Journal of Marketing and Communication

Adoption of Artificial Intelligence Technology and Its Impact on Insurance Company Performance in Kenya

Benjamin Abongo, PhD

ISSN: 2617-359X

Stratford Peer Reviewed Journals and Book Publishing
Journal of Marketing and Communication
Volume 8||Issue 2||Page 54-65 ||December||2025|
Email: info@stratfordjournals.org ISSN: 2617-359X

Adoption of Artificial Intelligence Technology and Its Impact on Insurance Company Performance in Kenya

Benjamin Abongo, PhD

Research Fellow, School of Business and Economics, Department of Business and Economics, Kenya Methodist University.

***How to cite this article*: Abongo, B. (2025). Adoption of Artificial Intelligence Technology and Its Impact on Insurance Company Performance in Kenya. *Journal of Marketing and Communication,* 8(2), 54-65.** https://doi.org/10.53819/81018102t4367

Abstract

This study investigates the adoption of artificial intelligence (AI) technologies and their impact on the performance of insurance companies in Kenya. While AI has been widely acknowledged for improving operational efficiency, risk management, and regulatory compliance, limited empirical evidence exists on its measurable influence within the insurance sector. A descriptive research design was employed, focusing on 71 insurance companies registered with the Insurance Regulatory Authority (IRA). Both qualitative and quantitative data were collected to assess the relationship between AI adoption and organizational performance. The results indicate that AI adoption has a significant positive effect on performance, explaining 57.9% of the variability observed. Technologies such as generative AI, machine learning and deep learning, blockchain, natural language processing (NLP), computer vision, and IoT were found to contribute substantially to operational improvements and customer service delivery. The findings highlight the strategic importance of AI integration in enhancing competitiveness and efficiency within Kenya's insurance industry. Broader adoption of AI technologies is recommended to strengthen performance outcomes across the sector. This study provides empirical evidence on the relevance of AI adoption in the Kenyan insurance industry, addressing a critical gap in existing literature and offering insights for both practitioners and policymakers.

Keywords: *Artificial Intelligence, AI Adoption, Insurtech Artificial Intelligence Technology*

1.0 Introduction

Technological advancements in the financial sector have been deeply transformative, reshaping how financial services are delivered and changing industry practices. Among these innovations, artificial intelligence (AI) has emerged as a disruptive force with widespread effects on the global economy, including the insurance industry (Avenga, 2024). AI's capacity to analyze large datasets, generate predictive insights, and automate complex decision-making processes has made it a vital tool for improving efficiency, accuracy, and customer satisfaction in insurance operations (Luciano et al., 2023).

Core AI technologies, such as machine learning, deep learning, and natural language processing (NLP), are revolutionizing financial decision-making and risk management. In life and non-life insurance, AI-driven systems have improved fraud detection, streamlined claims verification, and accelerated service delivery. By identifying anomalies and fraudulent patterns with greater precision and lower costs, AI reduces financial losses while strengthening operational resilience (Smith, 2023). In life insurance, AI enables faster and more accurate claims validation, thereby improving customer trust and satisfaction (Charlton, 2024). Similarly, in non-life insurance, including auto and property coverage, AI facilitates rapid damage assessment and claim validation, minimizing reliance on manual inspections and reducing turnaround times (Bhumichai et al., 2023).

Beyond operational efficiency, AI plays a pivotal role in regulatory compliance. Automated monitoring and reporting systems allow insurers to meet evolving regulatory requirements, mitigate risks of non-compliance, and reduce associated penalties. Continuous transaction analysis and anomaly detection ensure timely reporting, thereby enhancing compliance frameworks while lowering operational costs (Smith, 2023).

This study investigates the adoption of AI technologies and their impact on insurance company performance in Kenya, with a focus on Insurtech innovations. Specifically, it examines how machine learning and deep learning algorithms enable more accurate risk assessment, premium pricing, and fraud detection, while NLP applications enhance customer service and outreach. By analyzing these dimensions, the research highlights how AI adoption contributes to efficiency gains, improved risk management, regulatory compliance, and expanded market access, ultimately shaping the performance and competitiveness of insurance companies in Kenya (Business Daily Africa, 2024).

