2023 using Google Scholar as our chosen search engine. This broader search period of over four decades, concluding at the time of our search (September 30, 2023), aimed to encompass the historical evolution and the most recent advancements in artificial intelligence within insurance. Google Scholar was selected due to its comprehensive and timely article indexing capabilities (Gusenbauer, 2019), aligning with similar timeframe criteria utilized in previous studies (Lim, 2021; Paul and Mas, 2020).

To conduct the search, we employed specific keywords determined by the scope of the review. Given that the main objective of this review is to understand the application of artificial intelligence insurance, all selected keywords are used along with the term “insurance”, with some combined with Boolean operator “and” these included (1) “Artificial Intelligence” AND Insurance, (2) “AI application” AND insurance, (3) “Machine Learning” AND Insurance, (4), “Artificial Intelligence” AND Underwriting, and (5) “AI” AND Claims Processing as the concepts are pivotal to our review.

We utilized the "title of the article" option in "advanced search" to yield more precise results. The use of these keywords in both American and British English ensured consistency, excluding alternative spellings. This approach of employing five distinct combinations of keywords in our search strategy aligns with recommendations from recent systematic reviews (Lim, Yap, and Makkar, 2021), reflecting the appropriateness and efficacy of utilizing combinations for comprehensive search results.

Limiting the key words aligns with recent systematic review recommendations, ensuring effective and comprehensive search results (Lim, Yap, and Makkar, 2021). The search yielded a total of 418 articles. Specifically, 208 articles were identified through the keywords "Artificial Intelligence” AND Insurance, 3 articles through “AI application” AND insurance, 200 articles from "Machine Learning” AND Insurance, 5 articles from "Artificial Intelligence” AND Underwriting, and 2 articles from "AI” AND Claims Processing. This extensive collection was then subjected to the screening stage.

3.2.2 Screening

In the screening stage, articles were subjected to a systematic evaluation based on source type, language proficiency and duplication. The selection of this methodology was determined as the most effective through careful consideration by the authors. Notably, the screening process of the publication source, resulted in the exclusion of 268 articles (comprising 221 from the category "Artificial Intelligence AND Insurance," 1 from "AI application in insurance," 44 from "Machine Learning in Insurance," and 2 from "AI AND Claims Processing"). These were not eliminated as they were not published in journals but rather in alternative formats such as books, book chapters, conferences, and working papers.

This is in line with Paul et al. (2021), who suggested that non-journal articles may lack the requisite rigor and thoroughness of a peer-review process. Subsequently, the remaining pool of 150 were screened for language and duplication. Within this stage, 6 articles written in languages other than English were eliminated (comprising three from "Artificial Intelligence AND Insurance" and three from "Machine Learning in Insurance"). We further removed 29 duplicates to prevent double counting. Consequently, a total of 115 articles fulfilled the established screening criteria, and their full texts were retrieved via databases (e.g., JSTOR, ScienceDirect) and publishers (e.g., Emerald, Springer, Taylor & Francis), laying the foundation for the subsequent stage of eligibility assessment.

3.2.3 Eligibility

In the eligibility stage, we perform manual content screening of the 115 articles based on the following exclusion criteria: article type and source quality, conceptual and empirical articles as foundational knowledge contributors. Editorials and book reviews were deliberately excluded given their potential limitations in comprehensive and rigorous knowledge-building compared to conceptual and empirical articles. Additionally, to prevent redundancy in reporting, systematic reviews such as meta-analysis were excluded. In total, 10 non-conceptual and non-empirical articles were excluded from our review. Following that, we assessed the remaining articles for source quality. In this process, we included only articles indexed on web of science database to ensure a selection of high-quality, peer-reviewed articles with global relevance and recognized impact within academic circles, a practice deemed acceptable for niche fields by Paul et al. (2021). We distinguish journals with the new metric, The Journal Citation Indicator that measures the average Category Normalized Citation Impact (CNCI) of citable items over a recent three-year period, aiding in evaluating journals beyond the Journal Impact Factor (JIF). In total, 68 articles were eliminated as they did not meet the specified threshold. This resulted in 37 considered for the subsequent review stage.

Table 2 Articles included in the systematic review.

Authors	Journal	Year	Journal Citation Indicator (JCI) 2022
Arumugam, S., & Bhargavi, R.	International Journal of Software Innovation (IJSI)	2023	0.18
Aslam, F., Hunjra, A. I., Ftiti, Z., Louhichi, W., & Shams, T.	Research in International Business and Finance	2022	2.05
Azzone, M., Barucci, E., Moncayo, G. G., & Marazzina, D.	Expert Systems with Applications	2022	1.73
Banks, D.	Applied Stochastic Models in Business and Industry	2020	0.45
Banulescu-Radu, D., & Yankol-Schalck, M.	Journal of Risk and Insurance	2023	0.59
Castellani, G., Fiore, U., Marino, Z., Passalacqua, L., Perla, F., Scognamiglio, S., & Zanetti, P.	Applied Stochastic Models in Business and Industry	2021	0.45
dos Santos, J. R. R., Dias, C. M., & Chiavegatto Filho, A.	Health Policy and Technology	2021	1.37
Ekin, T.	Applied Stochastic Models in Business and Industry	2020	0.45
Fenton, D., Diaz, A., Chen, H., Armstrong, M., Auger, S., Bujnowski, D., Pedroza, A., Polster, S., Das, P., & Horowitz, P.	International Forum of Allergy & Rhinology	2023	2.29
Fung, G., Polania, L. F., Choi, S.-C. T., Wu, V., & Ma, L.	Frontiers in Applied Mathematics and Statistics	2021	0.39
Hamdoun, N.	International Journal of Applied Pattern Recognition	2021	0.11
Henckaerts, R., Côté, M. P., Antonio, K., & Verbelen, R.	North American Actuarial Journal	2020	0.60
Henckaerts, R., Côté, M.-P., Antonio, K., & Verbelen, R.	North American Actuarial Journal	2021	0.60
Ho, C. W. L., Ali, J., & Caals, K.	Bulletin of the World Health Organization	2020	2.16
Hu, S., O'Hagan, A., Sweeney, J., & Ghahramani, M.	Annals of Actuarial Science	2021	0.60
Hur, J., Tang, S., Gunaseelan, V., Vu, J., Brummett, C. M., Englesbe, M., Waljee, J., & Wiens, J.	The American Journal of Surgery	2021	1.14
Imam, M., Soliman, H. Y., & Abdel-Atty, H. M.	Journal of Health Management	2023	0.17
Islam, M. M., Yang, H.-C., Poly, T. N., & Li, Y.-C. J.	JMIR Medical Informatics	2020	0.68
Itri, B., Mohamed, Y., Omar, B., & Mohamed, Q.	International Journal of Advanced Computer Science and Applications	2020	0.17

