The Effect of Artificial Intelligence (AI)-Enabled Risk Assessment on the Business Strategies of Reinsurance Companies in Nairobi County, Kenya

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Abstract:

Purpose: *This study examined the effect of artificial intelligence (AI)-enabled risk assessment on the business strategies of reinsurance companies in Nairobi County, Kenya. Specifically, the study sought to establish whether AI-enabled risk assessment, through the application of machine learning, predictive analytics, automated risk evaluation, and data-driven decision-making, significantly influences business strategy as measured through strategic positioning, operational efficiency, and competitive orientation.*

Material/methods: *The study was anchored on Dynamic Capability Theory and employed an explanatory research design. The target population comprised 350 respondents, including 73 managers and 277 employees drawn from seven reinsurance companies operating in Kenya. Stratified random sampling was used to select respondents based on their respective organizations and managerial or employee classifications. A sample size of 349 respondents was established using Yamane's formula at a 3% margin of error. Primary data were collected using structured questionnaires based on a five-point Likert scale. A total of 281 questionnaires were returned, of which 250 valid questionnaires were retained for analysis, representing an effective response rate of 71.63% of the targeted sample. Data were analyzed using descriptive statistics, Pearson correlation analysis, and hierarchical multiple regression analysis, with firm size and organizational age treated as control variables. Statistical analysis was conducted using SPSS version 25.*

Findings: *The findings revealed a moderate positive and statistically significant relationship between AI-enabled risk assessment and business strategy ($r = .571$, $p < .001$). Hierarchical regression analysis further established that AI-enabled risk assessment had a significant positive effect on business strategy. The explanatory power of the regression model increased from 11.8% to 45.7% after introducing AI-enabled risk assessment, representing an additional 33.9 percentage points in explained variance. Firm size ($\beta = .279$, $p < .001$) and organizational age ($\beta = .220$, $p < .001$) also had significant positive effects on business strategy. These findings demonstrate that AI-enabled risk assessment contributes substantially to strengthening the strategic capabilities of reinsurance companies.*

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Conclusion: *The study concluded that AI-enabled risk assessment is a significant determinant of business strategy among reinsurance companies in Nairobi County, Kenya. The application of artificial intelligence in risk identification, evaluation, prediction, and monitoring enhances organizational capacity to make informed strategic decisions, improve operational efficiency, strengthen market positioning, and respond effectively to competitive market dynamics. Consequently, integrating AI-powered risk assessment into strategic management processes is essential for improving organizational competitiveness and long-term sustainability.*

Value: *The study contributes to Dynamic Capability Theory by demonstrating how AI-enabled risk assessment strengthens organizational capabilities through improved risk sensing, strategic decision-making, and resource optimization. The findings provide practical insights for reinsurance company management, policymakers, particularly the Insurance Regulatory Authority (IRA), and industry practitioners on the importance of investing in AI technologies, employee competencies, technological infrastructure, and responsible AI governance to strengthen strategic positioning and operational competitiveness in Kenya's reinsurance industry.*

Keywords: *Artificial Intelligence, AI-Enabled Risk Assessment, Business Strategy, Strategic Positioning, Operational Efficiency, Competitive Orientation, Dynamic Capability Theory, Reinsurance Companies, Nairobi County, Kenya*

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1. Introduction

Insurers and reinsurers, such as Aegis, are increasingly moving towards a strategic and operational approach with the use of Artificial Intelligence (AI) in risk assessment practices, which will strengthen the ability to detect, analyze, predict and prevent potential risks by applying advanced data analysis and machine learning techniques. Widely, reinsurers are turning to AI-driven risk assessment technologies to boost the precision of risk modelling, boost underwriting decisions, diversify into riskier markets, and inform risk-based pricing. According to Mordor Intelligence (2025), the global digital insurance platform market is estimated at USD 148.15 billion in 2025 and is expected to reach USD 255.43 billion by 2030 and highlighting the increasing importance of technology in the insurance sector for managing risk. AI platforms are being used in the United States to enhance the speed of underwriting and predictive risk analysis, helping insurers analyze vast amounts of data and detect new risk trends, which contributes to more precise risk selection (CoinLaw, 2025). Likewise, German insurance companies have also started to integrate AI-powered analytical systems to enhance their risk assessment capabilities and streamline underwriting procedures. The latest progress illustrates how AI-powered risk assessment is emerging as a significant strategic tool that enables reinsurers to enhance their market positioning and boost operational efficiency.