1.1 Statement of the Problem

The insurance industry in Kenya is undergoing rapid transformation driven by technological innovation, regulatory reforms, and evolving customer expectations. Among these innovations, artificial intelligence (AI) has emerged as a potentially disruptive force, offering opportunities for enhanced efficiency, improved risk assessment, fraud detection, and customer service personalization. Despite the global momentum in AI adoption, evidence suggests that many insurance companies in Kenya remain hesitant or slow in integrating AI into their operations. This reluctance is often attributed to challenges such as high implementation costs, lack of technical expertise, regulatory uncertainties, and organizational resistance to change.

Existing literature on AI adoption has predominantly focused on developed markets, with limited empirical studies addressing its application and impact within African contexts, particularly Kenya. As a result, there is insufficient understanding of how AI adoption influences the performance of insurance companies in Kenya, including operational efficiency, profitability, customer satisfaction, and competitive advantage. This knowledge gap creates uncertainty for managers, policymakers, and stakeholders seeking to leverage AI for sustainable growth in the sector. Without clear evidence of the relationship between AI adoption and insurance company performance in Kenya, firms risk underutilizing technologies that could enhance competitiveness, while policymakers may struggle to design supportive frameworks that encourage innovation. Therefore, there is a pressing need to investigate the extent of AI adoption in Kenyan insurance companies and to evaluate its impact on organizational performance. Addressing this problem will contribute to both academic discourse and practical decision-making by providing context-specific insights into the role of AI in shaping the future of insurance in Kenya.

1.2 Research Objectives

The study sought to investigate the potential of AI adoption in enhancing the performance and reach of Kenya's insurance industry. Specifically, the study aims to:

i. Explore behavioral intentions toward AI adoption,
ii. Examine current usage patterns, and
iii. Identify actionable strategies to address sector-specific challenges.

2.0 Theoretical and Literature Review

This study is anchored on the disruptive innovation theory. Proposed by Clayton Christensen, this theory suggests that innovations create new markets and value networks, eventually disrupting existing ones. Christensen's disruptive innovation theory has developed for over 20 years and become one of the most important theories in the field of entrepreneurship and innovation, as it has engendered a significant impact on entrepreneurship and innovation practices. Disruptive innovation theory is also mired in some disputes among scholars and practitioners. The first dispute is whether disruptive innovation is 1meaningful to companies, especially to those incumbents. For this issue, a common question is whether the incumbents should proactively respond to or adopt disruptive innovation (Charitou & Markides, 2002). To further understand disruptive innovation, it is very important to uncover factors that influence disruptive innovation. Some researchers simply divide the influence factors into external and internal dimensions, (Damanpour & Wischnevsky, 2006; Nagano *et al.*, 2014), but a subtler division would have more implications and important values for research and practice. AI represents a disruptive innovation in the insurance industry by introducing new ways of processing claims, underwriting, and customer service. In Kenya, AI-driven solutions are transforming traditional insurance practices, making them more efficient and customer-centric (Muiruri, 2023). In the study, AI's role as a disruptive innovation is evident in its ability to streamline operations and reduce costs. For instance, machine learning algorithms for risk assessment leads to more precise pricing models and reduced fraud. However, the disruption also poses challenges, such as the need for significant investment in technology and training.

Adoption of Technology and Artificial Intelligence

There is a growing consensus on the potential of artificial intelligence to transform modern economies and societies by enabling computer systems to carry out numerous tasks and activities that are typically considered to require human intelligence, thereby significantly improving efficiency and efficacy (Abadie et al. 2023; Bolton et al. 2018; Boyd and Holton 2017; Makridakis 2017). The AI has infiltrated virtually all facets of present life; being widely applied in diverse sectors (Abadie et al., 2023; Dastjerdi et al., 2023; Dekker et al., 2020) such as healthcare, business operations, educational, and the financial sectors. Within the finance sector, the insurance industry is undergoing significant transformation driven by the integration of artificial intelligence (AI) technologies (Dwivedi et al., 2021; Erem 2022; Pathak and Bansal, 2024). However, despite the potential benefits, the adoption of AI in the insurance sector is commencing at a slow pace (Pathak and Bansal, 2024; Dekker et al., 2020).