Johnson, M., Albizri, A., & Harfouche, A.	Information Systems Frontiers	2021	0.56
Kelley, K. H., Fontanetta, L. M., Heintzman, M., & Pereira, N.	Risk Management and Insurance Review	2018	0.30
Kose, I., Gokturk, M., & Kilic, K.	Applied Soft Computing	2015	1.57
Kotb, M. H., & Ming, R.	International Journal of Advanced Computer Science and Applications	2021	0.17
Kreif, N., DiazOrdaz, K., Moreno-Serra, R., Mirelman, A., Hidayat, T., & Suhrcke, M.	Health Services and Outcomes Research Methodology	2021	0.53
Lee, Byung-Hyun, Kwang-Sig Lee, Hae-In Kim, Jae-Seung Jung, Hyeon-Ju Shin, Jong-Hoon Park, Soon-Cheol Hong, and Ki Hoon Ahn	Diagnostics	2022	0.85
Li, H.-J., Luo, X.-G., Zhang, Z.-L., Jiang, W., & Huang, S.-W.	Decision Support Systems	2023	1.36
Maillart, A.	European Actuarial Journal	2021	0.37
Monlezun, D., McCormack, M., Karla, A., Iliescu, G., Koutroumpakis, E., Khalaf, S., Park, J., Kim, J. W., Honan, K., & Cilingiroglu, M.	Cardiovascular Interventions	2023	0.58
Murray, N. M., Phan, P., Hager, G., Menard, A., Chin, D., Liu, A., & Hui, F. K.	The Neuroradiology Journal	2022	0.29
Neumann, Ł., Nowak, R. M., Okuniewski, R., & Wawrzyński, P.	Applied Artificial Intelligence	2019	0.42
Nguyen, K. A. T., Nguyen, T. A. T., Nguelifack, B. M., & Jolly, C. M.	Marine Resource Economics	2022	0.85
Park, J. K., Monlezun, D., Ali, A., Honan, K., Kim, J. wan, Patel, R., Javaid, A., Karla, A., Palaskas, N. L., & Cilingiroglu, M.	Journal of the American College of Cardiology	2023	4.89
Park, S. H., Choi, J., & Byeon, J.-S.	Korean Journal of Radiology	2021	1.41
Park, S. H., Park, C. M., & Choi, J.-I.	Journal of the Korean Medical Association/Taehan Uisa Hyophoe Chi	2021	0.08

Riikkinen, M., Saarijärvi, H., Sarlin, P., & Lähteenmäki, I.	International Journal of Bank Marketing	2018	1.07
Rushinek, A., & Rushinek, S. F.	Cybernetics and Systems: An International Journal	1987	0.24
Su, S.-C., Huang, C.-C., Gung, R. R., Hsiung, L.-K., Gao, Z.-W., & Tsai, C.-E.	Applied Sciences	2021	1.49

3.2.4 Inclusion

In the inclusion stage, we conducted in-depth content analysis on 37 conceptual and empirical articles that were under review and sourced from the Web of Science. The final dataset included journals spanning a wide range of disciplines, including computer science, business, finance, health sciences, mathematics, statistics, and actuarial science. Specifically, we systematically extracted Key information with regards to the bibliometric characteristics of the Studies; antecedents, decisions, outcomes, as well as the theories, contexts, and methodologies used in the study of AI in insurance. We followed the integrated ADO (Paul & Benito, 2018) and TCM (Paul et al., 2017) frameworks for systematic reviews, as highlighted by Lim, Yap, and Makkar (2021). Both authors collaborated on content analysis and thematic categorization. We followed the interrater agreement assessment steps which yielded a 90% score, surpassing the acceptable 80%. Systematically following these steps enhanced rigor, reliability and consistent application of the inclusion and exclusion criteria by the authors.

4.0 RESULTS

This section presents the results of our analysis of the application of artificial intelligence in the insurance industry. First, we examined the bibliometric characteristics of the studies, systematically extracting key information regarding citation patterns, authorship trends, and publication sources. In addition to exploring antecedents, decisions, and outcomes inherent in the integration of AI, we meticulously examined the theories, contexts, and methodologies applied in the study of AI within insurance. Finally, we addressed the potential directions for future research, discussing their implications for the advancing field of insurance artificial intelligence.

4.1 Bibliometric Characteristics of the Studies

This section analyzes journal statistics and publication trends.

4.1.1 Journal of Publication

Table 1 presents a breakdown of the distribution of articles across various academic journals considered in this study. The results showed that the dataset of 37 articles is spread over 34 journals (Table 1). Notably, the results reveals that the journal of Applied Stochastic Models in Business and Industry and the North American Actuarial Journal exhibited the highest frequency of articles in the area under review, highlighting a noteworthy presence in the explored literature. The dataset further signifies a diversified distribution of articles across journals covering a range of academic scopes, notably in computer science, business, finance, health sciences, mathematics, statistics, and actuarial science.