The level of adoption of AI-integrated risk assessment in the insurance and reinsurance sector is less consistent in Sub-Saharan Africa, varying across countries and regions based on factors such as technological infrastructure, institutional capacity, and market development (Emergen Research, 2021). South Africa, where the insurance sector is one of the most sophisticated in the region, has more recently adopted new and improved analytical technologies to better assess the risk of new hazards, to boost insurance operations and to increase the accuracy of insurance underwriting. The

market environment for the implementation of technology-based risk management practices in the country is relatively developed with an insurance penetration rate of about 11.5% (Agwunobi, 2025). Nigeria, with a penetration rate of about 0.34% of GDP in 2023, on the other hand, highlights the structural issues in less-developed insurance markets when it comes to implementing advanced risk assessment technologies (Intelpoint, 2025). This means that the different use of AI in the risk assessment process impacts the way reinsurers are looking for market opportunity, assessing risk exposures, allocating resources, and reacting to market conditions. The strategic and operational value of AI-driven risk assessment can hinge on how well companies can embed predictive analytics and automated risk assessment into their day-to-day operations.

Adopting AI-based risk assessment has become a growing trend among insurance and reinsurance companies in East Africa, influencing how they manage risks and compete in the market.AI-powered risk assessment is becoming a common practice in the insurance and reinsurance industry in East Africa, impacting the way these companies manage risks and compete. But, the level of integration differs in different countries as a result of variations in digital infrastructure, regulations, and technological capacity (Deloitte, 2025). Variations in insurance market development and technologies in insurance business practices are reflected in the region's insurance penetration rate which stood at 1.57% in 2023 and ranged from 2.61% in Kenya to 0.3% in Ethiopia (Deloitte, 2025). The use of predictive analytics, automated underwriting, and data-driven risk evaluation has led to opportunities in Kenya to better predict who will be a good credit risk, adjust pricing strategies to better match the risk, and better-manage portfolios (Ken Research, 2026). However, the degree of integration of advanced analytical technologies is comparatively low in less developed insurance markets, limiting the ability of firms to model the risks and be proactive on new risks. In the East African insurance market, the developments underscore the increasing significance of AI-driven risk assessment for reinsurers to bolster their strategic positioning and operational efficiency.

Risk assessment is gaining increasing relevance in Kenya's insurance and reinsurance sector competitiveness and performance with the advent of AI technology. The insurance market in the country is characterised by the growing digital financial ecosystem, which grants insurance firms opportunities to utilize machine learning, predictive modelling and automated risk evaluation in their underwriting and portfolio management processes (Deloitte, 2025; Eghosa, 2025). AI-powered risk assessment can help reinsurers gain deep insights into their historical claims data, uncover new risk exposures, predict the likelihood and financial impact of future losses, and enhance risk-based pricing. These capabilities can help bolster strategic positioning for companies by helping them find market segments that are attractive, better define their risk management services and products and make better decisions on portfolio selection and market expansion. Moreover, automated risk evaluation can increase the operational efficiency by saving time in risk evaluation, reduce manual processing, increase underwriting accuracy and enable faster decision making. However, the impact of these capabilities on organisational outcomes relies on how well organisations integrate AI risk assessment into their operations and strategies (Deloitte, 2025).

AI-based risk assessment has become more applicable to the strategic positioning and efficiency of reinsurers in Kenya's main financial and insurance capital of Nairobi County. Density of financial institutions, insurance companies, IT service providers and reinsurance business, results in a setting where firms are increasingly relying on sophisticated analytical tools to assess more complex and dynamic risk situations. AI-

powered risk assessment gives reinsurers the chance to shift away from traditional actuarial methods and towards predictive and data-informed risk assessment, as they can detect new loss trends, gain an understanding of the likelihood of catastrophic events, and establish their risk tolerance and pricing strategies. These capabilities can help firms strengthen their strategic positioning by helping them find niche markets, build competitive underwriting strategies, select the right portfolio, and anticipate the shifting client and market needs. Likewise, automated risk assessment and predictive analytics can boost operational efficiency by minimizing assessment time, improving risk classification accuracy, optimizing resource use, and minimizing manual underwriting processes.