As the adoption of AI in the insurance sector intensifies, it still faces challenges in compatibility, major among them being the language barrier within the community. Smith (2023) observed that one of the barriers affecting the uptake and servicing of insurance clients is language, with insurance products and contracts being designed in languages which are out of reach for many, and the AI's natural language processing and AI-driven chatbots can only provide 24/7 customer support, answering queries or guiding customers through processes in specific languages (Smith 2023; Green 2024). Despite the great interest that the AI technology currently attracts, majority of research studies done in this field, especially targeting the insurance sector, are mainly located within the developed countries. The situation is worse for the sub-saharan region where very little has been done to understand the relevance of AI in the insurance industry. Moreover, there are only a handful of collaborations between insurance institutions and companies that provide AI technologies in developing countries (EIOPA, 2019; Keller 2020; Okeleke et al., 2024), therefore highlighting a major gap in integrating and adopting the AI technologies effectively.

The Kenyan insurance sector faces unique challenges that obstruct the integration and optimization of AI technologies. Infrastructural constraints, such as inadequate digital frameworks and limited access to advanced computing resources, pose significant hurdles. Furthermore, the lack of localized AI solutions tailored to the specific needs of the Kenyan insurance market exacerbates the issue, making the technology less accessible and relevant to insurers and their customers. Compounding these structural barriers is the limited awareness among key stakeholders, insurers, policymakers, and customers of the potential benefits and applications of AI in the insurance landscape. This research seeks to reveal the potential of adopting AI and its utilization to improve the performance and reach of Kenya's insurance industry. Specifically, it aims to explore the behavioral intention of adopting AI, examine the current usage patterns, and identify actionable strategies to overcome the unique challenges faced by the sector. The specific objective of the study is to assess the influence of AI technology adoption on the performance of insurance companies in Kenya.

Role of Artificial Intelligence in Insurance Service Delivery

Artificial intelligence (AI) adoption is increasingly pervasive across the insurance sector, reshaping processes and decision-making throughout the value chain. Eling and colleagues (2021) together with EIOPA (2021) examine the six main stages of the insurance value chain, highlighting how AI contributes to efficiency, risk management, and customer-centric innovation. Tekaya et al. (2020) provide a broader overview of AI applications in financial services, underscoring its benefits in areas such as credit risk management, fraud detection, and insurance operations.

Within the insurance industry, several studies highlight AI's transformative potential, predicting significant operational changes and increased competitiveness. Fraud detection remains a key application, with research showing AI's ability to identify unusual patterns and reduce losses (Verma et al., 2017). Claims reserving has also gained attention, with advanced machine learning models enhancing accuracy and reliability (Baudry & Robert, 2019; Blier-Wong et al., 2021; Lopez & Milhaud, 2021; Wüthrich, 2018). Grize et al. (2020) further demonstrate the role of machine learning in non-life insurance, illustrating its positive effects on risk assessment and profitability.

Methodological advances have expanded AI's utility in insurance analytics. Fang et al. (2016) demonstrated the superiority of Random Forest models over traditional approaches such as linear regression and support vector machines in profitability modelling. Earlier explorations of fuzzy logic by Shapiro (2007) inspired subsequent studies on hybrid fuzzy regression (Baser & Apaydin, 2010) and neuro-fuzzy inference systems for forecasting (Khuong & Tuan, 2016). Clustering techniques have also been reviewed for their relevance to customer segmentation and risk profiling (Nallam Reddy et al., 2014). Decision Trees have been applied to claims prediction (Quan & Valdez, 2018), with Henckaerts et al. (2021) enhancing their interpretability for robust pricing models.

