E-ISSN: 1115 - 8530 P-ISSN: 3026-8958
MPRI-JFRBD | INTERNATIONAL JOURNAL OF FINANCIAL RES. AND BUSINESS DEVELOPMENT
VOL. 11 NO. 7 – JANUARY, 2026

INSURANCE PRE-LOSS RISK SURVEYING & SUSTAINABILITY UNDERWRITING OF NON-LIFE INSURANCE COMPANIES IN NIGERIA

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DOI: https://doi.org/10.70382/mejfrbd.v11i7.080

Keywords: Pre-loss risk surveying, sustainability underwriting, non-life insurance, hazard analysis, risk classification, Nigeria, structural equation modelling.

Abstract

This study explored the connection between insurance pre-loss risk surveying and sustainability underwriting in the Nigerian non-life insurance companies. The research design adopted was quantitative based on Structural Equation Modelling (SEM) with data gathered from underwriting managers, risk surveyors, and underwriting officers in the Nigerian non-life insurance companies registered under the National Insurance Commission (NAICOM). The study tested four hypotheses with effect of hazard analysis and evaluation, loss prevention consultation, risk classification and rating, and pre-acceptance survey frequency on sustainability underwriting of non-life insurance companies. The results show that the four dimensions have a significant and positive impact on the sustainability underwriting of non-life insurance companies. The strongest predictor ($\beta = 0.30$, $p < .001$) was Risk Classification and Rating, then Hazard Analysis and Evaluation ($\beta = 0.27$, $p < .001$), Loss Prevention Consultation ($\beta = 0.24$, $p = 0.003$), and Pre-acceptance Survey Frequency ($\beta = 0.20$, $p = .003$). The model fit indices of (SRMR = 0.013, RMSEA = 0.000, CFI = 1.000, TLI = 1.000), proved the strength of the structural relationships. The research finds that sustainable

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underwriting requires excellence across dimensions of pre-loss risk surveying. The study suggests that the non-life insurance companies in Nigeria should focus on advanced systems of risk classification, institutionalize the critical investigation of hazards, incorporate the loss prevention consultation model into the business model, and initiate the dynamic frequency of surveys.

Introduction

The non-life insurance industry is a key pillar of economic stability and risk management in contemporary economies, and it offers financial protection against unforeseen losses, while at the same time facilitating prudent risk management behaviours by individuals and organisations. In Nigeria, the non-life insurance business has witnessed a gradual evolution as a result of regulatory reforms, growing awareness of exposure to risks and imperatives of global best practices. However, in spite of these developments, the sector is still struggling with challenges relating to profitability, market penetration and alignment of underwriting practices with modern standards of sustainability (Iyodo et al., 2020; Etudaiye-Muhtar & Agboola, 2021). The core of non-life insurance business activities is risk underwriting. Conventional underwriting has relied significantly on desk underwriting where most of the information is revealed in proposal forms based on the principle of utmost good faith (Bąk & Jedynak, 2022). This given method has inherent restrictions due to information asymmetry, since the potential policyholders might know more about their risk exposures, may result in adverse selection and moral hazard (Asmussen and Steffensen, 2020). This premise of being purely reliant on information revealed causes the weakness in the underwriting process since non-disclosure of information intentionally or unintentionally may result in incorrect pricing of risks, leakage of premiums and high ratios of losses that put the sustainability of insurance portfolios at risk (Agboola et al., 2025).

Pre-loss risk surveying is an essential underwriting control mechanism that tries to address the information asymmetry that existed between insurers and insureds. This is done through physical and technical tests of the risks prior to the binding contract as it allows the underwriters to verify the actual state, control and exposure of the subject matter (Kiraly, 2024; Blokdyk, 2019). In contrast to passive reception of knowledge about information being shared, risk surveying introduces ground information by means of on-site verification and helps insurers to find discrepancies in reported values, assess external risks, and risk culture of the potential policyholders (Jonek-Kowalska, 2022). The elements of good pre-loss risk surveying are hazard analysis and evaluation, loss prevention consultation, proper risk classification and rating, and survey frequency are some of the

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components that collectively contribute to the quality of underwriting decision (Crouhy et al., 2023; Hillson, 2023).

The global insurance industry is experiencing a paradigm shift in the move toward sustainability underwriting that incorporates Environmental, Social and Governance (ESG) factors into traditional risk assessment frameworks. Sustainability underwriting is an approach that takes into account long-term resilience and systemic risks, such as climate change, social responsibility of liability, and failure of governance, going beyond the modeling of financial loss (Iacovino, 2025). The need for insurers to not only price climate risks but to be the agents of mitigation, incentivizing clients to use greener and safer technologies. This way, the underwriting mandate becomes more risk transformation rather than simple risk transfer, with insurers actively supporting the transition to a net-zero economy and providing rewards for future-proof businesses investing in renewable energy and resilient infrastructure (Bhattacharya et al., 2025; Asmussen & Steffensen, 2020).

The relationship between pre-loss risk surveying and sustainability underwriting is symbiotic by nature. Physical surveys are the source of empirical data required to validate ESG metrics and make sure sustainability claims are based on operational reality rather than marketing rhetoric (Gorge, 2016). While a sustainability report may report on energy efficiency or climate resilience, it is only through physical surveillance that the real situation of systems can be confirmed and their capacity to resist physical climate risks such as flooding or wildfires. Furthermore, the consultative nature of risk surveying is the key vehicle for providing sustainability expertise to clients through recommendations to improve sustainability thereby minimizing environmental liability and operationalizing sustainability goals of insurers at the policyholder level (Mulumbi et al., 2025).

In Nigerian, the non-life insurance sector has a regulatory structure set up by National Insurance Commission (NAICOM) which requires stakeholders to strictly manage their risks using Prudential Guidelines and Corporate Governance Guidelines that are geared towards deepening the market penetration while maintaining solvency. There is a shift toward improved risk culture in the market, whereby insurers are becoming more interested in the quality and chronic nature of the risks (Iyodo et al., 2020). However, the Nigerian insurance environment presents unique challenges of operations with importance thorough surveying of pre-loss risk. These include pervasive dependence on diesel generators as a result of power instability, which leads to certain fire and pollution issues, inadequate enforcement of building codes and fire safety guidelines by the municipalities, and extreme price competition, which may encourage insurers to skip the necessity of comprehensive physical surveying to cut down on costs of acquisition (Etudaiye-Muhtar & Agboola, 2021; Oluwaleye et al., 2023).

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The insurance risk surveyor addresses a regulatory gap in Nigeria, where the safety inspection mechanism is effectively a de facto mechanism in which there may not be any certainty of enforcement (Agboola et al., 2025). This role is especially important in local infrastructure deficiencies and the prevalence of informal construction practices that may not conform to international safety standards. The blending of pre-loss surveying of risk with sustainability underwriting therefore presents as an opportunity and a necessity to Nigerian non-life insurers who are seeking to boost the quality of their underwriting, improve their loss ratios, and keep up-to-date with global trends in sustainability and to respond to the unique risk landscape in the Nigerian operating environment.

Statement of the Problem

Despite the prominence of pre-loss surveying in improving underwriting quality and achieving sustainability goals, the Nigerian non-life insurance industry has a lot of issues in the consistent and effective implementation of these practices. The extreme price competition nature of the sector creates a basic struggle between the need for operational efficiency and the need for thorough underwriting that often leads to circumvention or superficial execution of pre-loss risk survey by the insurance companies in their pursuit of minimization of purchase cost (Etudaiye-Muhtar & Agboola, 2021). This practice exposes insurers to latent risks which may not be disclosed in proposal forms to result in adverse selection, pricing risks and high loss ratios which may threaten the sustainability of the portfolio (Agboola et al., 2025). To make this difficulty even more challenging is the fact that building codes, fire safety guidelines and environmental laws are not strictly enforced by the municipal government which increases the workload of insurance surveyors to assume the role of key evaluators of safety and operational requirements (Cornock, n.d.). Nevertheless, the technical skills, diagnostic tools, and training of the surveyors in many cases of the Nigerian insurers are insufficient to carry out a proper hazard assessment; moreover, the widespread case of informal construction activities and insufficient documentation further complicate the process of conducting a systematic risk assessment and rating that will be actuarial (Iyoda et al., 2020). Integration of the sustainability aspects into traditional underwriting models is fraught with additional conceptual and operational issues, with much of the non-life underwriting in Nigeria being defined by out-dated information systems and conservative risk pricing and measurement techniques that do not necessarily capture and quantify the ESG aspects (Epetimehin & Adeyemo, 201; Iacovino, 2025; Bhattacharya et al., 2025).

The link between pre-loss risk surveying such as hazard analysis and evaluation, loss prevention consultation, risk classification and rating, and survey frequency and sustainability underwriting outcomes is not well understood and empirically explored in

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the Nigeria. There is a dearth of empirical evidence on the extent to which the same elements specifically affect the ability of Nigerian non-life insurers to obtain sustainable underwriting outcomes (Oluwaleye et al., 2023). The frequency and timing of the pre-loss surveys poses practical dilemmas, as the cost implications of re-surveying on a regular basis to avoid risk and decay of information have to be weighed against potential benefits, yet insurers do not have empirical evidence of the optimal survey frequencies to apply to different types of risk (Murray-Webster & Pullan, 2012; Walker, 2013). Additionally, the consultative aspect of risk surveying, especially in the areas of loss prevention and sustainability enhancement, is still poorly developed in the insurance market in Nigeria, with many insurance firms relating with surveying to merely their gate keeping mechanism rather than their opportunity for value added consultation that can enhance the quality of the risk and develop long term relationship with clients (Hillson, 2023; Jigyasu & Chmutina, 2023; Oke et al., 2023).

Given these multifaceted challenges coupled with lack of empirical evidence at a domestic level that serves as a barrier to policy formulation and development of industry best practices, there is a dire need to empirically examine the relationship between pre-loss risk surveying practices and sustainability underwriting in Nigerian non-life insurance companies.

Objectives of the Study

This study therefore aims to achieve the following objectives:

i. Examine hazard analysis and evaluation effect on sustainability underwriting of non-life insurance companies in Nigeria.
ii. Determine loss prevention consultation effect on sustainability underwriting of non-life insurance companies in Nigeria.
iii. Investigate risk classification and rating effect on sustainability underwriting of non-life insurance companies in Nigeria.
iv. Determine pre-acceptance survey frequency effect on sustainability underwriting of non-life insurance companies in Nigeria.