Notwithstanding these benefits, whether the strategic value of AI-enabled risk assessment among the Nairobi County reinsurance companies is crucial remains an empirical question. While AI technologies promise to enhance risk prediction, precision underwriting and operational automation, they do not guarantee strategic positioning or operational efficiency when implemented. The sophistication of risk assessment algorithms, quality and availability of risk assessment data, predictive model accuracy, and integration into underwriting and risk management processes could impact individual firms results. This would therefore call for determination of the impact of AI based risk assessment on the strategic positioning and operational efficiency of Nairobi County insurance companies (reinsurance companies) in Kenya. This study thus aims to establish the impact of using the artificial intelligence-based risk assessment on strategic positioning and efficiency of reinsurers in Nairobi County, Kenya.

2. Theoretical Background

2.1. Dynamic Capability Theory

Dynamic Capability Theory, developed by Teece, Pisano and Shuen (1997), suggests a process by which firms can gain and maintain their competitive advantage through the capacity to integrate, build and reconfigure their internal and external resources as a result of changes in their business environment. The theory outlines the following important skills: spotting opportunities and threats, exploiting opportunities with strategic choices and making decisions, and adapting an organizations' resources and processes to stay competitive. The purpose of this study is to understand how dynamic capability theory and AI risk assessment impact the strategic positioning and operational efficiency of reinsurance companies in Nairobi County, Kenya. By leveraging AI's power in data analytics and machine learning, risk assessment enhances the sensing ability of reinsurers by enabling them to identify, predict, and evaluate new risks. It provides an improved seizing ability, allowing Management to make well-informed decisions about reinsurance portfolio selection, capital allocation, underwriting and risk pricing at the right time. Moreover, AI aids in organisational transformation by automating risk assessment procedures, optimizing resource utilization, minimizing operational expenses, and ensuring precise and quick decision-making. These features help reinsurers navigate market uncertainty, deliver better service to their clients and stand out from the crowd. Therefore, Dynamic Capability Theory is used to provide a theoretical framework for elucidating the role of AI-powered risk assessment in improving strategic positioning and operational efficiency of the reinsurers in Nairobi County, Kenya.

3. Empirical Review

Nettayanun and Brisker (2025) performed a significant study which identified strategic factors that influence reinsurance purchase decisions in the Property and Casualty (P&C) insurance sector. They analyzed the use of the Shapley Additive explanations

(SHAP) framework. In this study, they demonstrated how AI, in particular, explainable Ai enables companies to identify and organize pivotal strategic elements in a firm. They considered factors like cost, and competition and demand in the industry. The study confirmed that AI tools are capable of uncovering complex and non linear relationships between these key determinants and the ceding levels often missed by the traditional models. They discovered that an increase in writing a specific product would often results into a lower need to cover more within the same product type hence affecting the basis for strategic hedging as well as capital allocation.

Song et al. (2025) conducted an empirical study to investigate the impact of AI technology on organizational decision-making and efficiency. The research looked at how AI is being utilized across different business enterprises and its impact on their decision-making processes and business strategies. The authors adopted the quantitative technique, specifically, the structural equation modelling (SEM), and collected and processed data from 420 organizational respondents using questionnaires. The results indicate that the support of top management positively affects the level of AI adoption, whereas the perception of usefulness is an important driver of AI adoption. Companies that have a higher AI acceptance rate showed greater efficiency in decision making and improved strategic performance. As illustrated by this study, AI can play a crucial role in establishing data-driven decision-making models and strategic management in organisations (Song et al., 2025).