Sarkar (2020) emphasised AI's potential to enhance each stage of the insurance value chain, a perspective echoed by Walsh and Taylor (2020) and Eling et al. (2021). These studies highlight AI's ability to mimic or augment human capabilities through natural language processing, computer vision, and IoT integration. Applications such as AI-driven chatbots and virtual assistants provide continuous customer support, reducing operational costs while improving service quality. Johnson (2022) further demonstrated AI's effectiveness in risk assessment, fraud detection, and claims processing, showcasing its ability to analyse complex data patterns and predict risks with precision.

Complementary technologies reinforce AI's impact in insurance. Zarifis et al. (2023) highlighted blockchain's role in enabling decentralised, secure transactions, with smart contracts automating claims processing and reducing fraud. Green (2021) examined IoT devices, particularly telematics, which provide real-time data for personalised policies and promote safer customer behaviour. Shah (2024) explored big data analytics, showing how insurers leverage predictive analytics to forecast market trends and make informed strategic decisions.

Despite these benefits, AI adoption in insurance faces persistent challenges. Data privacy concerns, regulatory compliance requirements, and the substantial investment needed for technological infrastructure remain significant barriers. Addressing these issues will be critical to ensuring sustainable and responsible integration of AI into insurance practices.

3.0 Research Methodology

The positivistic research philosophy is the foundation upon which the study is built, allowing the operationalization of the study concepts and allowing the measurement of variables as hypothesized in a conceptual framework applying either qualitative or quantitative methods. The study adopted a descriptive research design, which allows the researcher to study a population, or a representative subset of the population, with the intention of describing the research phenomena (Saunders, Lewis & Thornhill, 2009). The study targeted a population of all the insurance companies, whether reinsurance, general, or life insurance companies, that are registered by the Insurance Regulatory Authority (IRA, 2024). These insurance companies are appropriate for this study as they are the leaders in the Kenyan insurance sector, and thus, they are at the forefront of AI technology adoption journey in the insurance sector. Given that the IRA has been able to ensure there is fully independent reporting for each of the three lines in insurance for insurance companies offering reinsurance, general, and life thus, even though there are 53 insurance companies, the total study sample was 71 companies, as some of the 53 insurance companies have been registered to provide more than one line of insurance products.

The study relied on both primary and secondary data, which were in qualitative and quantitative formats. Qualitative data was gathered through in-depth interviews with industry experts, insurance professionals, and AI specialists to gain insights into their experiences and perspectives. Quantitative data was collected via structured surveys distributed to a broad sample of insurance companies, focusing on the adoption rates, benefits, and challenges of AI implementation. The questionnaires were administered using an online data collection tool. To supplement the primary data, secondary data was collected from the sampled insurance companies, particularly on financial measures of performance. This data was extracted from the annual reports compiled by the insurance companies and the IRA. The secondary data solicited in the study included the annual income data, profitability data, funding, and expenditure information of each of the sampled insurance companies. The quantitative data was analyzed using descriptive statistics such as frequencies, mean, and standard deviation, and inferential statistics such as ANOVA and a regression model, which allowed assessment of the relationships. Inferential statistics were utilized to test the formulated hypotheses and to assess the relationship among the study variables which mainly involved the use of regression analysis, correlation analysis and goodness of fit tests. The moderating effect was tested using an OLS regression model.

4.0 Findings

The study considered the opinions and perceptions of the respondents regarding the insurance companies' usage of AI technology. The respondents were asked to indicate whether the various AI technologies are available or not available in the insurance companies. The outcomes are presented in Table 1.