Research Questions

i. What is the effect of hazard analysis and evaluation on sustainability underwriting of non-life insurance companies in Nigeria?
ii. What is the effect of loss prevention consultation on sustainability underwriting of non-life insurance companies in Nigeria?
iii. What is the effect of risk classification and rating on sustainability underwriting of non-life insurance companies in Nigeria?

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iv. What is the effect of pre-acceptance survey frequency on sustainability underwriting of non-life insurance companies in Nigeria?

Research Hypotheses

The following hypotheses were formulated to guide this study:

H_1: Hazard analysis and evaluation has no significant effect on sustainability underwriting of non-life insurance companies in Nigeria.

H_2: Loss prevention consultation has no significant effect on sustainability underwriting of non-life insurance companies in Nigeria.

H_3: Risk classification and rating has no significant effect on sustainability underwriting of non-life insurance companies in Nigeria.

H_4: Pre-acceptance survey frequency has no significant effect on sustainability underwriting of non-life insurance companies in Nigeria.

Pre-Loss Risk Surveying in Insurance

Pre-loss risk surveying, also known as pre-risk survey or risk inspection, is one of the most important underwriting control mechanisms designed to ensure the physical nature of an insurable risk is validated prior to binding coverage (Kirallan, 2024). Blokdyk (2019) defines pre-risk surveys as important assessment processes that enable underwriters to unpick the risk profile of a subject-matter, analyse the severity and frequency of potential hazards to make sensible coverage decisions. Unlike desk-based underwriting, which is based on the information that is provided and disclosed by the applicant in the proposal forms, in the case of risk surveying, inspection is made as an act of physical inspection aimed at verifying the existence, condition, and management of the assets (Bąk & Jedynak, 2022). This on-site verification is an important check against non-disclosure either intentional or accidental and enables the insurer to bridge the gap between the risk that is presented on paper and that available. By having technical experts visit the premises insurers can uncover discrepancies in declared values, they can see how close unlisted external hazards are, and they can see the risk culture of the prospective policyholder. These intangible things, the cleanliness of a factory floor or the attitude of a site manager to safety protocols, are rarely included in the ordinary application forms but are often predictive of future claims (Jonek-Kowalska, 2022).

Hazard Analysis and Evaluation

Hazard analysis is the basic element of the risk survey. It is the methodical identification of conditions that make the chance or magnitude of a loss more likely or severe (Jonek-Kowalska, 2022; Mulumbi et al., 2025). This is different than general risk assessment in that

it is focused specifically on physical and operational hazards like faulty wiring, poor housekeeping or proximity to combustible materials, in order to estimate potential loss scenarios. Crouhy et al. (2023) emphasizes that analysis needs to go beyond static observations, and include an evaluation of operational models, to ensure that underwriters understand the contribution that processes such as manufacturing workflows, supply chain dependencies or chemical storage make to the dynamic risk profile. Surveyors differentiate between physical hazards, which have to do with the physical aspects of the property such as construction materials, age of machinery, fire load), moral hazards which have to do with the dishonesty or character flaws of the management; and morale hazards, which refer to an attitude of indifference or carelessness because insurance will cover it. In an industrial setting, a physical hazard could be a lack of sprinkler system while a morale hazard would be demonstrated by a consistent negligence in following safety protocols or lack of maintenance records just because a policy is in place (Bąk & Jedynak, 2022). The evaluation process often makes use of more advanced diagnostic tools, such as infrared thermography to detect electrical hotspots or vibration analysis for machinery, giving a scientific basis to the underwriter's acceptance or rejection of the risk (Jonek-Kowalska, 2022).

Loss Prevention Consultation

Modern risk survey has transitioned from a policing role to that of a consultative partnership. Loss prevention consultation involves surveyors recommending specific risk improvement measures (RIMs) to mitigate identified hazards (Hillson, 2023). Recent industry analysis highlights that this function is critical in enhancing the risk profile as opposed to just accepting or rejecting the risk profile. By giving technical advices on safety protocols, fire suppression systems and security measures, surveyors act as the middlemen in the process of reconciling the insured's operational reality with the insurer's risk appetite. This consultative nature of the insurance transaction changes the insurance transaction from a zero-sum game to value-added service (Jigyasu & Chmutina, 2023). Rather than just penalizing a client for poor quality of risk with increased premiums, the surveyor provides a roadmap to de-risk the business. This could mean negotiating the use of safety features, such as installing fire doors, upgrading cybersecurity software or implementing hot work permit systems, as a condition of getting coverage or premium discounts (Oke et al., 2023). Empirical data from the Centers for Disease Control and Prevention (CDC) has suggested that flexible and consultative approaches to loss control have an important impact on reducing claim frequency compared to rigid compliance checks. Ultimately, this collaboration promotes business continuity for the insured,

changing the focus from indemnity to resilience which is invariably more economically efficient.

Risk Classification and Rating

Risk classification is the grouping of policy holders into groups of similar risk probabilities in order to facilitate actuarial equity. As described in a review of the classification of risks in contracting, effective classification reduces adverse selection as it enables insurers to price risks correctly on the basis of observable characteristics. The pre-loss survey allows for the granular data such as Construction, Occupancy, Protection, and Exposure, (COPE) that is needed to place a risk in the appropriate rating tier (Khatta, 2008).

Without this verified data, insurers are faced with classification risk, which an insured with high risk is classified with low-risk peers. This misclassification causes premium leakage, where the premium collected is not enough to cover the actual exposure, and cross-subsidization, where the prudent policyholders unfairly pay for the riskier ones (Cybellium, 2024). If left unchecked, this can lead to an adverse selection, where the pool is populated by low risk clients leaving the pool because the prices are too high, leaving the insurer with only unprofitable, high-risk accounts. For example, two warehouses may look the same on a proposal form, but a survey may show that in one warehouse the two warehouses have highly flammable chemicals stored whereas the other warehouse stores non-combustible metals. Accurate classification as a result of surveying ensures that the chemical warehouse is rated at a level commensurate to its hazard in order to protect the insurer's loss ratios and create fairness in the market (Murray-Webster & Pullan, 2012).

Pre-acceptance Survey Frequency

The frequency of the risk surveys is a determinant of the effectiveness of risk surveys, balancing the cost of the inspection and the risk of information decay (Murray-Webster & Pullan, 2012; Walker, 2013). While there is not a single universal standard, industry best practices generally require intervals that are determined by the risk complexity and volatility. KPI Depot claims that for dynamic environments, the KPI assessment must be done annually or even quarterly to prevent out-dated risk profiles. Conversely, commercial standards for particular systems, such as electrical installations in lower-risk offices, can be as long as five years (Molenaar and Ashley, 2006). CEERISK points out that renewal periods are considered critical trigger points for re-surveying, since equipment obsolescence and operational changes can silently change the risk landscape over time, rendering the original underwriting data invalid. This phenomenon of risk creep, occurs when minor operational changes are accumulated to create a major shift in exposure, e.g.

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a factory slowly increasing its stock levels beyond the design capacity of its fire protection system, or a neighborhood being changed to introduce new external exposure risks. Regular survey intervals are a sort of reset mechanism that the insurance contract is not only a historical snapshot of the risk, but a representation of the present reality of the risk (Youngberg, 2010).

Sustainability Underwriting

According to Iacovino (2025) sustainability underwriting is defined as the integration of Environmental, Social, and Governance (ESG) factors into the traditional risk assessment framework. It represents a paradigm shift from a purely financial loss modeling approach to a futuristic approach, taking into account long-term resilience as well as systemic risks, like climate change and social liability. Sustainable underwriting is not only about pricing in climate risks but about the insurer taking on the role of the agent of mitigation and incentivizing their clients to use greener and safer technologies. This approach shifts the underwriting mandate from risk transfer towards risk transformation where the insurer proactively supports the transition to a net zero economy. It is about screening the risks not only in terms of their immediate probabilities of loss, but also regarding their long-term viability in a changing world (Bhattacharya et al., 2025). For example, the sustainable underwriting framework may include penalties on companies that have high carbon footprints or poor labor practices, as they are viewed as long-term liability risks or stranded assets. On the other hand, it rewards future-proof business that invests in renewable energy or resilient infrastructure. This holistic view recognises that environmental degradation and social unrest represent material financial risks, known as the double materiality, which can threaten the solvency of the insured as well as of the insurer (Asmussen & Steffensen, 2020).

Relationship between Pre-loss Risk Surveying and Underwriting Sustainability

The relationship between physical risk surveying and sustainability underwriting is symbiotic. Physical surveys are used to obtain the ground truth data required to validate ESG metrics (Asmussen & Steffensen, 2020). For example, while a sustainability report may say a facility is energy efficient, a physical survey confirms the physical state of retrofitted systems and their resilience to physical climate risks such as flooding or wildfires. A desktop review may reveal that a company has a policy on flood resilience, but only a surveyor can ensure that flood barriers are deployed properly and that the backup generators are elevated above the flood plain. Furthermore, the consultative nature of surveying is the major vehicle for imparting sustainability expertise to the client. By suggesting improvements that will minimize environmental liability for example

improved chemical containment or fire prevention, surveyors are directly operationalizing the insurer's sustainability goals at the policyholder level (Gorge, 2016). Surveyors also have a very important role to play in helping to identify greenwashing, ensuring that the insurer's ESG portfolio is based on what they're actually measuring, rather than marketing copy. Additionally, they contribute to the understanding of trade-offs associated with sustainability: the installation of solar panels or Battery Energy Storage Systems (BESS) for example, create new electrical and fire loads that need to be evaluated and addressed to ensure that the goal of achieving sustainability does not come at the cost of physical safety (Mulumbi et al., 2025).

