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# Information Asymmetry and Operational Risk in Non-Life Insurance Claims: The Moderating Role of Risk Management and Regulatory Environment in Emerging Markets

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## Abstract

*Operational risk in non-life insurance claims remains a persistent concern in emerging markets, where institutional inefficiencies and limited data infrastructure exacerbate the underlying issue of information asymmetry. This study investigates how asymmetrical information between insurers and claimants fuels operational risks, and whether internal risk management mechanisms and external regulatory forces can effectively moderate this relationship. Drawing on Agency Theory and Institutional Theory, we developed and tested a structural equation model using SmartPLS with empirical data from 216 insurance professionals across diverse firm sizes and technological adoption levels in the 26 non-life insurance companies in Nigeria. The measurement model confirms reliability and validity across constructs, with strong internal consistency and discriminant validity. Structural model results show that information asymmetry significantly increases operational risk ($\beta = 0.55$, $p < 0.001$). However, this effect is moderated by internal risk management systems ($\beta = –0.28$, $p < 0.05$) and regulatory environment ($\beta = –0.22$, $p < 0.05$), both acting as buffers. Predictive relevance and model fit indices ($Q^2 > 0.35$, SRMR = 0.062) indicate a robust model. The findings offer theoretical integration by combining agency perspectives on opportunism with institutional insights on compliance pressures. Practically, the study highlights the value of digital risk tools, standardized claims data, and shared fraud registries. Ultimately, while eliminating information asymmetry may be unfeasible, building organizational resilience and institutional accountability offers a more sustainable path forward.*

**Keywords:** Information asymmetry, Operational risk, Insurance claims, Emerging markets, Risk management



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## 1. Introduction

The non-life insurance sector plays an indispensable role in the economic architecture of emerging markets by enabling individuals and enterprises to transfer risk and recover from financial loss events. Whether through motor insurance, fire coverage, or liability policies, non-life insurance ensures continuity in personal and commercial activities, thereby supporting economic stability and growth (OECD, 2018). However, as these markets expand and evolve, they increasingly grapple with a growing tide of claims-related risks, many of which are exacerbated by information asymmetry between insurers and insureds.

This challenge is more pronounced in emerging economies like Nigeria, Kenya, and India, where the operational capacity of insurers often lags behind the complexity of their environments. Claims processing in these contexts is routinely plagued by fraud, misrepresentation, delayed settlements, and disputes—issues that significantly inflate operational risks and erode customer trust (Swiss Re Institute, 2021). Fraudulent claims, for example, account for up to 30% of total paid claims in some African markets, particularly in motor and health segments (AKI, 2022; NAICOM, 2021). Furthermore, poor documentation, lack of real-time data verification tools, and the inability to cross-reference claim histories contribute to persistent asymmetries of information, especially during underwriting and claims adjudication phases.

### Problem Statement

Despite widespread recognition of operational inefficiencies in non-life claims processing, there remains limited empirical clarity on how information asymmetry directly contributes to operational risk. In many emerging economies, insurers face dual vulnerabilities: on one hand, they lack robust internal control systems that can reliably detect or prevent claim inflation, and on the other, they operate within regulatory environments that are often fragmented, under-resourced, and reactive rather than preventive (IRDAI, 2023; NAICOM, 2022). This makes it difficult to enforce penalties for fraudulent behaviour or mandate transparency across industry players.

Although previous studies have examined information asymmetry in underwriting (Rothschild & Stiglitz, 1976) and moral hazard in claims (Dionne & Gagné, 2001), very few studies have explored how these asymmetries translate into operational risk exposure at the claims level and what institutional mechanisms can buffer these effects in real-world emerging market contexts.

### Research Objectives

This study seeks to address the above gaps by pursuing the following objectives:

- To examine the extent to which information asymmetry drives operational risk in non-life insurance claims.
- To evaluate how internal risk management strategies such as fraud detection systems and claims audits can moderate this relationship.
- To assess the role of regulatory frameworks and enforcement capacity in shaping or weakening the impact of information asymmetry on operational risk.