Singh and Mishra (2025) focus on the extent of AI usage and sustainability of businesses in B2B companies globally. The subject of the study focused on understanding how the use of AI acted as a mediator between the competitive landscape and the environmental shifts, and their relationship to business sustainability results. The authors have adopted a mixed research method (quantitative method with PLS-SEM and artificial neural networks (ANN) analysis to examine the data collected from several B2B companies. The findings showed that AI adoption played a mediating role between competitive pressures and sustainability and that competitive pressure was the most significant relationship with sustainability performance. Singh and Mishra (2025) say that companies use AI strategically to optimize and improve operational efficiency as well as create more responsive sustainable business strategies to more complex and changing market dynamics.

Zuraina (2025) studied AI adoption, competitive pressure, and business sustainability in emerging markets in Kuala Lumpur, Malaysia. A quantitative survey design was employed and data were analyzed with multiple linear regression from 137 firms. The study examined how the adoption of AI can help businesses meet strategic goals when facing competition. The results indicate that the use of AI improves business sustainability positively and significantly; and competitive pressure accelerates the use of AI, enabling the fast-track of AI implementation. In this way, companies that make smart use of AI, likewise, will score a long haul competitive edge, particularly in developing economies where markets push for the adoption of innovation (Zuraina, 2025).

Martins (2025) investigated the transformation of business strategy and AI analytics. The study was global and mixed methodological design consisted of a literature review and empirical research with industry professionals and data analysts. The researcher investigated the impacts of AI analytics (predictive modelling, machine learning, natural language processing) on strategic decision making, operational responsiveness and competitive responsiveness. AI analytics, according to the study's results, improves operational responsiveness, makes decision making less biased, and improves market response. Some of the obstacles that were analyzed were associated with privacy and

ethical data, and the lack of staffing. The study's conclusion was that AI technology is a strategic facilitator that enhances a company's ability to incorporate technology into their business strategy. (Martins, 2025).

H1: AI-enabled risk assessment has significant effect on business strategy.

4. Research Methodology

An explanatory research design was used to determine the causal relationships between Artificial Intelligence (AI) and business strategies of reinsurance firms in Nairobi County in Kenya with organizational readiness a moderating variable. The unit of observation was the managers and employees from the seven reinsurance companies in Kenya and the unit of analysis was the individual reinsurance companies. A quantitative approach was used and respondents were chosen using stratified random sampling method for good coverage of organisational levels and participating firms.

A total of 350 respondents (73 managers and 277 employees) were targeted from seven reinsurance companies in Kenya. The companies involved include Kenya Reinsurance Corporation, ZEP-RE, Africa Reinsurance Corporation, Continental Reinsurance, WAICA Reinsurance, and East Africa Reinsurance and Ghana Reinsurance. Stratified random sampling was used, by stratifying respondents by their respective firms and then by the classification of manager and employee. Yamane's (1967) formula was used to calculate the sample size and the sample size was obtained at 3% margin of error of 349 respondents. Structured, self-administered questionnaire on five-point Likert scale was used to collect quantitative primary data. The questionnaire gathered information about business strategies (strategic positioning, operational efficiency and competitive orientation), Artificial Intelligence (AI-enabled risk assessment, AI-driven claims intelligence and AI-supported strategic decision-making), and organisational readiness (technological infrastructure, employee competencies and leadership support). A pilot study was carried out in Kiambu County, with a sample size of 35 representing about 10% of the target population in order to evaluate the reliability and validity of the research instrument. To determine the reliability of the items, the alpha coefficient of Cronbach was used, with a value of 0.70 as the minimum acceptable. Content validity was confirmed by supervisors in the School of Business and Economics at Moi University while construct validity was measured using a Kaiser–Meyer–Olkin (KMO) index with a value of > 0.60 accepted. Main method of data collection was a drop and pick-later technique with two trained research assistants, three weeks long.

Table 1: Measurement of Variables

Variable	Type	Indicator/Dimension
Business strategy	Dependent variable	strategic positioning, operational efficiency competitive orientation
AI-enabled risk assessment	Independent variable	AI-enabled risk assessment

Source: Author, 2026.