The Nigerian Non-Life Insurance Environment

The Nigerian non-life insurance sector operates under a regulatory framework aimed at deepening market penetration while ensuring solvency (Cornock, n.d.). The National Insurance Commission (NAICOM) requires strict risk management practices as stipulated in its Prudential Guidelines and Corporate Governance Guidelines. These regulations are meant to professionalize the sector and would compel insurers to adopt global best practices in terms of risk identification and capital adequacy. Recent studies suggest that there is a trend in the market to risk culture, in which insurers are increasingly concerned with the voluntariness and chronicity of risks (Iyodo et al., 2020). However, the market is still faced with the challenge of reconciling traditional underwriting with sustainable profitability. In an environment that is usually full of price competition, there is a risk that proper physical surveying will be skipped to cut down on acquisition cost (Etudaiye-Muhtar & Agboola, 2021). In a developing economy such as Nigeria, the risk surveyor is often filling a regulatory gap; where the enforcement of building codes and/or fire safety standards by municipal authorities is often patchy, the insurance survey becomes the de facto safety inspection (Agboola et al., 2025). This is especially so in light of local operational realities like the extensive use of diesel generators because of power instability, which brings certain fire and pollution hazards that can only be managed adequately by physical surveying that contributes significantly to national infrastructure resiliency (Oluwaleye et al., 2023).

Theoretical Framework

This study is based on Risk Management Theory and Information Asymmetry Theory. The integration of Risk Management Theory (Kenneth Arrow, 1963) and Information Asymmetry Theory (George Akerlof, 1970) offers a robust analytical framework for addressing the multifaceted challenges faced by non-life insurance companies in Nigeria. While these theories originate from distinct intellectual traditions, Arrow’s focus on

uncertainty and risk mitigation versus Akerlof's emphasis on unequal access to information, they converge in their application to pre-loss risk surveying and sustainability underwriting. Together, they offer a holistic lens through which insurers can increase transparency, mitigate uncertainties and encourage sustainable practices in an increasingly complex operational environment. This synthesis not only strengthens theoretical understanding but also offers actionable insights for improving the efficiency, equity, and resilience of Nigeria's non-life insurance sector.

At the centre of both theories is a common commitment to the identification, assessment and mitigation of risks in a pro-active way. Kenneth Arrow's Risk Management Theory recommends a systematic approach to risk management, which includes 4 key elements: risk identification, risk assessment, risk mitigation, and continuous monitoring. These principles reflect the importance of accounting for the unknown and implementing strategies that will result in minimised losses and maximised opportunities. Similarly, the Information Asymmetry Theory by George Akerlof emphasizes the importance of bridging the gaps of knowledge between transacting parties in order to avoid adverse selection and moral hazard, which are both cases of situations where one party has superior information.

In non-life insurance, pre-loss risk surveying serves as a practical embodiment of both theories. By making detailed inspections of insured properties, operations or activities, insurers can both proactively detect potential hazards (in line with Arrow's principles) and simultaneously minimize information asymmetry (as stressed by Akerlof). For example, a pre-loss survey may identify structural weaknesses in a building, poor fire safety measures or poor drainage systems that might lead to catastrophic claims. These findings allow insurers to make recommendations for corrective actions, adjust their premiums and also educate policy holders on risk reduction. This dual function is to ensure that risks are not only mitigated but also transparently communicated to promote trust and justice in the insurance market. Moreover, integration of these theories makes the point of continuous monitoring and adaptation (Alli & Ganiyu, 2025). Arrow's focus on iterative risk assessment is consistent with Akerlof's recognition of the possibility of changing information gaps through time. In Nigeria, where environmental and socio-economic conditions are extremely dynamic, insurers must adopt on-going evaluation mechanisms in order to ensure that their risk assessments remain accurate and relevant. This approach not only helps make pre-loss surveys more effective but it also helps with long-term sustainability and resilience.

Both theories converge in their advocacy of holistic assessments taking into account multiple dimensions of risk. Arrow's Risk Management Theory stresses the importance of holistic evaluations that prioritize the balancing of short-term goals and long-term

sustainability. Similarly, Akerlof's Information Asymmetry Theory makes the point about the need to fill in systemic gaps in knowledge, especially those of hidden or intangible risks.

These principles are especially pertinent to sustainability underwriting, which integrates environmental, social, and governance (ESG) considerations into the risk assessment process. For Nigerian non-life insurers, sustainability underwriting represents a convergence of both theories. By considering ESG factors such as carbon emissions, labor practices, and governance structures, insurers can have a more nuanced understanding of risks that traditional methods might not consider. For instance, determining the ecological footprint of a manufacturing plant or the impact on the community from a construction project allows for important information that helps us be less uncertain about the future while encouraging good business practices. This approach is consistent with Arrow's focus on proactive risk assessment, and Akerlof's issues with hidden or systemic information gaps. Furthermore, sustainability underwriting addresses broader societal challenges, such as climate change and social inequity, which have far-reaching implications for the insurance industry. In Nigeria, where infrastructure gaps and regulatory inadequacies add to risks, by incorporating ESG metrics when underwriting, insurers can anticipate and prevent systemic threats. For example, assessing the resilience of insured assets to climate-related events, such as flooding or drought, ensures that policies are based on the level of actual exposure, while promoting a sustainable development.

One of the most important problems of the insurance industry is the presence of adverse selection and moral hazard, both of which are the result of information asymmetry. Akerlof's theory underlines the problem that occurs when insured parties have superior knowledge in regards to their risks and consequently make disproportionately high claims or behave recklessly. Arrow's Risk Management Theory on the other hand provides solutions to these challenges with a proactive approach. Pre-loss risk surveying is a direct response to the problem of adverse selection by allowing the insurers to obtain the correct data about potential hazards before they write policies. In Nigeria, where regulatory enforcement is often poor, pre-loss surveys may reveal risks such as poorly built buildings, poor fire safety provisions or poor quality equipment that policyholders may try to hide from insurers. By identifying these vulnerabilities in advance, insurers are able to set premiums accordingly, taking into account the real level of risk and reducing the possibility of adverse selection. Similarly, sustainability underwriting reduces moral hazard by incentivizing ethical behavior. By including ESG criteria, insurers are incentivizing policyholders to engage in sustainable practices and knowing their actions will be considered through the underwriting process. For example, businesses that invest

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in renewable energy technologies, or that have strong safety protocols in place, may be eligible for preferential terms, while those with poor governance practices may be charged higher premiums or excluded from coverage altogether. This approach not only reduces moral hazard, it also brings insurance practices in line with global sustainability trends and plays its part in creating a safer and greener future.

Empirical Review

Olaiya et al. (2022) analysed the impact of risk management techniques on the performance of insurance companies in Nigeria empirical studies in this area are seemingly insufficient for objective assessment and justification for continuous involvement in this core aspect of nsurance strategy. The Structural Equation Model (SEM) of the primary data obtained from 41 randomly sampled insurance companies in Nigeria (Lagos State in focus) helped the researchers to establish that the adoption of loss prevention and control; risk avoidance; and loss/risk financing as risk management techniques significantly enhanced positively the performance (proxy by underwriting profitability) of insurance companies in Nigeria. It should be mentioned, however, that the loss prevention and control technique of risk management had higher positive correlation measured against underwriting profitability than the other two techniques of loss/risk financing and risk avoidance. Their study concluded that the risk management techniques have positively and significantly influenced the profitability of underwriting insurance companies in Nigeria. It is recommended, therefore, that insurance companies in Nigeria should put in place more preventive and control measures, which will help to reduce the frequency of certain specific loss that may be encountered in the course of business.

Oyetayo & Abass (2020) studied the effect of the joint underwriting capacity variables on the financial performance of non-life insurance companies in Nigeria. The research design adopted was the correlational research. A population of forty-one (41) non-life insurance companies that are in Nigeria as at December, 2019 were utilized for the study. The study made use of aggregate annual reports of all the forty-one companies operating in Nigeria over a ten year period of 2008 to 2017. The reserve, reinsurance utilisation and shareholders' fund as underwriting capacity variables and solvency, liquidity and profitability (ROA) as indicators of financial performance were used in the study. The results showed that the variables of underwriting capacity (reserves, reinsurance utilisation and shareholders' fund) have significant impact on the financial performance of non-life insurance companies in Nigeria jointly with p-value of 0.0054. However, the individual check of the variables indicated that reserve has no significant influence on the financial performance. This means that an insurance company will not want to exhaust its

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reserve as it is statutory and it is highly regulated. The study therefore recommended that non-life insurance companies in Nigeria must strive to constantly increase their financial capabilities and strategize their underwriting tentacles when assuming risk from insuring public.

Abdulkadir (2024) The Enterprise Risk Management (ERM) Practices and its effect on the performance of insurance firms in Nigeria. The study adopted the panel and correlational designs in examining the effect of ERM Practices, measured by strategy and operations objectives of the Committee of Sponsoring Organisation (COSO), on the financial performance of insurance firms, measured by Tobin's Q. Secondary data, i.e. the annual financial statements of the insurance firms for the periods of the years 2018-2022 were used in the analysis. The study involved the use of panel data regression model for estimating the relationship. The results indicated the presence of positive and significant effect of strategic goals on financial performance of insurance companies in Nigeria. However, a negative significant effect of operational objective on financial performance of insurance firms in Nigeria was documented. The study recommended insurance firms in Nigeria should continue to ensure full conformity to the provision of COSO components in carrying out their business operation. They should also re-strategize and monitor their financial performance outcomes in line with their established objectives in order to attain the holistic application of ERM strategic objectives in the overall business operations.

The work by Guo et al. (2025) developed a risk assessment model combining historical data to predict the property loss ratio in such regions in the coming year. By taking into account the perspectives of the insurers and the policyholders, we propose the utility value model by evaluating the utility values of risk free and risk exposed properties separately. This framework extracts the conditions for insurance underwriting and a reasonable range of premium rates which determines the optimal underwriting strategy for insurers. Finally, the model is applied to two regions in China, Fujian and Guizhou, to validate the model. Simulation results show that the proposed model has a high predictive accuracy and sensitivity in risk assessment, confirming the feasibility of the proposed underwriting strategy.