### Statement of Hypotheses

**$H_1$**: *Information asymmetry significantly increases operational risk.*

**$H_2$**: *Risk management moderates the relationship between information asymmetry and operational risk, such that the relationship is weaker when risk management systems are stronger.*

**$H_3$**: *The regulatory environment moderates the relationship between information asymmetry and operational risk, such that the relationship is weaker in stronger regulatory environments.*

## 2. Literature Review and Theoretical Framework

### 2.1 Information Asymmetry in Insurance

The concept of information asymmetry in insurance markets traces its intellectual roots to Akerlof's (1970) foundational work, *The Market for Lemons*, which illustrated how hidden information distorts market efficiency. In the insurance context, two major forms of asymmetry manifest: adverse selection (hidden information) and moral hazard (hidden actions). Adverse selection arises when insurers cannot accurately distinguish between high- and low-risk applicants due to incomplete or withheld information (Arrow, 1984; Cawley & Philipson, 1999). Moral hazard, conversely, emerges after a policy has been issued, when insured individuals alter their behaviour in ways that increase the probability or severity of claims (Picard, 2000).

In emerging economies, information asymmetries are exacerbated by fragmented data ecosystems and limited inter-insurer collaboration. For instance, in Nigeria, the absence of a centralized insurance database complicates claim verification and fosters fraud. Research shows that many insurers still rely on manual or semi-digital processes, undermining efforts to establish transparent and efficient claims management systems (OECD, 2020; Andia , 2021). Similarly, in Kenya, studies indicate that fraud in third-party motor insurance is often driven by unverified repair estimates, data silos, and limited cooperation among stakeholders in the claims value chain (Wang, 2022). These systemic weaknesses in data integration, verification protocols, and stakeholder accountability result in significant operational inefficiencies and heightened exposure to risk. The World Bank (2021) has also noted that weak institutional frameworks and inadequate digital infrastructure in Sub-Saharan Africa constrain effective risk pricing and actuarial assessment in insurance markets.

### 2.2 Operational Risk in Non-Life Claims

Operational risk—defined by the Basel Committee on Banking Supervision (2011) as the potential for loss due to failed internal processes, human error, or system breakdown—takes on heightened relevance in the claims processing environment of non-life insurance. Unlike market or underwriting risk, operational risk stems from executional and administrative vulnerabilities. Key manifestations include:

- Fraudulent claims, such as staged accidents or inflated losses (Browne & Hoyt, 2000);
- Data entry errors and delays due to manual verification processes;
- Litigation, often triggered by perceived unfair claim denials or slow settlements (Wang & Huang, 2020).

In markets such as India, for example, insurers routinely report claims cycle times exceeding 90 days, primarily due to document incompleteness and lack of real-time data integration (IRDAI, 2022). These inefficiencies are not merely operational—they signal structural

weaknesses that constrain the insurer's ability to respond to asymmetric information in a timely and cost-effective manner.

### 2.3 Risk Management and Institutional Context in Emerging Markets

Effective risk management forms the first line of defence against the operational risks that arise from information asymmetry in non-life insurance claims. When claimants possess knowledge advantages—whether related to the truthfulness, severity, or context of a loss—insurers face heightened exposure to fraud, dispute, and inefficiency. However, these exposures can be meaningfully reduced through structured internal practices and controls.

Best-practice risk management strategies in emerging market insurers increasingly include dual-approval mechanisms, segregation of roles, claims automation using AI and machine learning, and transparent policy language aimed at reducing ambiguity (Deloitte, 2021). Additionally, routine claims audits, external adjusters, and the use of forensic technologies are becoming commonplace as firms seek to proactively validate reported losses and monitor for manipulation.

For instance, India's ICICI Lombard has deployed AI-powered chatbots capable of flagging behavioural anomalies in claims reporting, which has enhanced fraud detection and reduced time-to-resolution (Deloitte, 2021). Similarly, Leadway Assurance in Nigeria now utilizes drone-based surveillance for agricultural and property insurance assessments, enabling real-time verification of asset conditions and reducing the scope for post-loss embellishment (Leadway, 2023).However, these innovations remain unevenly adopted, especially outside major urban centres. Smaller insurers in Nigeria, Ghana, and Pakistan often rely on manual claims processing, which increases exposure to error, delay, and fraud.

Beyond internal capabilities, the institutional environment—including regulatory oversight, enforcement capacity, and legal infrastructure—plays a decisive role in shaping how insurers approach operational risk. In many emerging markets, insurance regulators operate under severe constraints. Limited staffing, inadequate legal mandates, and fragmented policy enforcement dilute the impact of supervisory standards (OECD, 2018). Additionally, there is often no shared data infrastructure for flagging suspicious claims or identifying serial fraudsters.

