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Assessing the Impact of Ai-Driven Internal Processes on Organizational Performance in Kenya's Insurance Industry

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ABSTRACT: This research explores how Artificial Intelligence (AI) is transforming internal workflows within Kenyan insurance companies and, as a result, affecting overall firm performance. Key functions such as underwriting, risk profiling, premium determination, document parsing, claims automation, policy tailoring, and risk assessment are increasingly shifting to AI and Natural Language Processing (NLP) platforms. Positioned at the intersection of growing data resources, human–machine collaboration, and advancing machine learning capabilities, AI is gradually becoming the driving force behind changes in traditional insurance operations. Although the academic community has documented operational improvements related to AI, systematic analyses that directly link these gains to measurable firm-level performance are limited. Using Technology Diffusion Theory, this study adopts a descriptive research approach, surveying all 71 insurance companies licensed by the Insurance Regulatory Authority (IRA) of Kenya. The research combines both qualitative and quantitative methods to assess the extent of AI adoption and the resulting performance outcomes. Findings show a median AI-enabled workflow adoption rate (average rating: 3.833 on a 5-point Likert scale), with this technological implementation currently accounting for 48.6% of the variation in performance observed among respondents.

KEYWORDS: Artificial Intelligence. Natural Language Processing. AI-driven internal processes. Artificial Intelligence Technology. Neural Networks.

1. INTRODUCTION

The insurance sector has traditionally depended on manual workflows and disconnected legacy systems for key functions, including underwriting, claims processing, and premium calculation (Amenya, 2024). This reliance has led to significant operational inefficiencies, such as service delays, frequent data errors, and increased vulnerability to fraud (Higson, 2025). Integrating artificial intelligence technologies, especially machine learning and natural language processing (NLP), has ushered in a major transformative phase in the insurance industry (DhiWise, 2025). These tools have the potential to streamline internal operations, improve decision-making, and respond more adaptively to changing market demands, fundamentally reshaping core processes like underwriting, claims management, and fraud detection. According to Sloan (2025), AI boosts productivity, cuts operational costs, and enhances customer interactions along with risk assessment capabilities, creating unmatched opportunities for process reengineering, particularly in developing markets like Kenya, where insurers face pressure from shifting consumer expectations and regulatory standards.

Recent studies confirm tangible contributions from AI in fraud detection and claim optimisation; KPMG (2024) notes that platforms driven by AI can analyse extensive datasets instantly to enhance insurers' ability to detect fraudulent claims effectively. Avenga (2024) highlights improvements in claims management automation due to increased transparency speeds, while also boosting customer trust levels. Additionally, Zarifis et al. (2023) note that algorithmic trading has refined investment decision-making processes within insurance firms by enabling rapid responses grounded in data analytics amid market volatility. AI also plays an essential role in predictive analytics, enabling insurers to understand customer behaviour patterns better while forecasting market trends or adjusting premiums dynamically based on evolving circumstances, a fact evidenced by studies from Okeleke et al. (2024) along with Hafke (2024). These investigations showcase how predictive models intertwine external factors like economic states or weather conditions with historical claim records for accurate future risk assessments leading towards responsive pricing strategies paired with informed risk mitigation planning initiatives.

Further reinforcing these advancements is conversational AI demonstrated through chatbots or virtual assistants, revolutionising customer service delivery mechanisms via personalised engagement throughout complex procedures, resulting not only in increased satisfaction rates but also reducing administrative burdens, according to Evincedev (2023). Jaiswal (2023) argues that beyond mere automation, strategic decision support capabilities are introduced by artificial intelligence into underwriting practices, enabling insurers greater flexibility in balancing accuracy with speed during policy formulation phases.

In spite of accumulating evidence regarding operational benefits stemming from applying artificial intelligence techniques, however limited comprehension persists surrounding its direct ramifications affecting firm-level performances unique unto Kenya's specific context(s) Bonde L & M Nyakora (2023). This inquiry aims at addressing said gap by evaluating how internally driven processes facilitated through AI influence organizational performances among licensed players operating across this vibrant marketplace whilst adhering firmly against frameworks rooted within Technology Diffusion Theory principles thus analyzing degrees pertaining toward AI adoption rates alongside measuring impacts relayed forth across primary performance metrics including efficiencies attained thereafter enhanced client satisfaction measures incorporated together with overall profitability yields generated post-integration efforts undertaken herein.