Angima (2017) constructed the link between the actuarial risk management practices (ARMP), underwriting risk, firm features and performance of property and casualty (P & C) firms in East Africa. The relationship between ARMP and firm performance was first studied and then the effect of the intervening and moderating variables on this relationship was studied. The combined effect of all the variables on the firm's performance was also tested. ARMP variables included underwriting practices, pricing practices, claims management practices and reinsurance and retentions practices. Firm characteristics comprised of size, age, managerial competence, ownership structure and

country of domicile of the firms. Firm performance was measured using financial indicators of return on assets and average premium growth rate percent while non-financial performance measures comprises of composite score for quality of service, reputation and innovation. Population was all 82 P & C firms in Kenya, Uganda and Tanzania out of which a census survey was conducted. Primary data was collected by using structured questionnaire while secondary data was collected from annual financial statements of the firms for the period from 2010 to 2014. Data was analysed by using the techniques of descriptive statistics and multiple regression analysis for testing the hypotheses. The results showed that there is an insignificant relationship between ARMP and financial performance. However, the relationship with non-financial performance was significant, with pricing, reinsurance and retentions and claims management practices being the predictors of performance. Underwriting was not a significant predictor, which probably explained in market practices of price undercutting instead of basing price on risk evaluation. Loss ratio was found to mediate significantly between ARMP and non-financial firm performance. Loss ratio was predicted for non-financial firm performance and in turn predicted pricing, reinsurance and retentions and claims management practices predicted non-financial performance. The study established that firm characteristics have significant moderating effect on the relationship between ARMP and firm performance. Specifically, size (for financial performance), size, age, managerial competence and home country of the firm (for non-financial performance) were found to effect the direction of this relationship. The implication is that bigger firms in terms of asset base, have ability to engage in optimal risk management practices leading to better performance. The home country of the firms were important in that there was a difference when the countries were segregated. The finding on the relationship between ARMP and non-financial performance was significant for Kenya but insignificant for Uganda and Tanzania, which may be reflective of difference in various aspects of insurance risk management practices in each country. Ownership structure had no significant effect on the relationship between ARMP and both financial and non-financial performance. The results revealed that ARMP, underwriting risk and firm characteristics have a joint and significant effect on the non-financial firm performance implying that all the variables have to be considered in order to enhance the performance of these firms. The outcomes of this research add to theory and existing knowledge and makes contribution to policy and practice in the area of insurance risk management especially in formulation of the risk management framework for industry on what is expected to be done. The results may trigger practitioners, while strategizing for better performance, to reflect on their decision making with respect to the various challenges that the industries faces in insurance risk management practices and high loss ratios among others.

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Kiptoo et al. (2021) Relationship between risk management and financial performance of insurance firms in Kenya between 2013 and 2020 The information was obtained from 51 Insurance firms that were licensed to do business in Kenya as at 31 December 2020. Regression analysis was applied and the results indicated that risk management has a significant effect of the financial performance of insurance firms. In particular, the results show that credit risk has a negative and significant impact on the financial performance. The results suggest that the firms with higher proportion of non - performing receivables to total receivables perform poorly. Insurance firms should therefore implement credit management strategies in order to ensure that the receipts are collected within the stipulated time to prevent occurrence of non-performing receivables and hence improve performance. The results also revealed that the market risk management has a positive and significant impact on financial performance. The findings suggest that the sound investment decisions lead to increase in investment income and as a result financial performance also increases. Insurance firms should therefore take proper care of their investments to increase the performance. The results also suggest that the use of operational risk management has a positive and significant impact on financial performance. The findings indicate that, the proper management of the operations of firms lead to the reduced operating costs, which in turn lead to the increase in net premiums and has the positive impact on the performance of a firm. Insurance firms should therefore adopt appropriate operations management strategies to cut down costs and improve the financial performance of the firm. The results also indicated that liquidity risk management has a positive and significant impact on financial performance. The results imply proper management of liquidity ensures that there is an increase in the proportion of current assets to current liabilities and in turn improves the performance of a firm. Firms should, thus, ensure there is adequate liquidity to discharge obligations when due to enhanced performance. This study has shown that risk management plays an important role in the performance of the insurance firms. Therefore, we recommend that directors and other stakeholders to put in place Proper risk management strategies in order to boost financial performance. We further recommend that regulators and policy makers should come up with policies and regulations that will ensure that firms adopt appropriate risk management strategies to enhance performance. The study adds to the body of risk management literature by offering an empirical study of the impact of the various risk management approaches adopted by the insurance companies and offers some recommendations that can be used by policy makers in the evaluation of risk management mechanisms. The study also provides recommendations to managers and other stakeholders on risk management mechanisms that can be adopted in order to increase the performance of a firm.

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METHODOLOGY

This research showed a quantitative research design using a cross-sectional survey to assess the link between pre-loss risk surveying practices and sustainability underwriting in Nigerian non-life insurance companies. Structural Equation Modeling (SEM) was used as the main analysis framework, allowing concomitant analysis of measurement characteristics as well as structural relationships among latent constructs. This approach was especially appropriate because of the focus of this study in testing complex theoretical relationships among multiple predictor variables and for correcting for measurement error in observed indicators. The target population was all the 29 non-life insurance companies who are registered with the National Insurance Commission (NAICOM) in Nigeria. To determine an appropriate sample size, this study utilized a widely accepted formula for infinite populations, given that the exact number of female entrepreneurs in Kwara South is large not know. For a population size of N, the sample size (n) can be calculated using Cochran's (1977) formula for categorical data, which is suitable for survey research:

$$n_o \frac{Z^2 \times p \times (1-p)}{e^2}$$

Assuming:

$Z = 1.96$ (For 95% confidence level)

$P = 0.5$ (Maximum variability)

$e = 0.05$ (5% margin of error)

$$n_o \frac{1.96^2 \times 0.5 \times (1-0.05)}{0.05^2}$$

$$= \frac{3.8416 \times 0.25}{0.0025}$$

$= 384.16$

Therefore, the sample size is 384, which was distributed among all the respondents selected from the non-life insurance companies.

Purposive sampling was used to select the respondents who have expertise in underwriting, risk surveying, and decision-making related to underwriting, risk survey, and sustainability issues such as underwriting managers, risk surveyors, chief underwriting officers, and sustainability officers (Iyodo et al., 2020). The final sample was large enough to meet minimum requirements for an SEM estimation as recommended by Hair et al. (2010) and Kline (2016).

Data were collected using structured questionnaires, administered through various channels across in Nigeria from Lagos, Abuja and Port Harcourt. To reduce the risk of

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common method bias, procedural remedies such as psychological separation of constructs, random order of items, and focus on the lack of right or wrong answers (Podsakoff et al., 2003) were used in the design of the questionnaire. All constructs were measured using five indicators each on 5-point Likert scales. Hazard Analysis and Evaluation (HAE) was a method that evaluated the systematic identification and evaluation of loss situations in the form of physical, moral, and moral hazards (Crouhy et al., 2023). Consultation on Loss Prevention (LPC) measured the consultative services to risk improvement and mitigation (Hillson, 2023; Oke et al., 2023). Risk Classification and Rating (RCR) represented the accuracy and sophistication of risk classification and pricing processes (Khatta, 2008; Cybellium, 2024). Pre-acceptance Survey Frequency (PSF) measured how often and how early in the project the risk surveys were conducted (Murray-Webster & Pullan, 2012; Walker, 2013). Sustainability Underwriting (SUS) was a measure of Environmental, Social and Governance (ESG) factors integration in underwriting decisions (Iacovino, 2025; Bhattacharya et al., 2025). The instrument was expert reviewed and piloted with insurance practitioners to ensure clarity and reliability of the questions. Items were improved based on feedback from a pilot study before full-scale data collection.

Analysis was performed using the lavaan package (Rosseel, 2019) in R using the statistical programme jamovi (The jamovi project, 2022), the module SEMLj. Given the ordinal nature of Likert-scale items, weighted least squares estimation with mean and variance adjustment (WLSMV) was used, with polychoric correlations used as the input.

The analysis was based on three stages. First, preliminary data screening was used to look at response patterns, missing data, and distributional properties. Second, the measurement model was tested using confirmatory factor analysis (e.g. factor loadings, construct reliability (Cronbach's alpha, ordinal alpha, omega coefficients, Average Variance Extracted), and discriminant validity (Heterotrait Monotrait (HTMT) ratios). Third, the structural model was estimated in order to test hypothesized relationships. Model fit was determined with several indices: chi-square, Standardized Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI). Acceptable fit was suggested by Hu and Bentler (1999) and was indicated by SRMR < 0.08, RMSEA < 0.05, and CFI and TLI > 0.95. Path coefficients (beta) were interpreted following the guidelines of Cohen (1988) for effect size and significance was tested using z-tests at $p < 0.05$. Robust estimation procedures were used to insure the stability of the results (Satorra & Bentler, 1994).

Ethical approval has been received before data collection. All participants gave informed consent following provision of information about the purpose of the study, voluntary

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participation, and confidence. No personally identifying information was collected and data were stored securely. Results are only reported in aggregate form in order to protect participant and organizational anonymity.

RESULT AND DISCUSSION

Table 1: Demographic Profile of Respondents (n = 344)

Variable	Category	Frequency	Percentage (%)
Gender	Male	231	67.2
	Female	113	32.8
Age Group	Below 30 years	38	11.0
	31–40 years	146	42.4
	41–50 years	109	31.7
	Above 50 years	51	14.9
Educational Qualification	HND/BSc	96	27.9
	MSc/MBA	172	50.0
	PhD	18	5.2
	Professional Insurance Qualification	58	16.9
Job Role	Underwriting Manager	104	30.2
	Risk Surveyor	86	25.0
	Chief Underwriting Officer	64	18.6
	Sustainability Officer	52	15.1
	Other Senior Technical Staff	38	11.0
Years of Experience	Less than 5 years	41	11.9
	5–10 years	123	35.8
	11–15 years	107	31.1
	Above 15 years	73	21.2
Total		**344**	**100.0**

The distribution of gender among the respondents reflects a male-dominated workforce in the Nigerian non-life insurance underwriting and risk management space with males representing 67.2% of the sample. This pattern speaks to the traditionally technical and operational nature of underwriting and risk surveying functions with the latter having what would be considered as a higher male representation in Nigeria's insurance industry in the past. Nevertheless, the existence of 32.8% female respondents is noteworthy and indicative of a slow progress in inclusion of gender, especially in emerging activities like sustainability and ESG related underwriting functions.

In terms of age distribution, most of the respondents belong to the economically active and professionally mature age bracket. Specifically, the answers of respondents aged 31-

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40 years (42.4%) and aged 41-50 years (31.7%) together account for more than 74% of the sample. This suggests that mid-career professionals actively engaged in underwriting decisions, risk inspections and strategic sustainability considerations dominated the study. The relatively smaller proportion in the under 30 years old (11.0%) suggests that pre-loss risk surveying and sustainability underwriting functions are majorly handled by experienced personnel rather than the entry level personnel with a view to improving the credibility of the responses.