In Nigeria, for example, NAICOM mandates that large claims and suspected fraud be reported, but lacks the technological infrastructure to verify compliance or coordinate actions across insurers (NAICOM, 2022). Kenya's IRA has experimented with a Claims Transparency Portal, but uptake has been slow due to low digital literacy and weak enforcement (AKI, 2022).

These institutional weaknesses constrain insurers' ability to build standardized and scalable responses to information asymmetry. The absence of a cohesive regulatory architecture thus compounds internal vulnerabilities and increases systemic operational risk.

### 2.4 Theoretical Framework

Operational risk in non-life insurance claims, especially in emerging markets, cannot be explained by a single theory. This study adopts a multi-theoretical lens to understand how firms manage asymmetric information under conditions of institutional fragility and resource constraints. The theoretical foundations are drawn from four primary sources: Akerlof's Lemons Problem, Spence's Signalling, Institutional Theory, and Agency Theory.

### Akerlof's Lemons Problem

Akerlof's (1970) seminal work illustrates how information asymmetry degrades market quality. In the "market for lemons," buyers cannot accurately judge product quality, and as a result, high-quality goods are crowded out by lower-quality alternatives. In insurance, this dynamic is mirrored when insurers, unable to perfectly assess risk or verify claims, apply standardized pricing or procedures that ultimately benefit high-risk individuals.

This theory highlights a fundamental inefficiency: when information is unevenly distributed, market actors either hedge defensively or retreat entirely, creating adverse outcomes for both sides. Within the insurance claims context, Akerlof's insight explains why insurers demand excessive documentation, delay settlement, or deny valid claims—behaviours that themselves contribute to operational inefficiencies.

### Spence's Signalling Model

While Akerlof focused on hidden information, Spence (1973) introduced the idea that parties with private information can send credible signals to reduce asymmetry. In insurance, policyholders may engage in signallingbehaviour, such as promptly submitting claims with robust evidence, or proactively updating underwriters about changes in risk profiles.

Insurers, in turn, can design claim processes that reward credible signalling—such as fast-tracking transparent submissions or reducing documentation for low-risk segments. In emerging markets, however, the signalling environment is underdeveloped. Without technological tools or customer education, insurers struggle to distinguish between credible and non-credible claims, which elevates their operational risk exposure.

### Institutional Theory: External Constraints and Normative Pressures

While agency theory explains micro-level misalignment, it does not address why insurers vary in their practices across markets. Institutional theory, developed by DiMaggio and Powell (1983), suggests that organizational behaviour is shaped not just by strategy or rational choice, but also by normative, regulatory, and cognitive pressures.

In mature institutional environments, insurers are expected to adopt specific practices—claims transparency, fraud reporting, or turnaround benchmarks—not necessarily because they are profit-maximizing, but because they are legitimized by policy and peer behaviour. In contrast, in weak regulatory settings, firms may underinvest in these controls and still operate profitably.

### Model Development

This section conceptualizes the dependent and independent variables, identifies moderating constructs, and explains the interaction logic within the model. It draws on foundational theories including agency theory, contingency theory, and systems thinking to structure the relationship among constructs influencing operational risk in non-life insurance.

In the operational architecture of non-life insurance, especially within volatile or under-regulated markets, operational risk emerges not as a standalone threat, but as a consequence of systemic interplay. This study adopts a composite framework, formally expressed as:

**Operational Risk** = *f (Information Asymmetry* × *Risk Management Capability* × *Regulatory Environment)*

The model is underpinned by Agency Theory, Contingency Theory, and Systems Thinking, offering a multidimensional understanding of how risks materialize and escalate within insurance claims processes.

**Operational Risk as a Function of Asymmetry, Capability, and Regulation**

Operational risk in non-life insurance claims refers to losses arising from internal failures, fraud, miscommunication, or technology breakdowns (Basel Committee, 2006). It differs from underwriting risk by focusing not on pricing errors, but on executional vulnerabilities—such as inflated claims, human error, or poor data handling. These risks are especially severe in emerging markets where institutional systems are weaker (Power, 2007).