Table 1: AI technology adoption

AI Technology Adoption	N	Mean	S.D.
Insurtech	71	.7746	.42079
Generative AI	71	.5775	.49748
Machine learning /Deep learning	71	.6620	.47641
Blockchain technology	71	.5352	.50231
Natural language processing	71	.4930	.50351
Computer vision technology	71	.6197	.48891
IoT Integration	71	.3380	.47641
Aggregate Mean score & Standard deviation	71	.57146	.343921

Source: Field Data (2025)

The descriptive tests assessed the level of adoption of AI technology among the studied insurance companies, which comprised proportions, means, and standard deviation. The factor was measured as a binary categorical variable, with the presence of AI technology being represented by 1 and the lack of AI technology being indicated by 0. This ends up presenting the presence of AI technology as an index, with the lowest adoption level being closer to zero and the highest adoption level of various AI technologies being presented as being closer to 1. From the assessment of the mean, the study observed that overall, the adoption of insurtech within the studied insurance companies is at the highest level (aggregate mean index 0.7746 and standard deviation of 0.421, revealing high levels of deviation from the mean, which confirms that large majorities of the insurance companies have adopted insurtech AI systems. From the assessment, the adoption of various AI systems in the insurance sector includes technologies such as machine learning /deep learning (mean 0.6620); computer vision technology (mean 0.6197); generative AI (mean 0.5775); blockchain technology (mean 0.5352), natural language processing (mean 0.4930); and IoT Integration (mean 0.3380). On aggregate, the mean score of the adoption for AI technology is slightly above average, revealing that it has been adopted by slightly more than half the insurance companies, with a mean index of 0.5715 and a standard deviation of 0.343.

Tests of normality are essential when testing the model since they help to examine the shape of data distribution for each variable in the data set in relation to the Gaussian normal distribution.

Stratford Peer Reviewed Journals and Book Publishing
Journal of Marketing and Communication
Volume 8||Issue 2||Page 54-65 ||December||2025|
Email: info@stratfordjournals.org ISSN: 2617-359X

The Shapiro-Wilk test for a given variable is such that the test coefficient (W) should not be significant if the variable's distribution is not significantly different from normal. The test can be taken as the correlation between given data and their corresponding normal scores, with W = 1 when the given data are perfectly normal in distribution, and otherwise not met when W is significantly smaller than 1. Shapiro-Wilk's W is recommended for small and medium samples, up to n = 2000 (Garson, 2012). The analysis of the AI Technology Adoption variable was observed to have a low Kolmogorov–Smirnov and Shapiro-Wilk scores (K-S = 0.219, p = .077; S-W = 0.859, p = 0.188). This reveals that the Kolmogorov–Smirnov and Shapiro Wilk tests confirm that the data is normally distributed (none of the 2 tailed p-values, indicated as Sig., was lower than 0.05; confirming the failure to reject the KS-SW null hypothesis ($H_{o:}$ *Data is not significantly different from normal distribution*) that the data is normally distributed; and the S-W score is very close to 1 (S-W 0.859) revealing that the data points are close to perfectly normal distribution.

The study assessed the model fit by undertaking a Pearson correlation assessment for the variables in the linear regression model between AI technology adoption and the performance of insurance companies. The strength of the relationship increases the closer the correlation coefficient is to 1. Schober, Boer and Schwarte (2018) defined a correlation of 0.9 to 1 as very strong, 0.7 to 0.89 as strong, 0.4 to 0.69 as moderate, 0.10 to 0.39 as weak, and 0 to 0.1 as negligible. The findings revealed strong positive correlation coefficients that are all statistically significant between performance of insurance companies and AI technology adoption (r=.761; p=.00). This reveals presence of a linear relationship between the Ai technology adoption and the performance of insurance companies; with this linear relationship being positive and statistically significant.

Further, the Durbin-Watson test was utilized to test for autocorrelation. The Durbin-Watson (DW) test is a statistical test used to detect the presence of autocorrelation in the residuals of a regression model (Durbin and Watson, 1951). Though it may exist in cross-sectional data, it is mostly observed in time series data, hence, it is one of the assumptions of OLS stating that there should be no autocorrelation in the regression model. This test was done using STATA as the statistical tool able to develop the DW test information in a regression model. The direct regression model for AI technology adoption (DW 1.877) against the performance of insurance companies, where a DW statistic indicated no significant autocorrelation.