The educational profile of the respondents also provides further support for the reliability of the data. Half of the respondents (50.0%) have postgraduate qualifications (MSc/MBA) and 16.9% have professional certifications in insurance (ACII and other related designations). This is an indication of a high level of technical competence and professional training among the respondents. The availability of PhD holders, albeit in limited numbers (5.2%), reflects the evolving convergence between academic knowledge, high-tech analytics and underwriting practice, especially in sustainability-driven risk assessment frameworks.

With regard to job positions, the greatest number of surveyors (30.2%) and risk surveyors (25.0%) make up the largest sections of the sample. These roles are directly responsible for pre-loss risk surveying, hazard evaluation and risk classification which are central to conceptual framework of the study. The addition of both chief underwriting officers (18.6%) and sustainability officers (15.1%) help ensure that strategic and ESG-oriented views are appropriately represented. This balance of roles contributes to the holistic understanding of the translation of operational risk surveying practices into sustainability underwriting outcomes.

Finally, the distribution of years of professional experience shows that a rather high proportion of the respondents has a significant amount of industry experience. Respondents with 5-10 years (35.8%) and 11-15 years (31.1%) of experience are dominant in the sample, but more than 1/5 (21.2%) have over 15 years of experience. This depth of experience would suggest that respondents are in a good position to evaluate changes in underwriting practices, the development of pre-loss risk surveying and the incorporation of sustainability considerations in Nigeria's non-life insurance sector. Overall, the results of the demographic profile confirm that the sample is knowledgeable and appropriate as a subject to study the complex relationships tested in the structural equation model.

Table 1: Model tests

Label	X^2	df	p
User Model	51.2	265	1.000
Baseline Model	1.31e+6	300	<.001

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Label	X^2	df	p
Scaled User	246.0	265	0.793
Scaled Baseline	197300.0	300	<.001

Table 1 shows the results of the basic model fit statistics between the hypothesized structural model and the baseline models. The User Model chi-square (χ^2 = 51.2, df = 265, p = 1.000) is a great fit and the non-significant p-value implies that there is no significant difference between the covariance matrix that is produced by the model and the covariance matrix that has been observed. Kline (2016) suggests that the only thing one wants is non-significant chi-square although he states that with large samples, even trivial misspecifications can yield significant outcomes. In this case, the extremely non-significant value of p = 1.000 indicates that the model fits the observed data remarkably. The Scaled User model (χ^2 = 246.0, 265, p = 0.793) and Scaled Baseline model (χ^2 = 197300.0, 300, p = 0.001) also offers a powerful adjustment of possible non-normality of the data. Satorra and Bentler (1994) proposed the scaling adjustment to address the distributional violations that are prevalent when using ordinal data. The excellent fit is not due to distributional assumptions as evidenced by the fact that the scaled user model is not significant (p = 0.793). All these findings point to the fact that the theoretical model structure well reflects the associations in the data.

Table 2: Fit indices

			95% Confidence Intervals		
Type	**SRMR**	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
Classical	0.013	0.000	0.000	0.000	1.000
Robust	0.012				
Scaled	0.012	0.000	0.000	0.020	1.000

Table 2 provides various absolute and relative fit indices which give complementary information regarding the model adequacy. The Standardized Root Mean Square Residual (SRMR) values of 0.013 (classical), 0.012 (robust) and 0.012 (scaled) are very low. According to Hu and Bentler (1999), SMR value below 0.08 implies the goodness of fit, whereas below 0.05 implies excellent fit. The existing values lower than 0.02 indicate that the mean standardized covariance of residuals is negligible, which is that the association of relationships predicted by the model are close to the observed associations. Both scaled and classical estimates have the Root Mean Square Error of Approximation (RMSEA) of 0.000 with a 95% confidence interval of 0.000 to 0.020. The existing RMSEA is 0.000 which is an indicator of perfect fit. The p-values of 1.000 for RMSEA tests the null

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hypothesis that RMSEA is less than or equal to 0.05; the p-values are very insignificant, which indicates excellent close fit. The upper limit of the scaled RMSEA confidence interval (0.020) is significantly less than the standard cutoffs, which offers further evidence to the fact that the true population fit is outstanding.

Table 3: User model versus baseline model

	Model	Scaled
Comparative Fit Index (CFI)	1.000	1.000
Tucker-Lewis Index (TLI)	1.000	1.000
Bentler-Bonett Non-normed Fit Index (NNFI)	1.000	1.000
Relative Noncentrality Index (RNI)	1.000	1.000
Bentler-Bonett Normed Fit Index (NFI)	1.000	0.999
Bollen's Relative Fit Index (RFI)	1.000	0.999
Bollen's Incremental Fit Index (IFI)	1.000	1.000
Parsimony Normed Fit Index (PNFI)	0.883	0.882

Table 3 can be seen to have incremental fit indices that compare improvement of the proposed model to the baseline independence model. All indices have values close to or equal to the theoretical maximal of 1.000, which means that the user model is a significant improvement over the baseline model that considers no relationship between variables. The Comparative Fit Index (CFI) of both the standard model and scaled model is much higher than the 0.95 index suggested by Hu and Bentler (1999) as good fit and even higher in the 0.97 index suggested by Schermelleh-Engel, Moosbrugger, and Muller (2003). Similar indicators of excellent fit are the Tucker-Lewis Index (TLI), which is also 1.000 on both versions. The TLI has been very useful in that there is a penalty of the model complexity but yet the TLI is best and reaches the maximum value implying that the model fits with minimum excessive parameters. The original threshold in these indices was suggested by Bentler and Bonett (1980), 0.90 and since then most methodologists have increased this to 0.95. The values of the Bentler-Bonett Normed Fit Index (1.000 (model) and 0.999 (scaled)) also indicate exceptional incremental fit. Although the NFI is affected by the sample size, the existing values are close to the theoretical maximum. Additional confirmation is given by Relative Noncentrality Index (RNI) of 1.000 of both versions and Incremental Fit Index (IFI) of 1.000 of both versions by Bollen. The values of the Relative Fit Index of 1.000 (model) and 0.999 (scaled) indicate the degrees of freedom in both the models but still shows excellent fit. The Parsimony Normed Fit Index (PNFI) of 0.883 (model) and 0.882 (scaled) is not so large but high enough, which is an adjustment of model parsimony. James, Mulaik, and Brett (1982) came up with parsimony indices to

provide a balance between the model complexity and fit. Although there are no strict cutoffs of PNFI, values of 0.50 and above are acceptable, and those of 0.80 and above are strong. These findings suggest that the model fits very well, and it is not too complex or over-parameterized.

Table 4: Additional fit indices

	Model
Hoelter Critical N (CN), α=0.05	1182.041
Hoelter Critical N (CN), α=0.01	1250.067
Goodness of Fit Index (GFI)	1.000
Adjusted Goodness of Fit Index (AGFI)	1.000
Parsimony Goodness of Fit Index (PGFI)	0.662
McDonald Fit Index (MFI)	1.711

Table 4 gives additional fit measures which can give alternative views of the adequacy of the model. Hoelter Critical N values of 1182.041 (α = 0.05) and 1250.067 (α = 0.01) are the sample size which would render the chi-square test significant at the corresponding alpha levels. According to Hoelter (1983), the value above 200 showed that the model fitted well and the current values are way beyond this level. Also, the GPI of 1.000 and the AGPI of 1.000 attain their theoretical maximum. These indices were suggested by Joreeskog and Sorbom (1984) and nowadays the conventional cutoffs of 0.90 to acceptable fit and 0.95 to good fit are determined by other authors. The GFI is adjusted on the model parsimony by the PGFI of 0.662. The current value shows that there is a good balance between fit and parsimony.

Table 5: Parameters estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
SUS	HAE	0.270	0.0671	0.1388	0.402	0.270	4.03	<.001
SUS	LPC	0.237	0.0614	0.1166	0.357	0.236	3.86	<.001
SUS	RCR	0.300	0.0742	0.1541	0.445	0.300	4.04	<.001
SUS	PSF	0.195	0.0662	0.0652	0.325	0.195	2.94	0.003

Table 5 presents the core structural relationships between the predictor constructs (HAE, LPC, RCR, PSF) and the outcome variable (SUS - Sustainability). These regression paths represent the direct effects of each underwriting practice on sustainability performance. Risk Classification and Rating (RCR) shows the strongest relationship with Sustainability (unstandardized estimate = 0.300, SE = 0.0742, standardized β = 0.300, z = 4.04, p < .001).

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The standardized coefficient indicates that a one standard deviation increase in RCR is associated with a 0.300 standard deviation increase in underwriting of non- life insurance companies in Nigeria, holding other predictors constant. In addition, Hazard Analysis and Evaluation (HAE) demonstrates the second strongest effect (unstandardized estimate = 0.270, SE = 0.0671, standardized β = 0.270, z = 4.03, p < .001). This medium effect indicates that comprehensive evaluation of potential hazards significantly contributes to sustainability. The narrow confidence interval (0.1388 to 0.402) suggests this estimate is precise. Moreover, there is a strong positive relationship between Loss Prevention Consultation (LPC) and (unstandardized) = 0.237, SE = 0.0614, standardized β = 0.236, z = 3.86, p =.001). Although this is a somewhat smaller effect than HAE and RCR, it is nevertheless a significant effect. The standardized coefficient of 0.236 is an important contribution towards sustainability. Lastly, Pre-acceptance Survey Frequency (PSF) has the least, yet also significant the effect (unstandardized estimate = 0.195, SE = 0.0662, standardized 0.195, z = 2.94, p = 0.003). The standardized coefficient of 0.195 demonstrates a small to medium degree of effect in the standards of Cohen (1988). Although the z-value is not as high as the other predictors and the p-value is not as high (yet, much below 0.05), this correlation is statistically and practically significant. All the four parameters have confidence intervals that are not included in zero which proves the statistical significance. Standard errors are all quite small in comparison with the estimates meaning accurate estimation. The combined effect of all the above results is that there is support of the theoretical model that a combination of the various underwriting practices can lead to sustainability results separately..