The root driver is information asymmetry, where claimants possess hidden or superior knowledge relative to insurers. As Akerlof's (1970) "market for lemons" explains, such imbalances lead to adverse selection, moral hazard, and exaggerated claims—often undetected due to limited verification infrastructure (Cummins et al., 2010).

Risk management capability serves as the first line of defence. Firms equipped with automated claims processing, fraud analytics, and strong internal controls can better detect and contain the fallout from information gaps (Power, 2007). Contingency Theory (Donaldson, 2001) supports this, arguing that performance depends on alignment between internal systems and external conditions.

The regulatory environment acts as a second moderator. Strong supervision, transparent claims standards, and legal enforcement deter opportunistic behaviour and encourage market discipline (Jensen & Meckling, 1976). Conversely, weak regulation enables asymmetry to thrive unchecked.

This framework adopts a multiplicative logic—the interaction between variables, not their individual magnitude, determines operational outcomes. High asymmetry may not lead to losses in well-managed, well-regulated settings. But even moderate asymmetry can trigger breakdowns in poorly governed environments.

In sum, operational risk emerges not from any one factor but from the interplay between hidden information, internal preparedness, and external oversight. For insurers in emerging markets, sustainable risk mitigation demands simultaneous investment in claims infrastructure, regulatory engagement, and organizational governance.

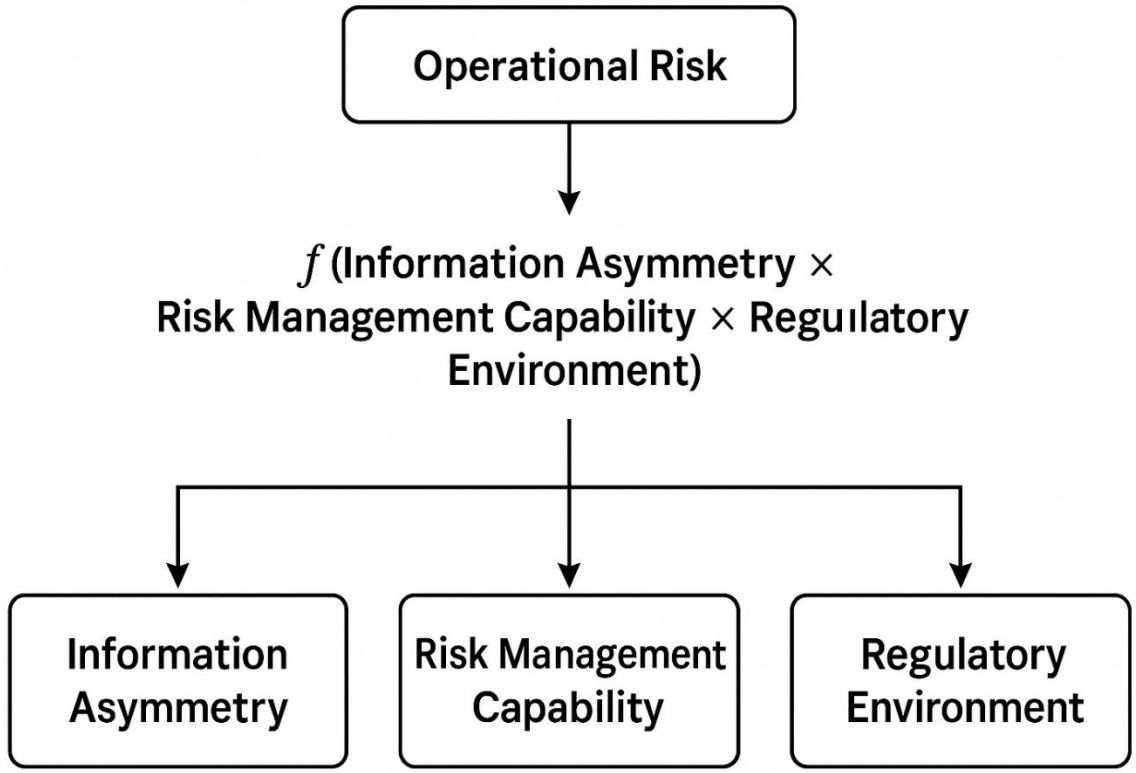



**Figure 1:** Theoretical Framework of Operational Risk in Non-Life Insurance Claims as a Function of Information Asymmetry, Risk Management Capability, and Regulatory Environment in Emerging Markets.