Data Analysis and Model Specification

The study used a strictly quantitative data analysis technique which involved both inferential and descriptive statistical analysis using SPSS version 25. Both inferential and descriptive which includes mean, standard deviation, percentages minimum and maximum were all used to summarize demographics and study variables. Inferential statistics was also used in the study as both correlation and regression analysis was

carried out. To test the proposed hypotheses the following regression equation was adopted:

Model1: Testing the effect of the control variables on business strategy

$$Y= \beta 0 +C \ldots\ldots\ldots 1$$

Model 2: Testing the effect of the independent variables on business strategy $Y= \beta 0 +C+ \beta 1 X1 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$

Y: business strategy

X1: AI-enabled risk assessment

5. Findings

The study used 349 questionnaires for the selected respondents from reinsurance companies in Nairobi County, Kenya. Of the questionnaires that were distributed, 281 were returned successfully for an 80.52% response rate. The returned questionnaires were screened for completeness, consistency and accuracy and only 250 questionnaires met the predetermined inclusion criteria were retained for analysis, thus, 71.63% of the total questionnaires sent out are effective. Questionnaires returned were 88.97% used. The rate of 61.7% was considered proper and acceptable for social science and management studies as the responses above the rate of 70% for social sciences are sufficient for statistical analysis and to increase the reliability of the research findings (Mugenda & Mugenda, 2019). The response rate achieved was adequate to analyse the moderating effect of organisational readiness on the relationships between Artificial Intelligence and strategic positioning, operational efficiency and how business strategies of reinsurance firms relate to competitive orientation in Nairobi County, Kenya.

Table 2: Response Rate

Distributed Questionnaires	Received Questionnaire	Usable Questionnaires	Response Rate
349	281	250	80.52

Source: Primary Data (2026)

Descriptive Statistics for Business Strategy

However, the mean was 3.50 with a standard deviation of 0.813 for SP1, suggesting that respondents generally agreed their organizations regularly find new market possibilities and they actively launch into new market segments before others do. The standard deviation was relatively low, indicating that there was a relatively consistent opinion among the respondents about this strategic positioning practice. The mean was 3.52 and the standard deviation 0.756 for SP2, indicating that there was a general consensus that firms make a conscious effort to distinguish their product/service from their competitors to provide increased value to their customers and to make their position in the market stronger. The lower standard deviation means that there is a high level of agreement among the respondents with respect to this statement.

For SP3, the mean was 3.50 and the standard deviation 0.808, indicating that people typically agreed that their organizations' strategic decisions are made on long-term goals to achieve a good competitive position instead of short-term financial returns. The standard deviation represents fairly uniform answers by the participants. The mean for SP4 was 3.47 with a standard deviation of 0.787, reflecting moderate agreement that organizations have a clear value proposition and it is communicated clearly to customers and stakeholders. The relatively small standard deviation indicates that there was little variation in views on this strategic positioning aspect amongst respondents. The mean score of SP5 was 3.47 with a standard deviation of 0.817, indicating that the respondents felt that their organizations follow actively monitor changes in the

competitive environment, and adapt their strategic direction, resource allocation, and business models accordingly. The standard deviation shows that there is a moderate amount of agreement between respondents, with minimal variation in their answers.

The mean score was 3.50 with a standard deviation of 0.818 in the OE1. It means that the respondents generally agreed that their organizations are always optimising the use of internal processes and resources to minimise operational costs while ensuring the quality of products and services. The relatively low standard deviation suggests that the respondents had fairly uniform perspectives on this practice. The mean for the respondents was 3.46 with a SD of 0.797 on the OE2 question which stated, "My organisation has implemented workflows, automated systems and standardised procedures to ensure smooth coordination across departments." Limited variation in the perception of the respondents is shown by the low level of standard deviation. The mean for OE3 was 3.48 with a standard deviation of 0.803, indicating that the general opinion was that operational performance metrics are regularly measured and improved by management, and that this process improves competitiveness. The relatively small standard deviations suggest uniformity in the responses of the organizations sampled. The mean score of 3.46 and the standard deviation of 0.792 showed moderate agreement that organizations invest in employee training, skills development, and technological improvements to increase operational productivity, for OE4. The low dispersion of responses indicates high consensus amongst respondents. The mean for the items for OE5 was 3.50 with a standard deviation of 0.847, indicating general agreement that the need for continuous monitoring of resource allocation and operational outcomes allows organizations to detect inefficiencies and take corrective action in a timely fashion. The standard deviation of this indicator is slightly larger than the other operational efficiency indicators, but is still reasonably small, suggesting that responses are fairly consistent.