Table 6: Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
HAE	**HAE1**	1.000	0.00000	1.000	1.00	0.988		
	HAE2	1.005	0.00452	0.996	1.01	0.992	222	<.001
	HAE3	1.005	0.00432	0.997	1.01	0.993	232	<.001
	HAE4	1.005	0.00443	0.996	1.01	0.993	227	<.001
	HAE5	1.004	0.00444	0.996	1.01	0.992	226	<.001
LPC	**LPC1**	1.000	0.00000	1.000	1.00	0.985		
	LPC2	1.007	0.00552	0.996	1.02	0.992	182	<.001
	LPC3	1.002	0.00558	0.991	1.01	0.987	180	<.001
	LPC4	1.005	0.00564	0.994	1.02	0.990	178	<.001
	LPC5	0.997	0.00621	0.985	1.01	0.982	161	<.001
RCR	**RCR1**	1.000	0.00000	1.000	1.00	0.991		
	RCR2	0.992	0.00554	0.981	1.00	0.983	179	<.001

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			95% Confidence Intervals					
Latent	Observed	Estimate	SE	Lower	Upper	β	z	p
	RCR3	0.998	0.00528	0.988	1.01	0.989	189	<.001
	RCR4	0.991	0.00575	0.980	1.00	0.982	172	<.001
	RCR5	0.992	0.00588	0.980	1.00	0.983	169	<.001
PSF	**PSF1**	1.000	0.00000	1.000	1.00	0.988		
	PSF2	0.996	0.00562	0.985	1.01	0.985	177	<.001
	PSF3	1.000	0.00542	0.989	1.01	0.988	185	<.001
	PSF4	1.003	0.00501	0.993	1.01	0.992	200	<.001
	PSF5	0.997	0.00520	0.987	1.01	0.986	192	<.001
SUS	**SUS1**	1.000	0.00000	1.000	1.00	0.989		
	SUS2	0.998	0.00519	0.988	1.01	0.987	192	<.001
	SUS3	0.995	0.00512	0.985	1.01	0.984	194	<.001
	SUS4	0.997	0.00511	0.987	1.01	0.985	195	<.001
	SUS5	1.000	0.00472	0.991	1.01	0.989	212	<.001

Table 6 presents factor loadings linking observed indicators to their respective latent constructs. Each latent variable is measured by five observed indicators, following standard measurement model specification in confirmatory factor analysis.

For Hazard Analysis and Evaluation (HAE), all five indicators show exceptionally high standardized loadings ranging from 0.988 to 0.993. The z-values (ranging from 222 to 232) are all highly significant ($p < .001$), confirming each indicator reliably measures the HAE construct. Hair et al. (2010) suggest that standardized loadings should exceed 0.70 for adequate reliability, and ideally exceed 0.80; the current loadings substantially exceed even the stringent threshold. For Loss Prevention Consultation (LPC) demonstrates similarly excellent measurement properties. Standardized loadings range from 0.982 to 0.992, all well above conventional thresholds. The unstandardized loadings (0.997 to 1.007) indicate relatively uniform contribution across indicators. The high z-values (161 to 182) confirm statistical significance. While Risk Classification and Rating (RCR) shows outstanding indicator reliability with standardized loadings from 0.982 to 0.991. The unstandardized estimates range from 0.991 to 1.000, suggesting extremely consistent measurement across the five items. The z-values (169 to 189) all strongly exceed the critical value of 1.96 for $\alpha = 0.05$ significance. Also, Pre-acceptance Survey Frequency (PSF) exhibits standardized loadings from 0.985 to 0.992, indicating that each indicator strongly represents the construct. The unstandardized loadings (0.996 to 1.003) are remarkably consistent. The z-values (177 to 200) confirm highly significant relationships. Lastly, Sustainability (SUS) demonstrates comparable measurement quality with standardized loadings from 0.984 to 0.989. The unstandardized estimates (0.995 to 1.000) show

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minimal variation, indicating balanced measurement. The z-values (192 to 212) are all highly significant. The consistent high loadings across all five constructs indicate that the measurement model is strong and that each construct is well-defined by its indicators.

The uniformly excellent measurement properties across all five constructs provide confidence that the latent variables are measured with minimal error. This is crucial because measurement error in structural equation modeling can attenuate relationships and lead to biased parameter estimates (Bollen, 1989). The high-quality measurement model strengthens confidence in the structural relationships reported in Table 5.

Table 7: Variances and Covariances

		95% Confidence Intervals						
Variable 1	**Variable 2**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
HAE1	HAE1	0.0244	0.00000	0.0244	0.0244	0.0244		
HAE2	HAE2	0.0156	0.00000	0.0156	0.0156	0.0156		
HAE3	HAE3	0.0146	0.00000	0.0146	0.0146	0.0146		
HAE4	HAE4	0.0149	0.00000	0.0149	0.0149	0.0149		
HAE5	HAE5	0.0161	0.00000	0.0161	0.0161	0.0161		
LPC1	LPC1	0.0297	0.00000	0.0297	0.0297	0.0297		
LPC2	LPC2	0.0167	0.00000	0.0167	0.0167	0.0167		
LPC3	LPC3	0.0260	0.00000	0.0260	0.0260	0.0260		
LPC4	LPC4	0.0198	0.00000	0.0198	0.0198	0.0198		
LPC5	LPC5	0.0352	0.00000	0.0352	0.0352	0.0352		
RCR1	RCR1	0.0178	0.00000	0.0178	0.0178	0.0178		
RCR2	RCR2	0.0330	0.00000	0.0330	0.0330	0.0330		
RCR3	RCR3	0.0220	0.00000	0.0220	0.0220	0.0220		
RCR4	RCR4	0.0358	0.00000	0.0358	0.0358	0.0358		
RCR5	RCR5	0.0340	0.00000	0.0340	0.0340	0.0340		
PSF1	PSF1	0.0230	0.00000	0.0230	0.0230	0.0230		
PSF2	PSF2	0.0299	0.00000	0.0299	0.0299	0.0299		
PSF3	PSF3	0.0235	0.00000	0.0235	0.0235	0.0235		
PSF4	PSF4	0.0168	0.00000	0.0168	0.0168	0.0168		
PSF5	PSF5	0.0282	0.00000	0.0282	0.0282	0.0282		
SUS1	SUS1	0.0226	0.00000	0.0226	0.0226	0.0226		
SUS2	SUS2	0.0260	0.00000	0.0260	0.0260	0.0260		
SUS3	SUS3	0.0319	0.00000	0.0319	0.0319	0.0319		
SUS4	SUS4	0.0288	0.00000	0.0288	0.0288	0.0288		
SUS5	SUS5	0.0218	0.00000	0.0218	0.0218	0.0218		
HAE	HAE	0.9756	0.00759	0.9607	0.9904	1.0000	128.52	<.001
LPC	LPC	0.9703	0.00874	0.9532	0.9875	1.0000	111.07	<.001
RCR	RCR	0.9822	0.00698	0.9685	0.9959	1.0000	140.67	<.001
PSF	PSF	0.9770	0.00849	0.9603	0.9936	1.0000	115.09	<.001
SUS	SUS	0.1600	0.02357	0.1138	0.2062	0.1637	6.79	<.001
HAE	LPC	0.7485	0.03360	0.6826	0.8143	0.7693	22.28	<.001
HAE	RCR	0.7893	0.03016	0.7301	0.8484	0.8063	26.16	<.001
HAE	PSF	0.7735	0.03181	0.7112	0.8358	0.7923	24.32	<.001

			95% Confidence Intervals					
Variable 1	Variable 2	Estimate	SE	Lower	Upper	β	z	p
LPC	RCR	0.7645	0.03262	0.7006	0.8285	0.7831	23.44	<.001
LPC	PSF	0.6765	0.04229	0.5936	0.7594	0.6948	15.99	<.001
RCR	PSF	0.7709	0.03255	0.7072	0.8347	0.7870	23.69	<.001

Table 7 presents the variance components for both observed and latent variables, as well as the covariances among latent constructs. The residual variances for observed indicators (HAE1 through SUS5) range from 0.0146 to 0.0358. The uniformly small residual variances indicate that the latent constructs explain most of the variance in their respective indicators, consistent with the high factor loadings observed in Table 6. According to principles outlined by Byrne (2016), smaller residual variances indicate more reliable measurement.

The latent construct variances show the variability in the underlying dimensions. HAE has a variance of 0.9756 (SE = 0.00759, z = 128.52, p < .001), LPC variance is 0.9703 (SE = 0.00874, z = 111.07, p < .001), RCR variance is 0.9822 (SE = 0.00698, z = 140.67, p < .001), PSF variance is 0.9770 (SE = 0.00849, z = 115.09, p < .001), and SUS variance is 0.1600 (SE = 0.02357, z = 6.79, p < .001). The four predictor constructs have variances near 1.0, which is expected given the standardization common in SEM. The substantially smaller variance for SUS (0.1600) represents the residual variance in sustainability after accounting for the four predictors - in other words, the variance not explained by the model.

The covariances among the four predictor constructs are all substantial and positive, ranging from 0.6765 to 0.7893 in unstandardized form. Converted to correlations (shown in the β column), these relationships range from 0.6948 to 0.8063. All covariances are highly significant (z-values from 15.99 to 26.16, all p < .001). The strongest correlation is between HAE and RCR (r = 0.8063), suggesting that organizations that excel at hazard analysis also tend to have sophisticated risk classification systems. The correlation between HAE and LPC is 0.7693, between HAE and PSF is 0.7923, between LPC and RCR is 0.7831, between LPC and PSF is 0.6948, and between RCR and PSF is 0.7870. The confidence intervals for all covariances exclude zero, confirming their statistical significance. The relatively small standard errors indicate precise estimation, likely due to the large sample size and well-specified measurement model.