Table 3: Articles distribution over journal publication.

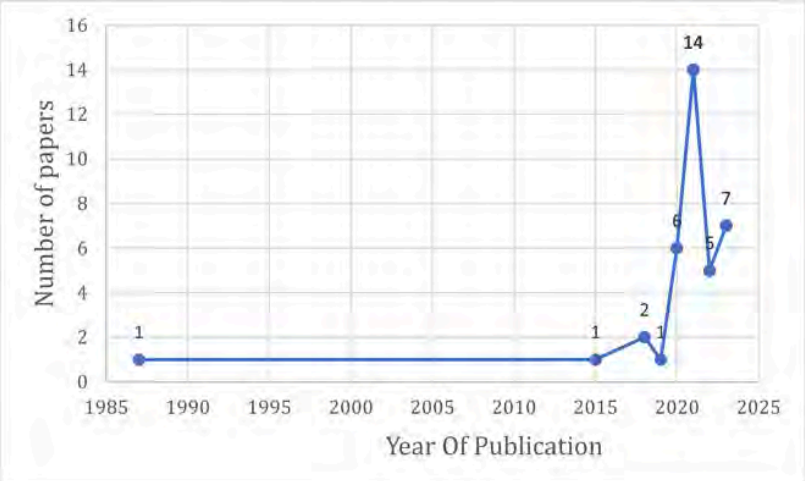
Journal Tittle	No. of Articles
International Journal of Software Innovation (IJSI)	1
Research in International Business and Finance	1
Expert Systems with Applications	1
Applied Stochastic Models in Business and Industry	3
Journal of Risk and Insurance	1
Health Policy and Technology	1
International Forum of Allergy & Rhinology	1
Frontiers in Applied Mathematics and Statistics	1
International Journal of Applied Pattern Recognition	1
North American Actuarial Journal	2
Bulletin of the World Health Organization	1
Annals of Actuarial Science	1

The American Journal of Surgery	1
Journal of Health Management	1
JMIR Medical Informatics	1
International Journal of Advanced Computer Science and Applications	1
Information Systems Frontiers	1
Risk Management and Insurance Review	1
Applied Soft Computing	1
International Journal of Advanced Computer Science and Applications	1
Health Services and Outcomes Research Methodology	1
Diagnostics	1
Decision Support Systems	1
European Actuarial Journal	1
Cardiovascular Interventions	1
The Neuroradiology Journal	1
Applied Artificial Intelligence	1
Marine Resource Economics	1
Journal of the American College of Cardiology	1
Korean Journal of Radiology	1
Journal of the Korean Medical Association/Taehan Uisa Hyophoe Chi	1
International Journal of Bank Marketing	1
Cybernetics and Systems: An International Journal	1
Applied Sciences	1

4.1.2 Publishing Trends

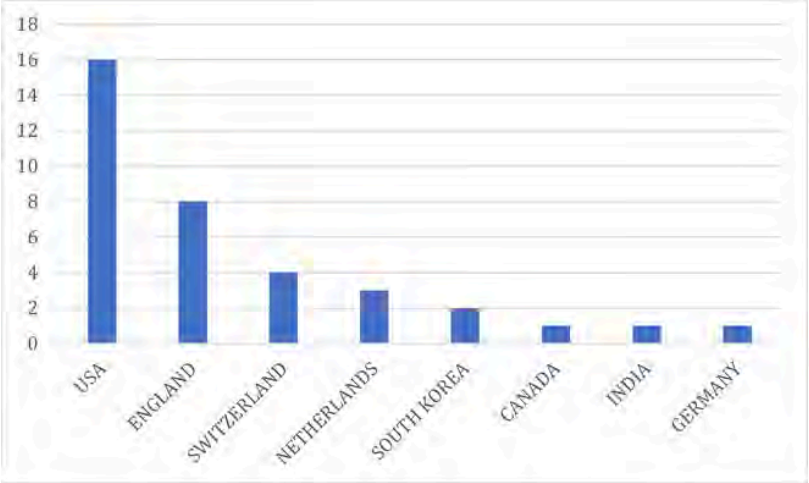
Graph 1 illustrates the evolving publishing trends within the field of artificial intelligence in insurance research. The graphical representation depicts an upward trajectory in recent years from 2015-2023, indicative of heightened scholarly interest among researchers and academicians. This surge in publication output attests to the growing focus on understanding the application of artificial intelligence in insurance.

Graph 1: Publishing trends



4.1.3 Geographic Origin of Published Papers

Graph 2: Country of sample data



Graph 2 outlines the origins of the sample data, depicting that the majority of studies were from the USA, constituting 16 out of the total sample. England followed with 8 studies, and Switzerland with 4. The Netherlands had 3 studies, while South Korea, Canada, India, and Germany each contributed 2, 1, 1, and 1 study(s) respectively.

4.1.4 Distribution of AI Applications in Insurance Studies by Context

Table 3 illustrates the broad spectrum of AI applications in insurance, as evidenced by the study results. The studies covered diverse contexts in which the studies on AI applications in insurance have been conducted. Fraud detection was a prevalent theme, with eight studies. Three studies focused on lapse prediction in life insurance contracts. Six studies explored usage-based insurance, reflecting the rise of personalized coverage. Health data segmentation, examined in three studies, aimed at improving evidence and segmentation. Four studies delved into AI-driven clinical recommendations. Three studies investigated policy impacts in health insurance using causal machine learning. Another three studied disparities in various medical procedures. Two studies explored the interplay between insurance and socioeconomic factors. Individual studies addressed an automated recommendation system, an interactive diagnostic system, claims frequency, improving insurance tariff plans, and predicting customer decisions in car insurance. These varied themes highlighted the multifaceted impact of AI in reshaping the insurance landscape.