The mean of CO1 was 3.49 with a standard deviation of 0.777, which suggests that generally, respondents agree that their organizations actively track competitors, market trends and emerging threats to secure competitive advantage. The standard deviation is relatively small, indicating high consistency of the respondents. The highest mean was CO2 (3.51) with a standard deviation of 0.842, indicating agreement that their companies foster an environment that allows employees and managers to see opportunities and move first over their competitors. There is moderate consistency in responses as shown by the standard deviation. The mean for CO3 was 3.48 with a standard deviation of 0.837, indicating that generally, respondents agreed that strategic planning is to create superior customer value to outperform competitors. The relatively small standard deviation indicates that the views of the respondents were similar in terms of this strategic practice. The mean value of CO4 was 3.46 with a standard deviation of 0.807 to show moderate agreement that organizational performance and strategic initiatives are regularly compared to those of competitors to enhance decision making and competitiveness. The results show a fairly uniform response from participants, as indicated by the standard deviation.

The mean of CO5 was 3.50 with a standard deviation of 0.803, indicating that generally, respondents agreed that organizations are well positioned to meet competitive challenges and maintain market leadership by aligning resources, technology and human capital. The Standard Deviation for the scores is relatively low which shows that there is good agreement among the respondents.

The descriptive statistics reveal that there is general agreement that their organizations have adopted effective business strategy practices. The overall mean score of business strategy practices was 3.4885 with a standard deviation of 0.66609, indicating that the

level of business strategy practices should be considered moderate to high according to the composite mean score. The relatively low standard deviation also suggests a uniformity of perception among the respondents about the operational efficiency and competitive orientation strategies, suggesting that both strategic dimensions are prevalent in the organizations included in the study.

Descriptive Statistics for AI-Enabled Risk Assessment

As of AR1 (M = 3.48, SD = 0.818), respondents moderately agreed that their organizations had integrated artificial intelligence into key operational processes to support automation, predictive analytics, and data-driven decision-making. The relatively low standard deviation indicates a fairly consistent perception among respondents regarding AI integration. AR2 (M = 3.47, SD = 0.827) similarly indicates moderate agreement that AI technologies are used to analyze large volumes of structured and unstructured data to generate actionable insights, with responses showing limited variability. AR3 recorded a mean of 3.51 (SD = 0.803), suggesting that respondents generally agreed that AI applications such as machine learning, natural language processing, and intelligent automation are aligned with strategic organizational goals, while the low standard deviation reflects considerable consensus. AR4 attained the highest mean within this dimension (M = 3.52, SD = 0.846), implying moderate agreement that management invests in AI tools, infrastructure, and employee training to strengthen organizational AI capabilities. AR5 (M = 3.49, SD = 0.827) further demonstrates moderate agreement that organizations continuously evaluate AI initiatives to improve performance, decision quality, and strategic agility, with respondents exhibiting relatively consistent opinions.

SP: strategic positioning, OE: operational efficiency, CO: competitive orientation. AR: AI-enabled risk assessment, AI: Artificial intelligence.

Correlation Analysis

From the Pearson correlation results, there is a moderate positive relationship between business strategy (BS) and AI-enabled risk assessment (AII) among the reinsurance firms in Nairobi County, Kenya and the correlation is statistically significant. The correlation coefficient (r = 0.571) indicates that there is a positive correlation between AI-enabled risk assessment and business strategy. This means that firms that have more advanced AI-enabled risk assessment capabilities – defined by their ability to use artificial intelligence to identify, evaluate, predict, and monitor risks, support risk-based decision-making, and identify emerging market opportunities – are associated with better business strategy. The level of relationship indicates that AI-enabled risk assessment is one of the key factors that influences the development of business strategies of the reinsurers in order to improve their market position and competitiveness. Statistical significance value (p = 0.000) means that the relationship is statistically significant on the 0.01 level (p

Table 3: Correlation Analysis

		BS	AII
BS	Pearson Correlation	1	.571**
	Sig. (2-tailed)		.000
	N	250	250
AII	Pearson Correlation	.571**	1
	Sig. (2-tailed)	.000	
	N	250	250

Regression Analysis and Hypothesis Testing

After satisfying the multivariate linear regression assumptions of linearity, normality, multicollinearity, and autocorrelation, the study employed a hierarchical regression model to evaluate the impact of the covariates (control variables) and the direct effect hypotheses.