Table 8: Reliability indices

Variable	α	Ordinal α	ω_1	ω_2	ω_3	AVE
HAE	0.990	0.996	0.990	0.990	0.990	0.983
LPC	0.987	0.995	0.987	0.987	0.987	0.975
RCR	0.986	0.994	0.986	0.986	0.987	0.971
PSF	0.988	0.995	0.988	0.988	0.988	0.976
SUS	0.987	0.995	0.987	0.987	0.987	0.974

Source: Author's Analysis (2025)

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Table 8 presents multiple indicators of construct reliability and internal consistency, providing evidence about the quality of measurement for each latent construct. Cronbach's alpha (α) values range from 0.986 to 0.990 across the five constructs: HAE = 0.990, LPC = 0.987, RCR = 0.986, PSF = 0.988, and SUS = 0.987. Nunnally and Bernstein (1994) established the 0.70 threshold for acceptable reliability, while more stringent criteria of 0.80 or even 0.90 are often applied in research contexts. Also, the ordinal alpha values (ranging from 0.994 to 0.996) are uniformly higher than standard Cronbach's alpha. Ordinal alpha, developed by Zumbo et al. (2007), is specifically designed for ordinal data and uses polychoric correlations rather than Pearson correlations. The consistently higher ordinal alpha values reflect the appropriate adjustment for the ordinal nature of the data. Furthermore, Omega coefficients (ω_1, ω_2, ω_3) all range from 0.986 to 0.990, essentially identical to Cronbach's alpha for these constructs. McDonald (1999) developed omega as an alternative to alpha that makes fewer assumptions about equal loadings and uncorrelated errors. Omega values above 0.90 are considered excellent according to Hair et al. (2010). Lastly, Average Variance Extracted (AVE) values range from 0.971 to 0.983 across constructs: HAE = 0.983, LPC = 0.975, RCR = 0.971, PSF = 0.976 and SUS = 0.974. Fornell and Larcker (1981) proposed AVE as an indicator of convergent validity, with 0.50 as the minimum acceptable threshold.

The uniformly excellent reliability and validity statistics across all five constructs provide strong evidence for the quality of the measurement model. These values substantially exceed minimum standards proposed by methodologists, indicating that each construct is measured with precision and that the indicators effectively capture their intended dimensions. However, the note about deprecation reminds users that AVE is not technically a reliability coefficient but rather a validity indicator, and that newer functions provide more flexibility in computing reliability for different model types.

Table 9: Heterotrait-monotrait (HTMT) ratio of correlations

	HAE	LPC	RCR	PSF	SUS
HAE	1.000	0.768	0.805	0.791	0.848
LPC	0.768	1.000	0.782	0.693	0.813
RCR	0.805	0.782	1.000	0.785	0.855
PSF	0.791	0.693	0.785	1.000	0.807
SUS	0.848	0.813	0.855	0.807	1.000

Source: Author's Analysis (2025)

Table 9 shows the HTMT ratios, which intends to give a rigorous evaluation of discriminant validity of the five latent constructs. The HTMT ratio was created by Henseler, Ringle, and

Sarstedt (2015) to be better than the conventional methods of evaluating discriminant validity, like the Fornell-Larcker criterion. Scores less than 0.85 indicate sufficient discriminant validity, although some scholars are more conservative with a cut of 0.90.

By looking at the matrix, the values of the HTMT are between 0.693 and 0.855. The vast majority of the values are below the 0.85 mark. LPC and PSF have the least discriminant validity (HTMT = 0.693), which indicates that these constructs are the most different. The fact that RCR and SUS (HTMT = 0.855), HAE and SUS (HTMT = 0.848), HAE and RCR (HTMT = 0.805), and LPC and SUS (HTMT = 0.813) are the highest values of HTMT.

The 0.855 HTMT between RCR and SUS is a little over the 0.850 cutoff, but still less than the more liberal 0.90 cutoff. The same is the same case with the HTMT between HAE and SUS, which is close to the threshold (0.848), indicating strong theoretical and empirical relationship between the two variables. The coefficients of HAE and RCR (0.805), HAE and PSF (0.791), RCR and PSF (0.785), and LPC and RCR (0.782) all show moderate and strong relationships but they retain discriminant validity based on the 0.85 criterion. The diagonal values of 1.000 are used as reference and they represent the correlation of every construct with itself. The symmetry of the matrix indicates that there is an equality of correlation between A and B and B and A. The HTMT findings indicate that although the five constructs are strongly connected with each other (in line with the covariances presented in Table 7), they still have enough unique character to be viewed as distinct theoretical dimensions.

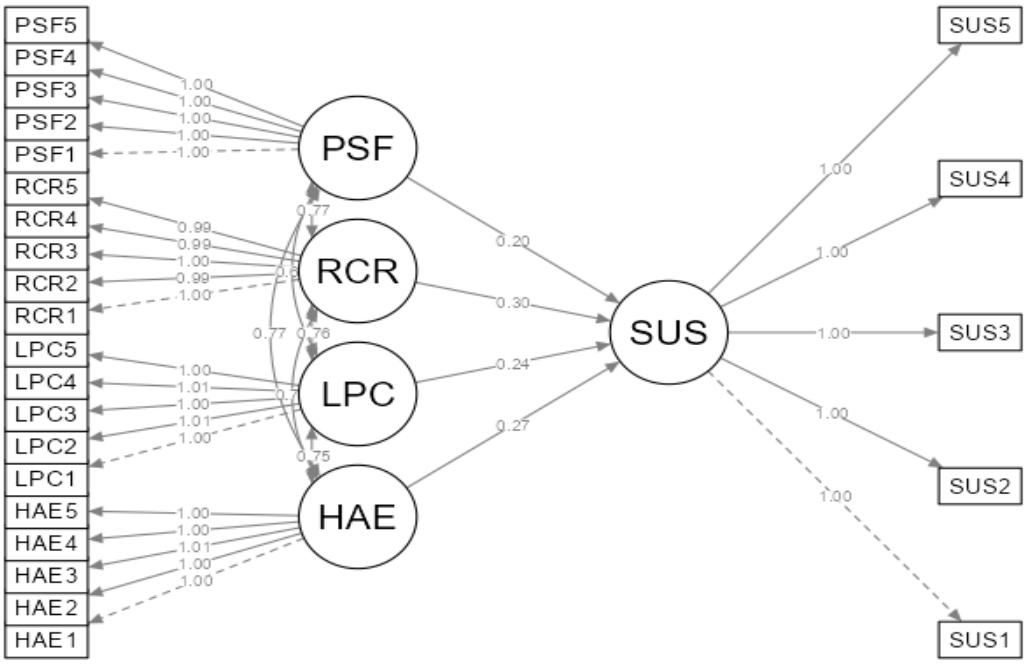

Fig. 1: SEM Path diagram

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This path diagram provides both the measurement model (relationships between latent constructs and their observed indicators) and the structural model (predictive relationships among latent constructs). The model follows a multiple indicators, multiple causes (MIMIC) structure with four exogenous (predictor) constructs and one endogenous (outcome) construct. The measurement model demonstrates exceptionally strong relationships between latent constructs and their observed indicators. Each of the five latent variables (HAE, LPC, RCR, PSF, and SUS) is measured by five observed indicators.

Hazard Analysis and Evaluation (HAE) is measured by indicators HAE1 through HAE5, with factor loadings of 1.00 for all five indicators. The uniformly perfect loadings indicate that each item contributes nearly equally to measuring the hazard analysis construct. The indicators load equivalently, suggesting these items are essentially parallel measures of hazard analysis and evaluation practices. **Also, Loss Prevention Consultation (LPC)** shows factor loadings ranging from 1.00 to 1.01 across its five indicators (LPC1-LPC5). The slight variation in loadings reflects minimal differences in how strongly each indicator relates to the underlying construct. For **Risk Classification and Rating (RCR), it** exhibits factor loadings ranging from 0.99 to 1.00 across indicators RCR1 through RCR5. These near-perfect values demonstrate that all five indicators are excellent measures of the risk classification construct. The consistency of loadings suggests the items form a highly coherent scale. While **Pre-acceptance Survey Frequency (PSF)** demonstrates uniformly perfect factor loadings of 1.00 across all five indicators (PSF1-PSF5). This pattern indicates that each item measuring survey frequency contributes identically to the latent construct. **Sustainability (SUS)** shows factor loadings of 1.00 across all five indicators (SUS1-SUS5). The uniform loadings indicate that each aspect of sustainability measured by these items contributes equally to the overall construct. The consistently high factor loadings across all five constructs (ranging from 0.99 to 1.01) provide strong evidence of convergent validity. According to Hair et al. (2010), standardized factor loadings should exceed 0.70 for adequate reliability, and ideally exceed 0.80 for well-measured constructs. The current loadings substantially exceed even the most stringent criteria, indicating that each construct is measured with exceptional precision and minimal random error.

Structural Model: Predictive Relationships

The structural part of the model indicates four single-headed arrows that run out of the predictor constructs (HAE, LPC, RCR, PSF) to the outcome construct (SUS). Risk Classification and Rating → Sustainability (**β** = 0.30) is the most powerful predictor of sustainability performance. This constant coefficient means that the standard deviation of one unit of RCR is related to the standard deviation of 0.30 units of sustainability, other

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three predictors being the same. The results of this finding indicate that methodical ways of classifying and pricing risk according to the environmental, social, and governance issues have significant organizational implications. **Hazard Analysis and Evaluation → Sustainability (β = 0.27)** shows the second strongest effect. One standard deviation increase in HAE is the predictor of a 0.27 standard deviation increase in sustainability outcomes. The medium effect size shows that holistic assessment of possible dangers used in the underwriting process plays a big part in contributing to sustainability. This relationship is strong enough to infuse the idea that insurance firm that keenly analyze the environmental risks, social effects, and governance concerns in the course of determining the potential policies attain better sustainability performance.

Loss Prevention Consultation (LPC) → Sustainability (**β** = 0.24) is significantly positive. The standardized coefficient of 0.24 shows that an increase in standard deviation in LPC will be accompanied by a quarter standard deviation in sustainability. This is a small to medium effect size according to conventional standards. Loss prevention consultation is a factor that affects sustainability by creating a relationship, transferring knowledge and collaborating in solving problems beyond the initial decision of underwriting to long term partnership in risk management. Pre-acceptance Survey Frequency → Sustainability (**β** 0.20) has the least, but still significantly important effect. The increase in the sustainability by one standard deviation is predicted by one standard deviation increment in the survey frequency. Although smaller than the rest of the predictors, this effect is an important contribution to sustainability outcomes that is not a trivial one. The relatively low coefficient indicates that the frequency of pre-acceptance surveys alone might be less significant because of content and quality of risk assessment activities that are reflected in other constructs. The positive relationship however confirms that the more often the assessment is done, the more sustainable it would be, maybe through more chances to identify the risks, information, and discussion of sustainability concerns with potential policyholders.