3. STATEMENT OF THE PROBLEM

Kenya's insurance sector plays a vital role within the financial landscape but faces challenges due to operational inefficiencies, outdated systems, and manual procedures that hinder responsiveness, accuracy, and scalability. Historically, insurance companies have depended on retrospective data and labour-intensive methods for tasks such as underwriting, claims processing, risk evaluation, and customer support. These traditional practices impede efficiency, elevate the risk of fraud, and negatively affect customer satisfaction.

In contrast, the swift rise of Artificial Intelligence (AI) has prompted global insurers to adopt automation, machine learning, and predictive analytics to overhaul their internal operations. This shift has led to improved efficiency, tailored services, and decision-making grounded in data. Innovations like natural language processing, AI-based fraud detection, and algorithmic trading are transforming operational frameworks and reshaping competitive dynamics. However, despite its evident advantages worldwide, the level of AI integration within Kenya's insurance industry is still largely unexamined and inadequately measured.

Existing research predominantly highlights theoretical possibilities related to AI while providing scant empirical evidence on how AI-enhanced processes influence key performance indicators, such as cost savings, service quality improvements, risk management efficiencies, and profitability, especially in local settings. This gap signifies a crucial area for further investigation. Consequently, this study aims to explore how AI-driven internal processes affect the performance of insurance firms in Kenya. Through this exploration, the research intends to offer evidence-based insights regarding the strategic importance of AI adoption while guiding industry stakeholders towards data-informed transformation efforts. Without such analysis, insurers may underutilise transformative technologies and struggle to meet increasing client expectations along with market demands.

3.0. THEORETICAL AND LITERATURE REVIEW

3.1. Introduction

Artificial Intelligence (AI) has become a driving force behind the restructuring of internal processes within organisations worldwide. In Kenya's insurance industry, this shift is accelerating, driven by goals like increased operational efficiency, better customer experiences, and strategic differentiation. This literature review consolidates both empirical and theoretical insights regarding the impact of AI-driven processes on organisational performance, specifically highlighting developments within Kenya's insurance sector.

3.2. AI and Operational Efficiency

AI has become essential in streamlining operational processes through automation, lowering error rates, and speeding up task completion. Coombs et al. (2020) and Kirchmer & Franz (2019) emphasise AI's role in improving organisational agility and responsiveness to changing market conditions. These studies underline efficiency improvements linked to AI technologies across various business functions. automating repetitive functions, AI enables employees to engage in strategic, cognitively demanding tasks. This reallocation of effort supports productivity and encourages a more engaged workforce. Balasundaram and Venkatagiri (2020) reinforce this position, noting that AI consistently outperforms human operators in tasks requiring precision and speed. The scalability enabled by AI permits organisations to expand operations without proportionally increasing labour costs, especially relevant in sectors managing high transactional volumes.

Wamba-Taguimdje et al. (2020) further illustrate how AI minimises latency and errors, promoting consistency and quality in service delivery. These improvements directly affect customer satisfaction and operational stability. Kenya's insurance sector provides real-world examples: AAR Insurance has adopted AI to digitise workflows, including client onboarding and claims processing. M-TIBA, a healthcare financing platform, employs machine learning to automate claims processing, achieving a 500% increase in throughput and approval times under one minute, demonstrating AI's tangible operational value.

3.3. Quality Enhancement and Personalisation

AI also facilitates quality improvement and tailored service provision through advanced data analytics. Davenport & Ronanki (2018) report that over half of the surveyed executives use AI to refine existing offerings, signalling a widespread turn towards innovation driven by data insights. Makarius et al. (2020) cite platforms such as Netflix and Spotify, which employ algorithms for personalised recommendations that heighten user engagement.