Context	Frequency
Fraud detection	8
lapse prediction in Life insurance	3
Usage-based insurance	6
Health data segmentation	3
Clinical recommendations using AI	4
Policy impacts in health insurance	3
Disparities in various medical procedures	3
Insurance and Socioeconomic Factors	2
Automated Recommendation System for Clinical Tests	1
Interactive diagnostic system	1
Claims frequency	1
Improving insurance tariff plans	1
Predictions of Customer Decisions in Car Insurance	1

The subsequent sections employ the ADO-TCM framework to ensure a thorough examination of the antecedents, decisions, and outcomes inherent in the application of AI. We meticulously examine the theories, contexts, and methodologies applied in the study of AI within insurance. Subsequently, we provide potential direction for future research.

4.2 Antecedents, Decisions, and Outcomes of AI Application in Insurance

The systematic literature review unearthed a spectrum of antecedents, decisions, and outcomes that characterize the application of artificial intelligence in the insurance sector. Antecedents which are the factors influencing the adoption of artificial intelligence encompassed aspects such as technological advancements, regulatory changes, and market dynamics triggered the adoption of artificial intelligence in insurance. Decisions involved strategic choices made by insurance firms regarding the types of AI technologies to employ, integration processes, and data management strategies. Outcomes were diverse, including enhanced operational efficiency, improved risk assessment, and the development of innovative insurance products tailored to individual customer needs. Overview of factors influencing the adoption of AI in insurance.

Table 3: Antecedents, decisions, and outcomes of AI Application in Insurance (current research

Antecedents	Decisions	Outcomes
External Factors	Technological	Operational
Internal Factors	Strategic	Business
Industry-specific Factors	Ethical and Regulatory	Social and Ethical

4.2.1 Antecedents of AI Application in Insurance

The insurance literature identifies different antecedents that lead to application in insurance.

External Factors

Technological Advancements

Technological advancements play a pivotal role in driving the adoption of AI in the insurance sector. The rapid progress in AI technologies, including advancements in machine learning algorithms, natural language processing, and computer vision, has significantly enhanced the feasibility and effectiveness of AI applications in insurance (Fung et al., 2021). Insurers are leveraging these advancements to develop innovative solutions for various aspects of insurance operations, such as underwriting, claims processing, and risk assessment.

Regulatory Changes

Changes in regulations related to data privacy, security, and AI usage have a profound impact on how insurance companies implement AI solutions. Regulatory bodies are increasingly focusing on ensuring ethical and responsible AI practices within the insurance industry. Compliance with regulations such as GDPR, CCPA, and regulatory guidelines on AI usage in insurance becomes imperative for insurers adopting AI technologies (Henckaerts et al., 2020). These regulatory changes shape insurers' decisions regarding data governance, algorithm transparency, and customer data protection.

Market Dynamics

Market dynamics, including shifts in consumer behavior, competitive landscape, and market trends, influence the strategic decisions of insurance firms regarding AI adoption. Insurers are under pressure to stay competitive and meet evolving customer demands in a rapidly changing market environment (Ho et al. 2020). The emergence of InsurTech startups, changing customer expectations for personalized services, and increasing competition from digital disruptors are driving insurers to explore AI solutions to enhance their market positioning and competitiveness.

Internal Factors

Need for Efficiency and Accuracy

The need to streamline operations, improve accuracy in risk assessment, and enhance decision-making processes within insurance companies is a critical internal factor driving AI adoption. Hamdoun (2021) discussed how machine learning is transforming the insurance sector, particularly in the case of fraud detection in Morocco, where the need for accurate fraud detection drives the adoption of AI technologies. Insurers face challenges in efficiently processing large volumes of data, conducting manual underwriting processes, and detecting fraudulent claims. AI technologies offer opportunities to automate and optimize these processes, leading to improved operational efficiency, faster decision-making, and better risk management.

Challenges in Traditional Processes

Insurance companies encounter challenges in traditional processes, such as manual underwriting, claims processing, and risk assessment, which create pressure for adopting AI solutions. Challenges in traditional processes, as identified by Henckaerts et al. (2021), create pressure for adopting AI solutions to address issues such as manual underwriting processes, rising data volumes, and fraudulent claims.

Manual processes are often time-consuming, error-prone, and lack scalability to handle the growing complexity of insurance operations. Rising data volumes, increasing fraud incidents, and evolving customer expectations necessitate the adoption of AI technologies to overcome these challenges and stay competitive in the market.

Cost-benefit Analysis

Insurance companies conduct cost-benefit analysis to assess the feasibility and potential benefits of implementing AI solutions. Cost-benefit analysis, as studied by Kotb and Ming (2021), plays a crucial role in decision-making regarding AI adoption, with insurance companies weighing the costs of implementation against the potential benefits in terms of efficiency, accuracy, and customer satisfaction. While AI adoption offers opportunities for efficiency gains, improved accuracy, and enhanced customer satisfaction, it also involves significant upfront investments in technology, infrastructure, and talent acquisition. Insurers weigh the costs of AI implementation against the expected benefits, considering factors such as operational efficiency, risk mitigation, and competitive advantage, to make informed decisions about AI adoption.

Industry-specific Factors

Customization and Personalization

The demand for personalized customer experiences and tailored insurance products is driving the adoption of AI in the insurance industry. Islam et al. (2020) discussed the development of an artificial intelligence-based automated recommendation system for clinical laboratory tests, highlighting the importance of customization in improving patient safety by ensuring accurate laboratory tests. Insurers are leveraging AI technologies to analyze vast amounts of customer data and gain insights into individual preferences, behaviors, and risk profiles. By offering personalized recommendations, pricing, and coverage options, insurers can enhance customer engagement, satisfaction, and loyalty, ultimately driving business growth and profitability.