Discussion of Findings

The analysis of the structural equation model has shown the compelling evidence of the relationship between pre-loss risk surveying practices and sustainability underwriting in Nigerian non-life insurance companies. The finding that Risk Classification and Rating (RCR) has the greatest influence on sustainability underwriting ($\beta = 0.30$, $p < .001$) is substantively consistent with theoretical predictions as well as empirical precedents. This result is similar to Angima's (2017) results in the East African property and casualty firms in which the pricing practices were found to be significant predictors of non-financial performance. The strength of this relationship underlines the fundamental importance of

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the concept of actuarial equity in sustainable insurance operations. When insurance companies correctly segment the universe of policyholders into homogenous groups of insureds based on verified COPE data (Construction, Occupancy, Protection, and Exposure), the cross-subsidization that compromises the stability of the portfolio is avoided. The mechanism of how RCR affects sustainability is through multiple pathways. First, proper classification ensures that there is less adverse selection, because high-risk insureds are not mistakenly classified with low-risk insureds, which would result in leaking premiums and the adverse selection spiral of the literature review. This finding builds on the work of Oyetayo and Abass (2020) on the underwriting capacity variables in that clarifies that it may be even more important than the quantum of financial reserves in order to determine sustainable outcomes in the quality of the classification processes. Second, sophisticated risk classification allows insurers to incorporate environmental, social, and governance considerations into their rating structures, institutionalizing sustainability considerations at the point of premium determination. Such an approach is consistent with the risk assessment model developed by Guo et al. (2025), which showed that combining historical data with frameworks of value to utilities yields optimal underwriting strategies. The Nigerian experience makes it increasingly important to RCR. In a market that is dominated by fierce price wars and varying levels of enforcement of the regulations, as narrated by Etudaiye-Muhtar and Agboola (2021), proper classification acts as a bulwark against the temptation to underprice the risks to gain market share. The fact that RCR has the greatest impact indicates that Nigerian insurers who invest in sophisticated classification methodologies that include verified survey data instead of just the disclosed data get better sustainability outcomes, as they maintain the actuarially sustainable portfolios with better resilience to withstand long-term environmental and social risks.

The significant positive impact of Hazard Analysis and Evaluation (HAE) on sustainability underwriting ($v = 0.27$, $p < .001$) offers empirical evidence to support the theoretical positing that methodical hazard identification serves as a link in the information asymmetry between insurers and insureds. This finding resonates well with the study by Olaiya, et al. (2022), which established the loss prevention and control techniques to have the highest positive correlation with the profitability of insurance underwriting by the insurance companies in Nigeria. The intersection of these findings indicate that proactive hazard assessment is not only a means for improving the quality of immediate underwriting, but is also a component of long-term sustainability. The importance of the physical check is underlined by the magnitude of the effect of HAE in the Nigerian operating environment. As the literature review highlighted, insurers are often de facto safety inspectors where the enforcement of building codes and fire safety standards by

municipalities may be variable. The hazard analysis function thus takes on a dual significance: it is a fundamental element in the protection of the insurer's financial interests, but also a fundamental element in wider social matters of safety and infrastructure resilience. This finding builds upon the work of Kiptoo et al. (2021), who also found a positive and significant relationship between operational risk management and financial performance using data collected in Kenya, by establishing that a specific practice, the evaluation of hazards, that is built into operational risk management is what drives sustainability outcomes. The relationship of HAE and sustainability works on the basis of reduction of information gap and risk mitigation. By using diagnostic tools such as infrared thermography and vibration analysis, surveyors are able to provide objective data to either validate or discredit disclosed information, which addresses the moral hazard and the issue of the morale hazard identified in Akerlof's Information Asymmetry Theory. Furthermore, overall hazard evaluation allows insurers to recognise emerging sustainability risks such as climate related physical hazards, chemical containment adequacy and fire load management which are increasingly vital for the long term sustainability of portfolio resilience. Interestingly, the near-equivalence of the effect of HAE (beta = 0.27) with that of RCR (beta = 0.30) indicates that the processes of risk assessment and pricing risk are mutually reinforcing. This finding challenges conventional underwriting hierarchies which may be biased in favor of pricing rather than assessment and shows that sustainable outcomes are achieved when there is excellence in both. The result also validates Abdulkadir's (2024) finding which found that the strategic objectives have a significant effect on insurance firm performance as hazard analysis is the strategic commitment to understanding risk at a granular level before assuming the exposure.

The positive significant relationship between Loss Prevention Consultation (LPC) and sustainability underwriting (beta = 0.24, $p < .001$) gives empirical support for the progression of risk surveying from gatekeeping function to value added partnership. This finding is consistent with the recommendation of Olaiya et al. (2022) that insurance companies in Nigeria need to develop more preventive and control measures to minimize the frequency of losses in order to demonstrate that consultative engagement brings about measurable levels of sustainability. The consultative dimension of risk surveying is carried out by a number of mechanisms identified in the literature review. First, recommending specific Risk Improvement Measures (RIMs) surveyors help policyholders to de-risk their operations, changing the insurance transaction from simple risk transfer to risk transformation. This is in line with the paradigm shift towards sustainability underwriting according to the International Association of Insurance Supervisors in which insurers actively support transitions to safer and greener operations rather than just indemnify losses. Second, loss prevention consultation helps in knowledge transfer to

enable policyholders to adopt global best practices in fire suppression, security measures and environmental management. This educational function is especially important in the developing economy such as Nigeria where technical expertise may be unevenly distributed. The effect size (beta=0.24) indicates that, although consultative engagement is meaningful, the extent of its effect may be tempered by client receptivity and capacity to implement. Unlike RCR and HAE, which have an immediate impact on underwriting decisions at policy inception, LPC's benefits accumulate through time as the recommended improvements are made. This temporal dimension may account for why the effect, although significant, is somewhat smaller than classification and evaluation activities. Nevertheless, the finding confirms the consultative approach promoted by Hillson (2023) as well as showing that those insurers that invest in advisory capabilities obtain better sustainability results than those that only survey but do not go beyond inspection and reporting. The finding also complements Angima's (2017) observation that underwriting practices were not significant predictors of performance in East African markets, possibly due to price undercutting and not risk-based evaluation. In the present study, it is interesting that the significant influence of LPC demonstrates its contribution to sustainable underwriting in the sense that when consultation forms part of a comprehensive risk surveying approach, and is not undermined by the pressures of competition, the contribution is meaningful. This brings the importance of institutional support for consultative practices and resistance to short term competitive pressures that may discourage in-depth risk improvement dialogue.

The positive significant relationship between Pre-acceptance Survey Frequency (PSF) and sustainability underwriting (β = 0.20, p = 0.003), whilst the smallest effect of all four predictors, nevertheless gives important insights to the temporal dimension of risk management. This finding supports the theoretical proposition that the use of regular assessment prevents risk creep, the slow creep of operational changes that move exposure profiles beyond those captured by initial underwriting data. The somewhat smaller magnitude of effect size means that it needs nuanced interpretation. Survey frequency alone may not be as determinative as the quality and content of surveys, which is captured better by the HAE, LPC, and RCR constructs. However, the significant positive relationship does confirm the existence of sustainability benefits from more frequent assessment, probably through multiple pathways. First, regular surveys provide updated information reducing the problem of information decay identified in the literature review. Equipment obsolescence, neighborhood shifts and operational changes may cause risk profiles to change silently, invalidating initial underwriting data. Second, frequent interaction helps preserve insurer-insured relationships and reinforces risk culture that may help mitigate moral hazard by signaling continued engagement and monitoring from

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insurers. The finding advances the risk management literature because it shows that the temporal dimension of risk assessment, the frequency with which the risks are re-evaluated, is an independent contribution to sustainability outcomes, even after controlling for the sophistication of hazard analysis, classification and consultation. This provides support for recommendations of Murray-Webster and Pullan (2012) on appropriate survey intervals while providing empirical support that frequency is important and that it is more than just procedural compliance. In the Nigerian context, where operational realities like dependence on diesel generators introduce dynamic hazards, regular re-surveying may be important in capturing the changing risk landscapes. The significant effect of PSF makes it possible to divide insurers who institutionalize periodic reassessment instead of limiting surveys to new business acquisition are better sustained for the long term. This finding also has practical implications in cost-benefit analyses of survey programs, showing that investments in regular reassessment have measurable returns in terms of sustainability performance.

CONCLUSION

The study conclusively shows that events such as pre-loss risk surveying practices significantly and positively affect the results of sustainability underwriting in the Nigerian non-life insurance companies. All four hypothesized relationships were empirically supported: Risk Classification and Rating, Hazard Analysis and Evaluation, Loss Prevention Consultation and Pre-acceptance Survey Frequency were each found to have significant positive effects on sustainability underwriting. This thorough going validation that systematic, thorough pre-loss risk surveying is not a procedural formalism but a strategic imperative to achieve sustainable underwriting results. Also, the relative magnitudes of effects are important to provide important insights about prioritization and resource allocation. Risk Classification and Rating emerged as the strongest predictor followed closely by Hazard Analysis and Evaluation and suggest that accurate risk assessment and actuarially sound pricing represent the twin pillars of sustainability. Loss Prevention Consultation and Pre-acceptance Survey Frequency while showing smaller effects, are substantively and statistically significant, indicating that value added services and temporal monitoring provided meaningful contributions to sustainability beyond the immediate decision to underwrite. The confluence of these findings creates the establishment that sustainable underwriting requires excellence in multiple dimensions of risk surveying rather than emphasis in any one practice.

The study provides good empirical validation to the theoretical integration of Risk Management Theory and Information Asymmetry Theory in understanding the dynamics of insurance underwriting. The great effects of all predictor variables indicate that both

pro-active risk management (Arrow, 1963) and information gap reduction (Akerlof, 1970) simultaneously function in influencing the outcomes of sustainability. The findings indicate that the pre-loss risk surveying is the practical mechanism through which these theoretical principles are operationalized: hazard analysis and classification are used to reduce information asymmetry and loss prevention consultation and regular monitoring are used to represent proactive risk management. This theoretical contribution goes beyond the Nigerian situation to improve the general understanding of the manner insurers can achieve sustainable operations in uncertain environments where information imbalance is prevalent.

RECOMMENDATIONS

Based on the empirical findings and conclusions of this study, four key recommendations are proposed for various stakeholders in the Nigerian non-life insurance industry:

i. Prioritization of sophisticated risk classification systems
ii. Institutionalization of comprehensive hazard analysis and technical capacity building
iii. Integration of loss prevention consultation into business models and client relationships
iv. Establishment of dynamic survey frequency protocols and continuous risk monitoring systems

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