Kenyan insurers have adopted similar strategies by leveraging AI to generate individualised policy options informed by customer data profiles. This shift from standardised to bespoke offerings improves service relevance and operational efficiency. Furthermore, AI-powered chatbots and virtual assistants are reconfiguring customer interaction frameworks by providing 24/7 support. These technologies enhance accessibility and consistency while alleviating the workload on human agents. Collectively, AI's deployment in these contexts underscores its role in fostering innovation and user-centred design.

3.4. Marketing Effectiveness

AI is reshaping marketing paradigms through its capacity for precise segmentation and targeted outreach. According to Mishra & Pani (2020), AI enables organisations to process extensive customer data, uncovering nuanced behavioural and lifestyle patterns that inform tailored marketing strategies. Afiouni (2019) explores how one-to-one marketing through AI significantly improves engagement and conversion metrics via predictive analytics and personalised messaging.

Dynamic adaptation is another advantage: AI models can recalibrate in response to shifting consumer behaviours, maintaining campaign relevance in real time. In Kenya's insurance sector, firms employ AI analytics to design targeted offerings aligned with specific consumer needs. This approach enhances outreach efficacy and improves alignment between product offerings and market demand.

3.5. Sustainability and Social Responsibility

Artificial Intelligence (AI) is increasingly recognised as a strategic instrument in advancing environmental and social goals, particularly through efficient resource utilisation and ethical alignment in organisational operations. As global emphasis on Environmental, Social, and Governance (ESG) standards intensifies, AI serves as a pivotal enabler in harmonising corporate practices with sustainability frameworks. Toniolo et al. (2020) highlight AI's capacity to curtail energy consumption and minimise waste through data-informed efficiencies such as predictive maintenance and intelligent scheduling. These capabilities facilitate a shift from reactive management approaches to proactive sustainability strategies.

Further supporting circular economy models, Borges et al. (2020) emphasise AI's contribution to optimising recycling workflows and reducing emissions. AI systems intelligently track material flows, identify recyclables, and streamline logistics for waste recovery, reinforcing closed-loop industrial processes. At the same time, AI enhances social responsibility by embedding ethical oversight and facilitating stakeholder engagement. Its integration into corporate governance has been linked to improved brand equity and competitive differentiation. Within Kenya's insurance sector, organisations are leveraging AI to align operations with ESG imperatives, enhancing transparency, reducing ecological disruption, and delivering socially responsible products. As such, AI is both a technological enabler and a strategic differentiator, underpinning ethical and sustainable enterprise development.

3.6. Fraud Detection and Risk Assessment

AI continues to redefine fraud detection and risk assessment paradigms by offering advanced pattern recognition and anomaly detection mechanisms. These tools assist organisations in reducing exposure to financial and operational threats while reinforcing systemic reliability. Among its most notable applications is the prevention of insurance fraud. AI algorithms rapidly detect irregularities in claims data, identifying patterns suggestive of fraudulent behaviour. This early detection mechanism curbs illegitimate payouts, conserves resources, and fortifies regulatory compliance.

In risk assessment, AI enables real-time evaluation through dynamic machine learning models, thereby increasing underwriting accuracy and agility. These models adapt to evolving datasets, surpassing traditional static frameworks and offering personalised coverage based on nuanced risk profiles. In motor insurance, AI-driven telematics technologies exemplify this advancement. By collecting behavioural data, such as speed, braking intensity, and mileage, AI enables risk assessments reflective of actual driving habits rather than generic demographic variables. This shift fosters more equitable pricing and incentivises responsible conduct, illustrating AI's broad utility in enhancing fraud resistance and risk calibration across the sector.

3.7. Innovation and Creativity

AI's expanding role as a driver of innovation is predicated on its ability to reallocate human effort from routine operations to high-value creative and strategic endeavours. Through automation and analytical insight, AI enables environments conducive to ideation and problem-solving. Amabile (2020) notes that AI supports creative processes by generating alternatives and identifying patterns, thereby enhancing human cognitive function rather than replacing it. This collaboration between human expertise and intelligent systems nurtures innovation ecosystems.