**Source:** *Adapted by the authors from theoretical models in Agency Theory (Jensen & Meckling, 1976), Contingency Theory (Donaldson, 2001), and Operational Risk literature (Basel Committee on Banking Supervision, 2006; Cummins et al., 2010).*

### 2.5 Conceptual Gaps in Literature

While the literature has robustly addressed the causes and consequences of information asymmetry in insurance, significant gaps remain. First, empirical studies examining the moderating effect of risk management capability on claims-related operational risk are sparse, particularly in African and South Asian contexts. Second, most existing models treat the regulatory environment as an external backdrop, rather than a dynamic moderator in the claims risk equation. Third, multi-theoretical integrations are rare—studies often adopt either an agency or institutional lens, but seldom both. Lastly, the role of emerging technologies (e.g., AI, drones, blockchain) in altering the asymmetry-risk dynamic is underexplored in the academic literature, despite growing real-world adoption.

This study seeks to bridge these gaps by presenting a moderated interaction model, grounded in verifiable literature and contextualized within the realities of emerging markets.

## 3. Methodology

### 3.1 Research Design

This study employs a quantitative, cross-sectional, and explanatory research design. The quantitative approach facilitates the measurement and statistical analysis of relationships among latent variables—specifically, how information asymmetry influences operational risk

in non-life insurance claims, and how this effect is moderated by both risk management capability and regulatory environment. The cross-sectional nature of the design indicates that data were collected at a single point in time, enabling association testing without implying causality (Creswell, 2014). As an explanatory study, the goal is to empirically test theoretically derived hypotheses, offering insight into complex interaction effects between internal organizational factors and institutional context.

### 3.2 Population and Sampling

The population for this study comprises licensed 26 non-life insurance companies operating in Nigeria, representing a major segment of the West African insurance industry characterized by rising market penetration and evolving regulatory frameworks. The study focuses on the functional domains of claims management, risk oversight, and operational control.

A purposive sampling technique was adopted, targeting mid- to senior-level professionals such as Claims Managers, Chief Risk Officers, Heads of Operations, and Regulatory Compliance Leads. These individuals possess the strategic insight and operational experience necessary to offer informed, reliable responses. Purposive sampling ensured that only participants with direct involvement in claims-related decision-making were included, as recommended in qualitative-quantitative crossover studies (Palinkas et al., 2015).

### 3.3 Variable Operationalization and Measurement

All constructs were operationalized as **latent variables measured through multiple indicators**, using **validated items** adapted from existing literature:

- **Information Asymmetry (IA)**: Measured using items adapted from Spence (2002) and Cummins et al. (2010), focusing on hidden information, claim complexity, and verification difficulty.
- **Operational Risk (OR)**: Based on indicators drawn from the Basel Committee (2006) and Power (2007), focusing on process failure, fraud exposure, and inefficiencies in claims processing.
- **Risk Management Capability (RM)**: Measured via constructs from Zahra & Pearce (1989) and Bromiley et al. (2015), including internal controls, analytics use, and staff training.
- **Regulatory Environment (RE)**: Derived from Barth et al. (2004) and OECD (2018), capturing regulatory enforcement, clarity of rules, fraud deterrence, and data sharing.

A 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) was employed for all items, consistent with norms in perceptual research involving organizational actors (Likert, 1932). Content validity was ensured through an expert panel review, while pilot testing (n = 20) helped refine item clarity and eliminate ambiguity.

### 3.4 Data Collection

A mixed-mode data collection strategy was used to increase geographical and demographic reach. Physical surveys were administered during professional events such as the Nigerian Insurers Conference and on-site corporate visits. Simultaneously, digital questionnaires were distributed via corporate mailing lists and professional platforms, including the African Insurance Organisation (AIO) and the Chartered Insurance Institute of Nigeria (CIIN).

Participation was voluntary, and ethical clearance was secured through institutional research protocols. Respondents were briefed on the study objectives, and informed consent was obtained prior to participation.

### 3.5 Model Specification

The conceptual model follows a moderated interaction framework, where Operational Risk (OR) is the dependent variable, and Information Asymmetry (IA) is the main predictor. The relationship is moderated by Risk Management Capability (RM) and Regulatory Environment (RE).