Ethical Consideration

Ethical considerations, as examined by Johnson et al. (2021), also shape insurers' choices in AI adoption and implementation, particularly in ensuring responsible artificial intelligence in healthcare and preventing insurance claim denials for economic and social well-being. Concerns about fairness, transparency, and accountability in AI decision-making processes influence insurers' choices in AI adoption and implementation. Ethical considerations arise in areas such as algorithmic bias, privacy protection, and algorithm explain-ability.

Insurers must ensure that AI systems are designed and deployed in a manner that upholds ethical principles, respects individual rights, and fosters trust and confidence among customers, regulators, and other stakeholders.

Operational Challenges

Operational challenges, including manual processes, data silos, and legacy systems within insurance companies, create opportunities for AI to streamline operations and improve efficiency, as discussed by Maillart (2021) in the context of claim frequency prediction in car insurance pricing with telematics data. Insurers face difficulties in integrating disparate data sources, extracting actionable insights, and automating repetitive tasks. AI technologies offer solutions to address these operational challenges by enabling data-driven decision-making, process automation, and workflow optimization, leading to cost savings, productivity gains, and enhanced competitiveness in the market.

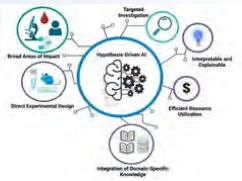
4.2.2 Associated Decisions of AI Application in Insurance

In the application of AI within the insurance sector, decisions are pivotal in shaping the trajectory of implementation and utilization. These decisions can be categorized into three main domains: Technological Decisions, Strategic Business Decisions, and Ethical and Regulatory Decisions. Each domain encompasses distinct factors that influence the adoption, implementation, and ethical usage of AI technologies in the insurance industry.

Technological Decisions

Selection of AI Technologies

Insurance companies must decide on the most suitable AI technologies to address their specific business needs. This involves selecting appropriate AI technologies, algorithms, and integration processes. Research by Fung et al. (2021) emphasized the importance of choosing AI technologies that align with the specific needs and objectives of insurance companies. This decision involves evaluating various AI techniques such as machine learning, natural language processing, and computer vision to determine which best aligns with the company's objectives.



Utilization of Specific Algorithms

Once the AI technology is chosen, the next decision revolves around selecting the appropriate algorithms or models to tackle specific tasks within insurance operations. This entails considering factors such as the complexity of the task, available data, and desired outcomes, leading to choices like deep learning architectures, recurrent neural networks, decision trees, and more. Hamdoun (2021) further illustrated the significance of utilizing machine learning for fraud detection in the insurance sector, highlighting the practical applications of AI in addressing industry challenges.

Integration Processes

Integrating AI technologies into existing systems and processes is a critical decision point. Companies must strategize how AI solutions will interact with legacy systems, databases, and workflows while minimizing disruptions to ongoing operations. This decision involves assessing compatibility, scalability, and potential challenges in deployment. studies by Henckaerts et al. (2020, 2021) emphasized the effectiveness of tree-based machine learning methods in gaining insights into insurance tariff plans, showcasing the relevance of algorithm selection in optimizing insurance operations.

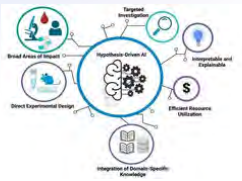
Strategic Business Decisions

Alignment with business goals

Insurance firms must ensure that AI adoption aligns with broader business objectives. This decision involves identifying areas where AI can provide the most significant impact, such as improving operational efficiency, enhancing risk assessment accuracy, and meeting evolving customer demands for personalized services. Hu et al. (2021) demonstrated the strategic importance of analyzing customer lapse behavior in life insurance using spatial machine learning models, emphasizing the alignment of AI adoption with business goals such as customer retention and risk management.

Cost-benefit analysis

Evaluating the costs associated with AI implementation against the expected benefits is crucial for decision-making. Companies need to assess factors such as initial investment, ongoing maintenance, training costs, and potential returns in terms of efficiency gains, cost savings, and competitive advantage.



Process Optimization

Identifying opportunities for process optimization through AI is another strategic decision point. Insurers must pinpoint areas within their operations where AI can streamline workflows, automate repetitive tasks, and augment decision-making processes to enhance overall efficiency and effectiveness. Moreover, Hur et al. (2021) highlighted the significance of predicting postoperative opioid use with machine learning and insurance claims data, showcasing how AI can inform strategic decisions in healthcare insurance to improve patient outcomes and mitigate risks.

Integration Processes

Integrating AI technologies into existing systems and processes is a critical decision point. Companies must strategize how AI solutions will interact with legacy systems, databases, and workflows while minimizing disruptions to ongoing operations. This decision involves assessing compatibility, scalability, and potential challenges in deployment. studies by Henckaerts et al. (2020, 2021) emphasized the effectiveness of tree-based machine learning methods in gaining insights into insurance tariff plans, showcasing the relevance of algorithm selection in optimizing insurance operations.

Ethical and Regulatory Decisions

Alignment with business goals

Ensuring fairness, transparency, and accountability in AI decision-making processes is paramount. Insurance companies must implement mechanisms to mitigate biases, promote fairness in underwriting and claims processing, and provide clear explanations for AI-driven decisions to build trust with stakeholders. Ho et al. (2020) emphasized the importance of ensuring trustworthy use of AI and big data analytics in health insurance, highlighting the need for ethical guidelines and safeguards to protect patient privacy and confidentiality.

Compliance with regulations

Adhering to relevant regulations and standards is a critical consideration in AI adoption. Insurance firms must navigate complex regulatory landscapes concerning data privacy, security, and ethical AI practices to avoid legal pitfalls and reputational damage. Studies by Imam et al. (2023) and Islam et al. (2020) underscored the ethical implications of AI applications in healthcare insurance, emphasizing the importance of transparency, fairness, and accountability in decision-making processes.