Mikalef and Gupta (2021) argue that AI facilitates optimal resource allocation, allowing personnel to focus on strategic pursuits. This transition enhances organisational responsiveness and encourages experimentation. Raisch and Krakowski (2021) further underscore AI’s value in managing uncertainty, contending that predictive analytics empower decision-makers to navigate ambiguity with greater confidence. Together, these studies suggest that AI significantly bolsters creative capabilities and adaptive strength, providing organisations with the tools to innovate in dynamic and competitive landscapes.

3.8. Organisational Transformation in Kenya

Kenya's insurance sector is experiencing a significant digital transformation, with AI leading the way in reshaping operational and strategic frameworks. Companies are investing in AI technologies to boost competitiveness and advance digital maturity. At the core of this change is the implementation of AI-driven solutions that enhance efficiency, customer experience, and risk management. The Insurance Regulatory Authority (IRA) supports this shift through regulatory sandboxes, which allow controlled testing of AI applications while ensuring sectoral compliance and ethical standards.

However, the journey toward AI integration faces challenges, particularly in data quality and availability. Inadequate data infrastructure can compromise the reliability of machine learning outputs and impede informed decision-making. Accordingly, firms are prioritising data governance reforms to support robust analytic capabilities. Moreover, this transformation necessitates workforce evolution. The emergence of AI demands new skill sets, including data science, AI ethics, and customer-centric digital strategies, prompting investment in upskilling initiatives. These efforts promote inclusive growth and empower employees to contribute meaningfully to innovation-led environments. In conclusion, AI is shaping Kenya's insurance industry not merely as a tool for efficiency but as an enabler of systemic transformation. Its impact spans sustainability, integrity, creativity, and strategic agility, underscoring its foundational role in building future-ready organisations.

3.9. Challenges and Considerations

While Artificial Intelligence (AI) offers considerable advantages across industries, its adoption is not without significant challenges. As organisations increasingly incorporate AI into their operational and strategic frameworks, concerns surrounding data privacy, ethical accountability, and organisational change management have emerged as critical areas of focus. In Kenya, adherence to data protection regulations is paramount. Compliance with the Data Protection Act remains essential to ensure the ethical handling of personal information. As AI systems often rely on vast datasets for training and decision-making, organisations must implement rigorous data governance policies that align with legal standards and safeguard user privacy.

Ethical considerations also pose substantial challenges to AI adoption. The development and deployment of intelligent systems must prioritise transparency, fairness, and accountability. Ensuring that algorithms are free from bias, explainable in their decisions, and subject to oversight is vital for maintaining stakeholder trust and preventing unintended harm. These requirements call for robust ethical frameworks and interdisciplinary collaboration in AI design and governance. Moreover, successful AI integration demands effective change management strategies. Organisational cultures must evolve to embrace digital transformation, which may involve overcoming employee resistance, redefining job roles, and fostering a mindset geared toward innovation. Upskilling and inclusive communication are key to easing transitions and sustaining morale during periods of technological adaptation. Collectively, these challenges underscore the importance of a balanced approach to AI adoption, one that maximises value while mitigating risk through regulatory compliance, ethical design, and thoughtful organisational development.

AI-driven internal processes are reshaping Kenya's insurance industry, enhancing efficiency, personalisation, marketing, sustainability, and innovation. While challenges persist, the strategic adoption of AI promises significant improvements in organisational performance. As insurers continue to embrace AI, they must balance technological advancement with ethical responsibility and workforce development to unlock its full potential.

3.10. Theoretical review

The Diffusion of Innovation (DOI)) theory, conceptualised by Rogers, offers a fundamental framework for understanding how technological advancements like Artificial Intelligence (AI) spread within organisations. The theory suggests that innovation adoption occurs gradually, unevenly, and is influenced by different adopter categories (Chatterjee et al., 2021; Chen & Tan, 2004). Although this theoretical model provides useful insights into the step-by-step process of AI adoption, its relevance in the context of AI-driven organisational change in Kenya’s insurance sector warrants a careful critique.

Kenyan insurers such as Jubilee Insurance and Britam exemplify early adopters harnessing AI to enhance customer experience and internal process efficiency (Shah, 2024). These firms display traits typical of innovators and early adopters in Rogers' framework, including high resource capacity, strategic vision, and openness to technological experimentation. However, the theory’s linear adoption curve may oversimplify the complexity of digital transformation in emerging markets, where systemic constraints and resource disparities significantly influence the diffusion pace and scope.