The multicollinearity assumption was tested in all the regression models which revealed that with the performance of insurance companies and AI technology adoption (T 1.00; VIF 1.00) does not reveal any multicollinearity problems as they show tolerance higher than 0.20 and VIF is lower than 4.0 – more so because they have only one variable in the model. Therefore, both VIF and tolerance indicate that all the regression models lack the multicollinearity problem.

The study also considered whether the model met the assumption of homoscedasticity, which assumes constant error variance and independence of the independent variables. This was measured using the Breusch Pagan/ Cook-Weisberg (BP/CW) test for the null hypothesis (H_o: constant variance of error). The regression model between AI technology adoption and the performance of insurance companies show that the P-values for the Chi-square tests in BP-CW test is higher than 0.05, leading to the failure to reject the null hypothesis in the direct study models (AI_ technology adoption - $X^2 = 6.0155$, p .0825). This confirms that the homoscedasticity test fails to reject the null hypothesis for all study models confirming that 'the variance is the same across different groups being compared' in the regression models and homoscedasticity is present in the model.

The study sought to understand the relevance of AI adoption within the insurance environment, looking at the effects of AI technology adoption on the performance of insurance companies, which necessitated undertaking an OLS regression. The outcomes are presented in Table 2.

Table 2: Effects of AI technology adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.761[a]	.579	.573	.649429

a. Predictors: (Constant), AI Technology Adoption

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	39.983	1	39.983	94.802	.000[b]
	Residual	29.101	69	.422		
	Total	69.085	70			

a. Dependent Variable: Performance
b. Predictors: (Constant), AI Technology Adoption

Coefficients [a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.867	.150		-5.769	.000
	AI Technology Adoption	2.198	.226	.761	9.737	.000

a. Dependent Variable: Performance

Source: Field Data (2025)

The regression model summary shown in Table 2 reveals the goodness of fit of the regression model indicating that the regression model between AI technology adoption and performance of insurance companies had a high correlation and coefficient of determination ($R = 0.761$; $R^2= 0.579$) confirming great ability of AI technology adoption to explain the variance in the performance of insurance companies. The coefficient of determination (R^2) revealed that AI technology adoption explains 57.9% of the variation in the performance of insurance companies. A 57.9% influence from AI technology adoption is relatively high and significant to the insurance companies.

The ANOVA model allowed for the testing of the study hypotheses. The null hypotheses for this undertaking stated that: H_{01}: *There is no influence of AI technology adoption on the performance of insurance companies in Kenya*. From the ANOVA analysis section, the study found that the relationship between AI technology adoption and the performance of insurance companies was confirmed to be statistically significant ($P = 0.000$) at a 95% confidence level, with the sum of squares and mean squares showing considerably different regression and residual values. This further depicts the ability of AI technology adoption to influence insurance company performance, as observed in the goodness of fit model (model summary), is statistically significant. These ANOVA findings confirm the presence of an effect of AI technology adoption as a factor of insurance companies' performance. These findings led to the rejection of the null hypothesis testing for this effect. The study rejects the null hypothesis: H_{01}: *There is no influence of AI technology adoption on the performance of insurance companies in Kenya*, with the realization that there is a statistically significant influence of AI technology adoption on the performance of insurance companies.

The regression model coefficients indicate the level of influence arising from AI technology adoption on the dependent variable of the performance of the insurance company. The regression model was observed to have a negative statistically significant constant ($\beta o1$ = - 0.867; p = 0.000, indicating that it is statistically different from zero – p = 0.000 < 0.05). The adoption of AI technology ($\beta 1$ = 2.198; p 0.000) showed a statistically significant positive regression coefficient ($P<0.05$), confirming that the coefficient is statistically significantly different from zero. This means that AI technology adoption impacts the performance of insurance companies. The study therefore confirms that AI technology adoption has a positive impact on the performance of insurance companies as indicated in the regression model. The regression model of this relationship can be written as:

$$IP = -\ 0.867 + 2.198\ ATA + \varepsilon$$

Where: *IP – Insurance performance; ATA – AI technology adoption.*

Therefore, the study confirms the presence of a statistically significant influence of AI technology adoption on the performance of insurance companies.