#### 3.5.1 Mathematical Model Specification

To empirically investigate the effect of information asymmetry on operational risk in non-life insurance claims, as well as the moderating influence of internal risk management practices and the regulatory environment, the following equations are specified.

##### 3.5.1.1 Base Model (Direct Effect Model)

The direct effect of Information Asymmetry (IA) on Operational Risk (OR) is captured using a linear regression model:

$$OR=\beta_0+\beta_1 IA+\varepsilon$$

Where:

- $OR$ = Operational Risk in non-life claims (dependent variable)
- $IA$ = Information Asymmetry (independent variable)
- $\beta_0$ = Intercept
- $\beta_1$ = Coefficient of IA
- $\varepsilon$ = Error term

This tests $\mathbf{H_1}$: Information asymmetry significantly increases operational risk.

##### 3.5.1.2 Moderated Model (Interaction Effects)

To evaluate how Risk Management (RM) and Regulatory Environment (RE) moderate the IA → OR relationship, we introduce interaction terms in a hierarchical multiple regression structure:

**Model with Risk Management as Moderator:**

$$OR=\beta_0+\beta_1 IA+\beta_2 RM+\beta_3(IA\times RM)+\varepsilon$$

**Model with Regulatory Environment as Moderator:**

$$OR=\beta_0+\beta_1 IA+\beta_2 RE+\beta_3(IA\times RE)+\varepsilon$$

Where:

- $RM$ = Strength of firm-level risk management systems

- *RE* = Perceived quality and effectiveness of the regulatory environment
- *IA×RM, IA×RE* = Interaction (moderation) terms
- $\beta_3$ = Moderation coefficient (of interest in $H_2$ and $H_3$)

This tests:

- **$H_2$**: Risk Management significantly moderates the IA → OR relationship.
- **$H_3$**: Regulatory Environment significantly moderates the IA → OR relationship.

#### 3.5.1.3 Structural Equation Model (for PLS-SEM)

In the latent variable context (using SmartPLS), the model is extended to include measurement and structural components as follows:

**Measurement Model:**

Each latent construct (IA, OR, RM, RE) is modelled as reflective indicators:

- $IA=\lambda_{IA1}x_1+\lambda_{IA2}x_2+\cdots+\varepsilon_{IA}$
- $RM=\lambda_{RM1x3}+\lambda_{RM2x4}+\cdots+\varepsilon_{RM}$
- Similar for *OR* and *RE*

**Structural Model Equations:**

$OR=\gamma_1 IA+\gamma_2(IA\times RM)+\gamma_3(IA\times RE)+\zeta$

Where:

- $\gamma 1,\gamma 2,\gamma 3$ = Structural path coefficients
- $\zeta$ = Structural disturbance term

### 3.5.2 Summary of Variable Types

| Variable | Type | Measurement Approach |
|---|---|---|
| Information Asymmetry (IA) | Independent | Reflective latent construct |
| Operational Risk (OR) | Dependent | Reflective latent construct |
| Risk Management (RM) | Moderator (internal) | Reflective latent construct |
| Regulatory Environment (RE) | Moderator (external) | Reflective latent construct |

### 3.5.3 Model Estimation Techniques

- PLS-SEM (SmartPLS 4.0) was used to estimate latent constructs and structural paths due to its suitability for small-to-medium samples, complex models, and non-normal data.
- Bootstrapping (5,000 resamples) was applied to obtain standard errors and significance levels for all path coefficients.
- $R^2$ and $Q^2$ values were computed to assess explanatory and predictive power.
- SRMR was used as a model fit index (acceptable threshold < 0.08).