Mitigation of biases

Mitigating biases in AI algorithms and decision-making processes is essential to prevent discrimination and ensure equitable treatment of policyholders. Companies must implement strategies such as bias detection tools, diverse dataset curation, and ongoing monitoring to identify and address biases in AI systems.

4.2.3 Outcomes of AI Application in Insurance

Operational Outcomes

Enhanced Operational Efficiency

Research by Fung et al. (2021) highlighted how AI adoption leads to enhanced operational efficiency in insurance processes. By leveraging AI technologies such as machine learning and natural language processing, insurance companies can automate routine tasks, streamline workflows, and optimize resource allocation. This results in reduced manual effort, improved productivity, and cost savings across various operational functions.

Faster Claims Processing

Hamdoun (2021) demonstrated the impact of AI on expediting claims processing in the insurance sector. Using machine learning algorithms for fraud detection and pattern recognition, insurers can identify suspicious claims more quickly and accurately, leading to faster resolution and reduced processing times. This not only improves operational efficiency but also enhances customer satisfaction by minimizing delays in claim settlements.

Improved Risk Assessment

Henckaerts et al. (2020, 2021) illustrated how AI-driven analytics improve risk assessment in insurance. By analyzing large volumes of data and employing predictive modeling techniques, insurers can gain deeper insights into risk factors and anticipate potential losses more effectively. This enables them to make informed underwriting decisions, price policies more accurately, and proactively manage risks, ultimately leading to improved profitability and resilience.

Business Outcomes

Development of Innovative Products

Hu et al. (2021) discussed how AI enables the development of innovative insurance products tailored to customer needs. By analyzing customer data and preferences, insurers can identify emerging trends, anticipate market demands, and design customized insurance solutions. This fosters product innovation, expands market reach, and enhances competitiveness in the insurance industry.

Competitive Advantage

Hur et al. (2021) emphasized the role of AI in providing a competitive edge to insurance companies. By leveraging AI for risk prediction, customer segmentation, and personalized services, insurers can differentiate themselves from competitors, attract new customers, and retain existing ones. This strategic advantage enables insurers to strengthen their market position and achieve sustainable growth in a competitive landscape.

Cost Management

Islam et al. (2020) highlight the cost-saving benefits of AI in insurance through fraud detection and risk mitigation. By automating fraud detection processes and improving accuracy through AI-driven analytics, insurers can minimize financial losses due to fraudulent claims. Additionally, AI helps optimize resource allocation, reduce operational overheads, and improve cost efficiency, contributing to overall profitability and financial stability.

Social and Ethical Outcomes

Ethical AI Practices

Ho et al. (2020) emphasized the importance of ethical AI practices in insurance. By adhering to ethical guidelines and regulatory standards, insurers can ensure fairness, transparency, and accountability in AI decision-making processes. This fosters trust among stakeholders, protects consumer rights, and upholds ethical standards in the use of AI technologies.

Customer Trust and Satisfaction

Imam et al. (2023) discussed how ethical AI practices enhance customer trust and satisfaction in insurance. By prioritizing transparency, fairness, and data privacy, insurers can build trust and confidence among customers, leading to higher satisfaction levels, increased loyalty, and positive brand reputation. This strengthens customer relationships and fosters long-term engagement with the insurance provider.

Mitigation of Biases

Kotb and Ming (2021) highlight the importance of mitigating biases in AI algorithms to ensure equitable treatment of all stakeholders. By identifying and addressing biases in data collection, algorithm design, and decision-making processes, insurers can minimize the risk of discrimination and ensure fair outcomes for policyholders, employees, and other stakeholders. This promotes social equity, diversity, and inclusivity in the insurance industry.

4.3 Theories, Contexts, and Methods Used to Study Artificial Intelligence in Insurance

Theories

Theories are the foundations on which the findings of the studies are built (Lim et al., 2021). A total of 23 theories are used to study artificial intelligence in Insurance. Table 2 shows the list of 23 theories used and a brief description of each.

Table 4 List of theories

Theory	Description
Risk management theories	Theories related to managing risks within the insurance industry.
Organizational learning theories	Theories concerning how organizations learn and adapt to new technologies, such as AI.
Innovation diffusion theories	Theories explaining how innovations, like AI, spread and are adopted within organizations.
Machine learning theories	Theoretical frameworks underpinning the development and deployment of machine learning models.
Fairness, accountability, and transparency (FAT) theories	Theories focusing on ensuring fairness, accountability, and transparency in AI systems.
Economic theories	Theoretical frameworks related to economic principles, such as information asymmetry and risk management.
Decision-making theories	Theories explaining how individuals and organizations make decisions, potentially influenced by AI-assisted processes.
Evidence-based medicine (EBM)	A framework for integrating collaborative and participatory methods to establish evidence-based solutions.

4.3.1 Theoretical Frameworks

Theoretical frameworks in the study of artificial intelligence (AI) in insurance encompass various disciplines, including risk management, organizational learning, innovation diffusion, and machine learning theories (Fung et al., 2021). These frameworks provide the conceptual basis for understanding the implications of AI adoption in the insurance domain. For example, risk management theories guide insurers in assessing and mitigating risks associated with AI applications, while organizational learning theories help insurers adapt to technological changes and optimize their operational processes. Innovation diffusion theories shed light on the factors influencing the adoption and diffusion of AI technologies within the insurance industry.

4.3.2 Contexts

The contexts in which AI is studied within the insurance sector are diverse and multifaceted. They range from mature insurance markets in developed countries to emerging markets in developing nations (Ho et al., 2020). Each context presents unique challenges and opportunities for AI adoption, influenced by factors such as regulatory environments, market dynamics, and customer preferences. Understanding this contextual background is essential for tailoring AI solutions to address specific industry challenges and requirements effectively (Park et al., 2021). Additionally, studies explored different insurance domains, including health insurance, property and casualty insurance, life insurance, and reinsurance, each with its own set of contextual factors shaping AI implementation strategies.