Hierarchical regression analysis was conducted to determine the incremental contribution of the control variables and independent variables, in explaining variations in business strategy (BS). The variables were entered into the regression model in two successive stages to assess changes in the explanatory power of the model.

Model 1: Addition of Control Variables

The first model included the control variables, firm size (FSS) and age of the organization (AGG). The results indicated that the model was statistically significant ($F = 16.508$, $p < .001$), demonstrating that the control variables jointly predicted business strategy. The model produced an R value of 0.343 and an R^2 of 0.118, indicating that firm size and organizational age explained 11.8% of the variation in business strategy. The adjusted R^2 of 0.111 suggests that after adjusting for the number of predictors, the model still explained 11.1% of the variance. The regression coefficients revealed that both control variables significantly influenced business strategy. Firm size had a positive and significant effect ($\beta = 0.279$, $B = 0.254$, $t = 4.654$, $p < .001$), implying that larger organizations were more likely to adopt stronger business strategies. Similarly, organizational age positively influenced business strategy ($\beta = 0.220$, $B = 0.196$, $t = 3.668$, $p < .001$), suggesting that older organizations possessed greater strategic capability, possibly due to accumulated experience and established organizational processes.

Model 2: Addition of Independent Variables

In the second model, the independent variables comprising AI-enabled risk assessment (AR) together with the control variables, were entered into the regression model. The overall model remained statistically significant ($F = 41.013$, $p < .001$). The R value increased substantially from 0.343 to 0.676, while the coefficient of determination (R^2) increased from 0.118 to 0.457, indicating that the predictors collectively explained 45.7% of the variation in business strategy. The adjusted R^2 increased to 0.446, implying a considerable improvement in the explanatory power of the model. The increase in R^2 from 11.8% to 45.7% represents an improvement of 33.9 percentage points, demonstrating that the artificial intelligence dimensions contributed substantial additional explanatory power beyond the control variables. This finding suggests that integrating AI capabilities significantly enhances organizations' ability to formulate and implement effective business strategies.

6. Discussion

The study found a moderate positive and statistically significant relationship between AI risk assessment and business strategy amongst the Nairobi County Reinsurance companies in Kenya ($r = 0.571$, $p = 0.000$, $N = 250$). The study reveals that the use of AI for risk identification, evaluation, prediction and monitoring is positively correlated with the adoption of successful business strategies by reinsurers. The findings indicate that AI-driven risk assessment offers significant insights that can assist in evidence-based strategic decision-making, enhance risk management, and help companies capture new market opportunities. The hierarchical regression results also confirmed the importance of the AI-enabled risk assessment in understanding the variations in business strategy. The first model (firm size and organisational age) accounted for 11.8% of the variance in business strategy. AI-powered risk assessment added to this,

however, increased the explanatory power to 45.7%, adding 33.9 percentage points. Thus, the results show that the use of AI for risk assessment can significantly impact business strategy, even when considering only organizational features. Moreover, firm size ($\beta = 0.279$, $p = 0.000$) and organisational age ($\beta = 0.220$, $p = 0.000$) are positively and significantly related to strategic development, suggesting that organisational resources and accumulated experience are also associated with strategic development. Overall, the results confirm that AI-powered risk assessment is a valuable organisational capability that can boost strategic positioning and competitiveness among Nairobi County's reinsurers.