5.0 Conclusion and Recommendations

The study found that all the studied insurance companies have adopted at least one of the various AI technologies available for usage within the sector; the most popular being insurtech, machine learning/deep learning, and compute vision technology. Other AI technologies include generative AI, block chain technology, natural language processing (NLP), and internet of things (IoTs). The overall adoption rating for these AI technologies is at 0.775, revealing that the insurance companies in Kenya have widely adopted the AI technologies. This is in line with findings made by Hawkins (2024) who revealed that machine learning/predictive analytics (ML/PA) and natural language processing (NLP) had higher rates of adoption and deployment, though large language models (LLMs) showed great potential. Smith (2023) links these AI technologies to driving efficiency, improving customer experiences, and creating new business models in insurance. Johnson (2022) revealed usage of AI in risk assessment, fraud detection, and claims processing. This is in line with findings by Abongo (2019) who found that innovation capabilities of Kenyan insurance companies are directed to a large extent on the preparation for adopting emerging external innovations rather than internal development of the innovations.

The relevance of AI in Kenya's insurance industry is underscored by its potential to drive innovation, efficiency, and customer satisfaction. The application of theories such as Disruptive Innovation, Diffusion of Innovations, and Resource-Based View provides a comprehensive understanding of AI's impact. The study makes a significant contribution in offering empirical support to the disruptive innovations theory by confirming its hypothesis within the insurance sector that AI technology adoption influences organization performance, with introduction of a moderating variable in this relationship in dynamic environment being introduced to the disruptive innovations discourse. Further, AI driven internal processes, AI driven operational efficiency have a direct effect on the performance of insurance companies, which is in line with the postulations of diffusion of innovation theory, explaining how innovation effects spread within various spheres of a firm. The study also revealed the contribution of dynamic environment on the AI-usage and organization performance, contributing to a deeper understanding dynamic environment as a key cog in the resource based view discourse. Therefore, these findings are an empirical evidence and contribution to the disruptive innovation theory, diffusion of innovation theory, and resource based view within the concept of AI adoption and the context of the insurance sector.

The study underscored the role of AI technologies, particularly insurtech, machine learning, and computer vision, in enhancing operational efficiency and improves customer satisfaction. The study expands the existing body of literature by confirming the transformative potential of AI technologies like generative AI and blockchain in problem-solving and secure data management, while highlighting opportunities for growth in underutilized areas such as natural language processing and Iot integration.

Based on these findings, future research should focus on key areas that can unlock AI's transformative potential across the insurance industry and beyond. First, there is a need to explore emerging AI technologies, particularly underutilized applications such as natural language processing (NLP) and the Internet of Things (Iot). Investigating the barriers to adoption and uncovering their potential efficiency gains could pave the way for broader implementation. Another important focus is industry-specific solutions, emphasizing AI customization to tackle unique challenges in different insurance sectors. This includes advancements in personalized policies and sophisticated risk profiling methods.

REFERENCES

Abadie A., Roux M., Chowdhury S., and Dey P., (2023). Interlinking organizational resources, AI adoption and omnichannel integration quality in Ghana's healthcare supply chain. *J. Bus. Res*. 162. 113866, https://doi.org/10.1016/j.jbusres.2023.113866.

Abongo B., (2019). Innovation Capabilities and Process Design for Business Model Transformation in Kenyan Insurance companies: A Service Dominant Logic Paradigm. *Journal of Information and Technology*, 3(1). 15- 45. ISSN: 2617-3573

Avenga. (2024). The future of insurance: Integrating AI for risk assessment. *Insurance Management Review*, 44(2), pp.55-64.

Bhumichai, D., Smiliotopoulos, C., Benton, R., Kambourakis, G., & Damopoulos, D. (2024). The Convergence of Artificial Intelligence and Blockchain: The State of Play and the Road Ahead. *Information*, 15(5), 268.