One limitation of DOI theory is its relative underemphasis on institutional, infrastructural, and regulatory dynamics. For instance, while the Insurance Regulatory Authority (IRA) has introduced sandboxes to encourage AI experimentation, smaller firms often face data quality challenges and limited technical capacity, inhibiting widespread adoption. The assumption that innovation spreads through influence alone does not sufficiently account for structural asymmetries, such as access to capital or specialised talent. Moreover, DOI theory assumes relatively passive reception of innovations among later adopters, yet the integration of AI demands active organisational change management, including cultural adaptation and workforce upskilling.

Resistance to automation and apprehension around data privacy, especially in light of Kenya's Data Protection Act 2019, further complicate the adoption trajectory in ways not fully explained by the theory. Therefore, while the DOI framework remains useful in mapping AI adoption patterns, its explanatory power is limited in contexts characterised by regulatory evolution, digital inequality, and sociotechnical complexity. A critical, contextualised application of DOI, supplemented by organisational change and institutional theories, offers a more robust lens for evaluating the impact of AI-driven internal processes on performance in Kenya's insurance industry.

4. METHODOLOGY

The positivist research philosophy is the foundation on which the study is built, enabling the operationalisation of the study's concepts and the measurement of variables as hypothesised in a conceptual framework, using either qualitative or quantitative methods. The study employed a descriptive research design, which enables the researcher to examine a population or a representative subset of it to describe the research phenomena (Saunders, Lewis, & Thornhill, 2009). The targeted population comprises all insurance companies registered with the Insurance Regulatory Authority (IRA, 2024), including reinsurance, general, and life insurance firms. These companies are appropriate for this study because they are the leaders in the Kenyan insurance sector and are at the forefront of AI technology adoption. Since the IRA ensures independent reporting for each of the four lines of insurance, reinsurance, general, life, and health, although there are 53 insurance companies, the total study sample comprises 71 companies, as some of the 53 are 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 were 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 analysed using descriptive statistics such as frequencies, mean, and standard deviation, and inferential statistics such as ANOVA and regression model, which allowed assessment of the relationships. Inferential statistics were utilised 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.

5. FINDINGS

The descriptive tests of choice in assessing the manifestation of AI-driven internal processes among the studied insurance companies included the proportion, mean and standard deviation. The factors were measured as categorical variables with a point Likert scale indicating level of agreement with the statement highlighting level of channel integration in the stores, where 1 indicated strongly disagree, 2 - disagree, 3 – moderate, 4 – agree, and 5 – strongly agree. The outcomes of the manifestation of AI-driven internal processes in insurance companies are presented in Table 4.1.

Table 4.1: AI-driven internal processes

AI-Driven Internal Processes	N	Mean	S.D.
Data-driven pricing and underwriting	71	3.8028	.83870
AI-driven risk profiling/Engineering	71	3.7183	.95891
AI-driven premium setting	71	3.8732	.86072
NLP in document review	71	3.8028	.80391
Automated claims processing	71	3.8028	.98008
Personalized policies	71	3.7465	.99597
Optimised risk assessment	71	4.0704	.76203
Aggregate Mean score & Standard deviation	71	3.83301	.434622

Source: Field Data (2025)

From the assessment of the mean, the study observed that overall, the manifestation of AI-driven internal processes within the studied insurance companies falls under the fourth category (agree - aggregate mean score 3.833 and standard deviation of 0.4346), confirming that the large majority of the insurance companies agreed to the statements used to measure AI-driven internal processes. From the assessment, none of the practices making up the seven AI adoption in internal processes constructs were observed to have a mean of less than 3.5 within the 5-point Likert scale, an indication that the insurance companies agree to have integrated AI-driven internal processes. The mean scores of the practices ranged between 3.7183 and 4.0704 on a 5-point Likert scale, revealing relatively high ratings of these practices, with standard deviation ranging from a high of 0.99597 to a low of 0.76203, revealing a significant level of variability from the observed mean. The respondents agreed that the insurance companies can access AI driven internal processes such as: data driven pricing and underwriting (mean 3.8028); AI driven risk profiling/Engineering (mean 3.7183); AI driven premium setting (mean 3.8732); NLP in document review (mean 3.8028); automated claims processing (mean 3.8028); personalized policies (mean 3.7465); and optimized risk assessment (mean 4.0704). These findings imply that most of the insurance companies have integrated to a moderate extent the various AI components aiding in internal processes.