7. Conclusion

The study findings indicate that there is positive and statistically significant relationship between AI supported risk assessment and business strategy of the reinsurance companies operating in Nairobi County, Kenya. The Pearson correlation coefficient ($r = 0.571$, $p = 0.000$) shows that the better the use of artificial intelligence in the identification, evaluation, prediction and monitoring of risk, the better the business strategy. The hierarchical regression results also confirmed that the prediction power of the regression equation is significantly increased when adding the AI-based risk assessment system, rising from 11.8% to 45.7% of the coefficient of determination. This adds 33.9 percentage points to the percentage of business strategy variance accounted for by the predictors added to Model 2. Hence, AI-driven risk assessment proves to be a crucial strategic tool for reinsurers to make informed decisions, proactively foresee future risks, and capitalize on market opportunities while bolstering their competitive edge. Furthermore, the results indicate that the size of the firm and its age had positive and significant associations with the business strategy, indicating that business resources and institutional experience build on the capabilities enabled by AI. Thus, it is advisable for reinsurance companies to think of AI-powered risk assessment as more than just a technological investment; it becomes part of strategic management and organisational competitiveness.

8. Recommendations

8.1. Managerial Recommendations

According to the study, Nairobi County's reinsurance companies are urged to invest in cutting-edge AI-powered risk assessment tools to boost their business strategies. In particular, companies need to leverage machine learning, predictive analytics, and automated risk assessments in their strategic management to enhance the ability to detect, assess, forecast and track new risks. Moreover, management should also integrate AI-generated risk intelligence into their strategic planning, underwriting decisions, portfolio diversification, and market positioning. In addition, reinsurers need to dedicate efforts to employee capacity building, ensuring that risk management, actuarial and strategic management staff have the technical skills necessary to interpret and put AI-generated insights into practice. As organisational size and age have a positive impact on business strategy, smaller and relatively younger firms must consider strategic partnerships, technology sharing platforms and joint investment opportunities as a way to surmount resource constraints. Management should also set up suitable governance, cybersecurity measures, and performance assessment systems regularly to guarantee reliability, transparency, and efficiency of the risk assessment systems that have been enabled by AI. These would help to promote evidence-based decision making and enhance strategic competitiveness of reinsurers.

8.2. Implications for Policymakers

The study calls for policy makers especially the Insurance Regulatory Authority (IRA) to create and toughen up regulations that foster responsible use of AI in the reinsurance market in Kenya. The guidelines must outline the use of AI in risk assessment, data management, algorithmic accountability, cybersecurity and insurers' confidential insurance information. The competent authority shall also foster industry-wide standards for the quality, accuracy and reliability of the data used in AI-assisted risk assessment systems. Moreover, a policy framework should enable cooperation between reinsurers, technology vendors, research organizations and professional organizations to foster knowledge transfer and technological development. Especially for smaller and new entrants to the reinsurance industry, capacity-building initiatives and technical training and incentives for innovation and technology should be encouraged to reduce technology gaps. The results also highlight the necessity of implementing regulatory sandboxes to enable companies to experiment with new AI use cases within a controlled regulatory environment. These interventions can shape an enabling regulatory environment for the responsible uptake of technology, augment strategic decision-making and build the resilience and competitiveness of Kenya's reinsurance market.

8.3. Theoretical Recommendations

The study suggests that Dynamic Capability Theory should be applied in the future and extended to a relationship between AI-based risk assessment and business strategy for reinsurers. The theory gives a justified explanation of the development of organisations, their integration and reorganization of internal and external resources for adapting to a changing business environment. These results, including the moderate positive correlation $r = 0.571$, and the extra 33.9 percentage points in explanatory power after adding AI-based risk assessment, highlight the strategic significance of technological capacities in adaptation within organisations. AI-powered risk assessment enhances the risk-sensing ability of reinsurers by identifying new risks and market opportunities. It serves to strengthen the capacity to act swiftly by providing predictive intelligence to facilitate timely strategic decisions, and to contribute to the organizational change by embedding AI technologies in the organization's risk management and strategic processes. The study, therefore, suggests that AI-based capabilities should be added to the theoretical applications as driving factors of the dynamic capabilities of technology intensive financial institutions in the future. Organisational learning, technological readiness and innovation capabilities are also worthy of further investigation in relation to AI adoption and its contribution to differences in business strategy and competitive positioning by future researchers.

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