Context	Description
Mature insurance markets in developed countries	Contexts involving established insurance markets in developed nations.
Emerging markets in developing nations	Contexts involving emerging insurance markets in developing countries.
Health insurance	Contexts specific to the health insurance sector, focusing on medical coverage and related services.
Property and casualty insurance	Contexts specific to property and casualty insurance, covering damages to property and liability claims.
Life insurance	Contexts specific to life insurance, encompassing policies related to death benefits and financial planning.
Reinsurance	Contexts specific to reinsurance, involving insurance for insurance companies.
Regulatory landscapes	Contexts related to the regulatory environment governing the insurance industry.
Market dynamics	Contexts involving the dynamics of supply and demand, competition, and pricing within insurance markets.
Customer demographics	Contexts related to the characteristics and behaviors of insurance customers.

4.3.2 Methods

Methodologically, studies investigating AI in insurance employ a mix of quantitative analyses, case studies, and qualitative approaches. Quantitative analysis involved statistical modeling, machine learning algorithms, and predictive analytics to evaluate the performance of AI applications in insurance processes such as claims processing, risk assessment, and customer segmentation. Case studies provide insights into real-world implementations of AI technologies by insurance companies, highlighting successes, challenges, and lessons learned. Qualitative approaches, such as interviews and surveys, help researchers understand stakeholders' perspectives, organizational readiness, and ethical considerations surrounding AI adoption in insurance. Overall, a multidisciplinary methodological approach is essential for comprehensively studying the implications of AI in the insurance industry, accounting for both technical and non-technical dimensions of AI implementation (Su, Huang, Gung, Hsiung, Gao, & Tsai, 2021).

5.0 DISCUSSION OF FINDINGS

Significance of AI Adoption in the Insurance Industry in Uganda:

The adoption of AI in the insurance sector in Uganda holds significant implications for the industry's future trajectory. Technological advancements, coupled with evolving market dynamics and regulatory changes, underscore the importance of embracing AI technologies. By integrating AI into various facets of insurance operations, companies can enhance efficiency, accuracy, and customer satisfaction. In Uganda, there is a glimmer of hope for the insurance industry's adoption of AI, albeit through gradual steps. However, for full integration, a robust digital infrastructure is imperative. Presently, the country grapples with bandwidth limitations, restricted internet access, and the affordability of smartphones. Despite these challenges, promising initiatives by telecom providers like MTN, introducing 5G technology, offer a beacon of progress. This technological advancement holds the key to digitalization, laying a solid foundation for AI integration in insurance operations.

Implications for Operational Efficiency:

The findings highlight the potential for AI application to revolutionize operational processes within Ugandan insurance companies. Specifically, AI-driven solutions in underwriting, claims processing, and risk assessment can streamline workflows, reduce manual effort, and expedite decision-making. However, challenges such as data integration and talent acquisition must be addressed to maximize the benefits of AI adoption.

Enhanced Risk Management and Customer Service:

AI-driven risk assessment models and customer service solutions have the potential to significantly improve risk management practices and elevate customer satisfaction in the Ugandan insurance market. By leveraging AI algorithms to analyze vast datasets and personalize interactions, insurers can better understand and mitigate risks while offering tailored services to customers. This could lead to more informed decision-making and increased loyalty among policyholders.

Ethical and Regulatory Considerations:

The ethical and regulatory implications of AI adoption cannot be overlooked in the insurance sector in Uganda. Transparency, fairness, and accountability must be prioritized in AI decision-making processes to uphold consumer trust and regulatory compliance. Regulatory frameworks should be established or strengthened to ensure responsible AI usage, safeguarding consumer rights and promoting industry integrity.

5.1 Implication

The implications of the study on artificial intelligence (AI) in insurance are far-reaching, with significant effect on various stakeholders involved in the insurance ecosystem. For insurance companies, the study underscores the potential benefits of AI adoption, ranging from operational efficiency gains to enhanced risk assessment capabilities. By leveraging AI technologies, insurers can streamline their processes, reduce administrative costs, and offer more personalized products and services to their customers. This not only improves the overall customer experience but also enables insurers to remain competitive in an evolving market landscape. In the context of Uganda, the insurance industry to fully embrace AI, there is need for better digital infrastructure, today we still struggle with limited bandwidth and internet reach, However, amidst these challenges, there are glimmers of promise, particularly with the introduction of initiatives like MTN's 5G network. this will support digitalization which in turn supports the use of AI.

collaborations and partnerships between insurance companies and non-insurance entities present a compelling avenue for advancing the adoption of AI. By joining forces with organizations outside the insurance realm, such as technology firms or financial institutions, insurers can access expertise, resources, and innovative solutions that accelerate the implementation of AI-driven initiatives. For instance, partnerships focused on offering micro-insurance services capitalize on the strengths of both parties to deliver accessible and tailored insurance products to underserved communities.

we can't ignore the idea of insurance in Uganda is still sold by trust and relationships. As an African country, we still treasure connectivity which is a big aspect embedded in culture hence this will slow down the fast growth of AI in general. Policyholders also stand to benefit from the widespread adoption of AI in insurance. AI-driven processes, such as claims processing and risk assessment, can lead to faster and more accurate decisions, resulting in improved customer satisfaction and potentially lower premiums. With AI-enabled risk assessment, insurers can better tailor insurance policies to individual policyholders' needs and behaviors, fostering a more equitable and transparent insurance market.

Regulators play a crucial role in overseeing the responsible adoption of AI in the insurance industry. The study highlights the importance of regulatory frameworks that balance innovation with consumer protection and privacy concerns. Regulators need to ensure that AI applications comply with existing laws and regulations while fostering an environment that encourages innovation and competition. By establishing clear guidelines and standards for AI governance, regulators can help mitigate potential risks associated with AI adoption and safeguard consumer interests.