Charitou, C. D., & Markides, C. C. (2002). Responses to disruptive strategic innovation. *MIT Sloan Management Review*, 44(2), pp.55-64.

Charlton, J. (2024). *Digital Transformation in the Insurance Industry* (With Case Studies). Passkit.

Damanpour, F. and Daniel Wischnevsky, J. (2006). Research on innovation in organizations: Distinguishing innovation-generating from innovation-adopting organizations. *Journal of Engineering and Technology Management*, 23(4), pp. 269-291.

Dastjerdi M., Keramati A., and Keramati N., (2023). A novel framework for investigating organizational adoption of AI-integrated CRM systems in the healthcare sector; using a hybrid fuzzy decision-making approach. *Telemat. Inform.* Rep. 11: 00078, https://doi.org/10.1016/j.teler.2023.100078.

Dekker I., De Jong E.M., Schippers M.C., De Bruijn-Smolders M., Alexiou A., Giesbers B., (2020). Optimizing students' mental health and academic performance: AI enhanced life crafting. *Front. Psychol*. 11: 1063.

Durbin, J. and Watson, G.S. (1951). Testing for Serial Correlation in Least Squares Regression. II. *Biometrika*, 38, 159-177.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994.

EIOPA, (2019). Big data analytics in motor and health insurance. Frankfurt. [Online]. Available: https://register.eiopa.europa.eu/Publications/EIOPA_BigDataAnalytics_ThematicReview_April2019.pdf.

Erem C.I., (2022). The Effects of Artificial Intelligence on the Insurance Sector: Emergence, Applications, Challenges, and Opportunities. *The Impact of Artificial Intelligence on Governance, Economics and Finance.* 2, 225-241.

Garson, G. D. (2012). Testing Statistical Assumptions. Statistical Associates Publishing.

Green, D. (2024). The Future of AI in Insurance: Balancing Innovation and Regulation. *Insurance and Technology Today*, 12(1), 22-35.

IRA (2024). List of registered insurers 2024. Insurance Regulatory Authority.

Johnson, A. (2022). Integrating AI with Legacy Systems. Insurance Business Review, 10(4), 112-130.

Keller B. (2020). Promoting Responsible Artificial Intelligence in Insurance. Geneva Assoc. *Insur: a Better World*, no. ,1. 1–4, [Online]. Available: www.genevaassociation.org.

Luciano, E., Cattaneo, M., & Kenett, R. S. (2023). *Adversarial AI in Insurance: Pervasiveness and Resilience.* In arXiv (Cornell University). Cornell University. https://doi.org/10.48550/arxiv. 2301.07520

Muiruri D., (2023). How Artificial Intelligence Will Revolutionize Kenya's Insurance Industry. Cio Africa. https://cioafrica.co/tag/david-muiruri/

Nagano, M. S., Stefanovitz, J. P., & Vick, T. E. (2014). Innovation management processes, their internal organizational elements, and contextual factors: An investigation in Brazil. Journal of Engineering and Technology Management, 33, 63-92.

Okeleke, P. A., Ajiga, D., Folorunsho, S. O., & Ezeigweneme, C. (2024). Predictive analytics for market trends using AI: A study in consumer behavior. International Journal of Engineering Research Updates, 7(1), 36-49.

Pathak A. and Bansal V., (2024). *Factors Influencing the Readiness for Artificial Intelligence Adoption in Indian Insurance Organizations*. Department of Management Sciences, Indian Institute of Technology Kanpur, Kanpur 208016, India.

Saunders, M. N. K., Lewis, P. & Thornhill, A. (2009). *Research Methods for Business Students* (5th Edition). London: Pearson Education.

Schober, P., Boer, C. and Schwarte, L. (2018). Correlation Coefficients: Appropriate Use and Interpretation. *Anesthesia & Anesthesia*, 126, 1763-1768.

Smith, J. (2023). The cost of AI implementation in insurance. Journal of Insurance Technology, 15(2), 45-60.