The performance of the studied insurance companies was assessed from the point of AI relevance where the overall performance was calculated at an aggregate mean index of 0.389 which was converted to a Likert scale rating of 2.153 on a five (5) point Likert scale and a standard deviation of 0.527, revealing that the insurance companies are mostly experiencing improving performance over the 5 years, and the ratings are an indication of high performance in these insurance companies. The mean scores of insurance companies' performance measures lie between a low of -0.0089 and a high of 0.9716, expressing good performance ratings for the studied insurance companies. These outcomes are as shown in Table 4.2 below.

Table 4.2: Performance of insurance companies

Performance (5-Year Average)	N	Index Measure		Visual Binning (5 point)	
		Mean	S.D.	Mean	S.D
Profitability	71	.9716	.96902	3.49	.791
Product innovation	71	.1135	.93124	2.83	1.363
Process improvement	71	.3459	1.77015	2.41	1.379
Market share	71	-.0089	.97475	1.66	.877
Customer perception rating	71	.0390	3.72018	1.72	1.098
Customer retention	71	.7176	2.18909	1.56	.937
Efficiency ratio	71	.5446	.74107	1.39	.643
Aggregate Mean score & Standard deviation	71	.38903	.993441	2.15285	.527619

Source: Field Data (2025)

The study sought to understand the relevance of AI adoption within the insurance environment by looking at the effects of AI-driven internal processes on the performance of insurance companies, which necessitated undertaking an OLS regression. The outcomes are presented in Table 4.3.

Table 4.3: Effects of AI-driven internal processes on the performance of insurance companies

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	.697[a]	.486	.478	.717511

a. Predictors: (Constant), Internal Processes

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
2	Regression	33.562	1	33.562	65.191	.000[b]
	Residual	35.523	69	.515		
	Total	69.085	70			

a. Dependent Variable: Performance
b. Predictors: (Constant), Internal Processes

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	-5.718	.761		-7.512	.000
	Internal Processes	1.593	.197	.697	8.074	.000

a. Dependent Variable: Performance

Source: Field Data (2025)

The regression model summary shown in Table 4.3 reveals the goodness of fit of the regression model indicated that the regression model between AI driven internal processes and the performance of insurance companies indicated a high correlation and coefficient of determination ($R = 0.697$; $R^2 = 0.486$) confirming that AI driven internal processes can explain the variance in the performance of insurance companies. The coefficient of determination (R^2) revealed that AI-driven internal processes are able to explain 48.6% of the variability in the performance of insurance companies. A 48.6% influence from AI-driven internal processes is relatively high and significant to the insurance companies.

The ANOVA model allowed for the testing of the study hypothesis, which posed that: t*here is no influence of AI-driven internal processes on the performance of insurance companies in Kenya (H_{o2})*. The ANOVA analysis section revealed that the relationship between AI-driven internal processes 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 confirms that the ability of AI-driven internal processes 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-driven internal processes as a factor of insurance companies' performance. These findings lead to the rejection of the null hypothesis testing for this effect, thus rejecting the null hypothesis that *there is no influence of AI-driven internal processes on the performance of insurance companies in Kenya*, *w*ith the realisation that there is a statistically significant influence of AI-driven internal processes on the performance of insurance companies.