Ethical considerations surrounding AI adoption are also paramount. As AI technologies become more prevalent in insurance, concerns related to fairness, transparency, and accountability come to the forefront. The study emphasizes the importance of ethical guidelines and standards to govern the use of AI in insurance, ensuring that AI systems are deployed responsibly and ethically to benefit society.

6.0 DIREC TIONS FOR FUTURE RESE ARCH

Future research in insurance artificial intelligence (AI) should prioritize several key areas to address the industry's evolving needs. Firstly, understanding the long-term impacts of AI on customer behavior and satisfaction is crucial for tailoring AI strategies to meet evolving needs and enhance satisfaction levels. Secondly, addressing ethical considerations, such as algorithmic bias and transparency, is essential to ensure responsible AI adoption in insurance operations. Thirdly, exploring the implications of AI for workforce dynamics and developing strategies for upskilling employees are vital for maximizing the benefits of AI adoption while mitigating challenges. Additionally, developing context-specific AI solutions tailored to diverse insurance markets and collaborating across disciplines hold promise for driving innovation and ensuring compliance with regulatory frameworks. Interdisciplinary collaborations between insurers, regulators, researchers, and technology providers can further advance the field of insurance AI by developing holistic solutions to complex challenges.

7.0 CONCLUSION

In conclusion, the systematic literature review has provided valuable insights into AI's application in insurance. Key findings underscore its transformative role in risk management, customer service, and claims processing. The review highlighted diverse theoretical frameworks, contexts, and methods, emphasizing the need for a multidisciplinary approach to tackle industry challenges. Understanding AI's applications is crucial for future advancements, as it has the potential to revolutionize insurance processes and enhance customer experiences. However, addressing ethical, regulatory, and workforce implications is essential. Continued research and collaboration are needed to fully harness AI's benefits and drive industry growth toward a more efficient and customer-centric insurance landscape.

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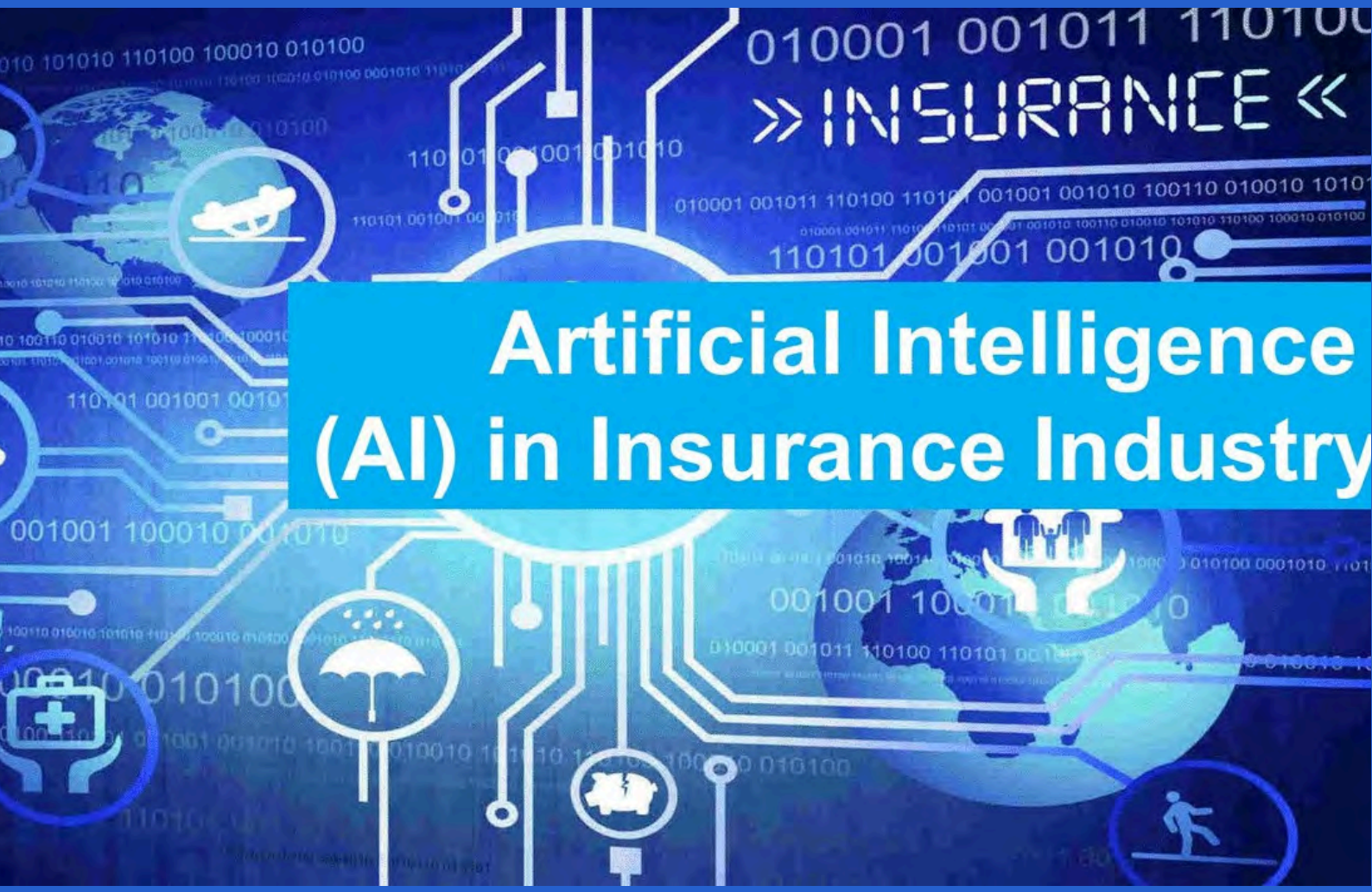

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