The regression model coefficients shown in Table 4.3 highlight the level of influence arising from AI-driven internal processes on the dependent variable of the performance of the insurance company. The regression model was observed to have a negative statistically significant constant ($\beta_{o2} = -5.718$; $p = 0.000$, indicating that it is statistically different from zero – $p = 0.000 < 0.05$). The AI-driven internal processes ($\beta_2 = 2.198$; p 0.000) showed statistically significant positive regression coefficients ($P < 0.05$), confirming that the coefficient is statistically significantly different from zero. This means that AI-driven internal processes impact the performance of insurance companies, thus confirming that AI-driven internal processes have 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:

$$\mathbf{IP = - 5.718 + 1.593\ ADIP + \varepsilon}$$

Where: IP – Insurance performance; ADIP – AI-driven internal processes.

Therefore, the study confirms the presence of a statistically significant influence of AI-driven internal processes on the performance of insurance companies.

6. CONCLUSIONS

Further, a look at the AI-driven internal processes of the insurance companies and their influence on their performance was undertaken. It was observed that insurance companies, to some extent, apply AI-driven internal practices such as data-driven pricing and underwriting, AI-driven risk profiling/Engineering, AI-driven premium setting, NLP in document review, automated claims processing, personalised policies, and optimised risk assessment. As observed by Wamba-Taguimdje et al. (2020), AI is an innovative and disruptive technology that enables organisations to innovate and transform their business processes. AI-driven internal processes are therefore a key practice among insurance companies, with companies being observed to apply various AI tools to improve their internal operations.

The study looked at the effect of AI-driven internal processes on the performance of insurance companies by conducting a regression analysis. It was found that AI-driven internal processes and the performance of insurance companies have a positive correlation, confirming the presence of a relationship between the two factors. The study further found that the regression model testing for this relationship (with AI-driven internal processes as independent variable and the performance of insurance companies as dependent variable) indicated that though the independent variable (AI-driven internal processes) has an impact on dependent variable (performance of insurance companies), the AI-driven internal processes has a statistically significant influence on the performance of insurance companies. These outcomes support findings by Mishra &Pani (2020), who found that AI-driven internal processes allow insurance companies to optimise pricing, improve underwriting accuracy, and enhance claims management. These findings were further highlighted by Vijayanarayanan et al. (2025), revealing that the AI's ability to reduce claims processing time by up to 80% and lower costs by 30% significantly boosts operational efficiency. Companies have observed applying various AI tools to improve their internal operations. This is in line with the conceptualisation of the disruptive innovation theory, which opines that innovations create new markets and value networks, eventually disrupting existing ones. The study found that the AI-driven internal processes significantly influence the performance of insurance companies.

The study found that AI-driven internal processes are moderately applied in the insurance companies in Kenya, where internal processes such as underwriting, risk profiling/engineering, premium setting, document review, automated claims processing, personalised policies, and risk assessment are automated through the use of AI and NLP technologies. This is in line with findings by Mishra & Pani (2020), who observed that AI enables the redesign of business processes, which radically changes how current operations are executed. It was observed that the adoption of these AI technologies in the management of the internal processes influences the performance of insurance companies. According to Mikalef and Gupta (2021), using AI technology to automate internal processes in insurance companies reduces the time and complexity of these practices, allowing insurers to offer a seamless experience that enhances customer satisfaction, thus driving higher conversion rates and improved customer engagement, leading to an improvement in the overall performance of the insurance company. The study, therefore, concludes that AI-driven internal processes have a positive influence on the performance of insurance companies.

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 organisation performance, with the introduction of a moderating variable in this relationship in a dynamic environment being introduced to the disruptive innovations discourse. Further, AI-driven internal processes and 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 the dynamic environment on AI AI-usage and organisation performance, contributing to a deeper understanding of the dynamic environment as a key cog in the resource-based view discourse. Therefore, these findings are empirical evidence and a 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 realised policy implications in terms of decision-making within the insurance sector. Insurance companies play a key role in our economy, and their performance is an important agenda for all within the country, more so when the sector can benefit from emerging innovations from AI technology. This study realised findings that would assist policy makers in the insurance sector to make sound decisions regarding the adoption of AI technology with a view to improving the performance of insurance companies in Kenya. From the outcomes observed, insurance firms should leverage AI technology adoption, AI-driven internal processes, AI-driven operational efficiency, and AI-driven relationships and interactions while ensuring the rightful dynamic environment is maintained.

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