**Figure 2: Conceptual Model of the Study**

**Conceptual Model Diagram:**

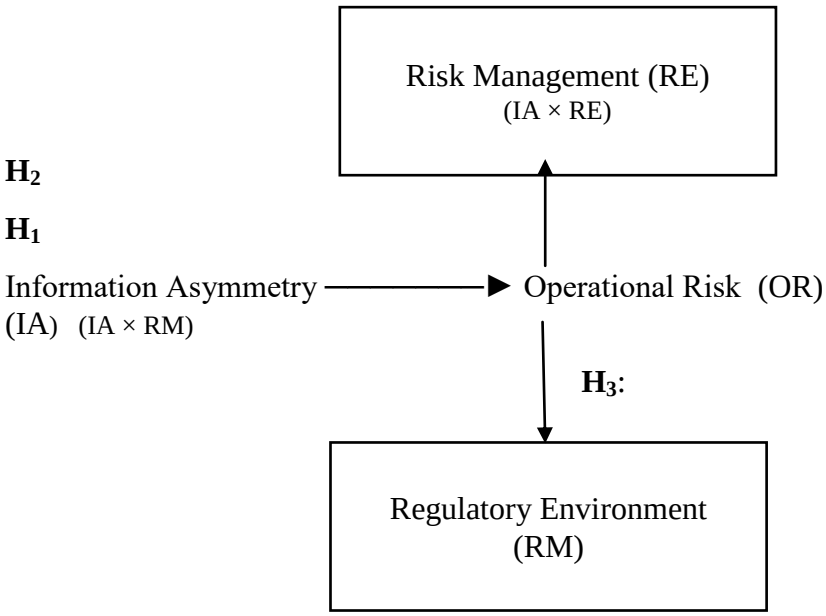



**Figure 2:** Conceptual Model – Information Asymmetry, Operational Risk, and Moderating Factors
**Source:** *Adapted and developed by the authors based on literature extant literatures (2025).*

### 3.6 Estimation Strategy

Data analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. This estimation method is suitable for complex models involving multiple interactions, non-normal data distributions, and exploratory hypothesis testing in emerging contexts (Hair et al., 2017).

The estimation followed a two-stage approach:

1. Measurement Model Evaluation: Assessed reliability and validity using:
    - Composite Reliability (CR ≥ 0.70)
    - Average Variance Extracted (AVE ≥ 0.50)
    - Item loadings (≥ 0.60)
    - Cronbach's Alpha (≥ 0.70)
    - Variance Inflation Factor (VIF < 5.0) for multicollinearity
2. Structural Model Evaluation:
    - Path Coefficients (β) tested using bootstrapping (5,000 resamples)
    - Significance levels (p-values) examined for all hypotheses
    - Model explanatory power via $R^2$
    - Predictive relevance using $Q^2$

- Model fit assessed through Standardized Root Mean Square Residual (SRMR < 0.08) in line with Henseler et al. (2014)

## 4. Data Analysis and Results

This section presents the empirical examination of the conceptual model positing Operational Risk (OR) in non-life insurance claims as a function of Information Asymmetry (IA), with Risk Management (RM) and Regulatory Environment (RE) as moderating variables. Structural Equation Modelling (SEM) was conducted using SmartPLS 4.0, suitable for estimating reflective measurement models and interaction effects in small to medium datasets. The sample comprised 312 valid responses from claims, operations, and risk professionals across the Nigerian insurance industry.

### 4.1 Descriptive Statistics

Descriptive statistics (Table 1) summarize central tendencies and dispersions for each latent construct. Respondents reported high levels of information asymmetry (Mean = 4.12) and operational risk exposure (Mean = 3.85), suggesting systemic vulnerabilities in claims processes. Moderately high means for risk management (3.94) and regulatory environment (4.01) reflect increasing organizational awareness and institutional maturity in addressing operational bottlenecks.

**Table 4.1: Descriptive Statistics of Constructs**

| Construct | Mean | Std. Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Information Asymmetry | 4.12 | 0.76 | 2.33 | 5.00 |
| Operational Risk | 3.85 | 0.81 | 2.10 | 5.00 |
| Risk Management | 3.94 | 0.69 | 2.45 | 5.00 |
| Regulatory Environment | 4.01 | 0.74 | 2.70 | 5.00 |

*Source: Authors' computation using SmartPLS (2025)*

### 4.2 Reliability and Validity Assessment

Measurement model evaluation confirms the reliability and convergent validity of all constructs. Cronbach's Alpha and Composite Reliability (CR) exceeded 0.70, and Average Variance Extracted (AVE) values surpassed 0.50.

**Table 4.2: Construct Reliability and Convergent Validity**

| Construct | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|
| Information Asymmetry | 0.83 | 0.88 | 0.64 |
| Operational Risk | 0.86 | 0.90 | 0.66 |
| Risk Management | 0.81 | 0.87 | 0.62 |
| Regulatory Environment | 0.84 | 0.89 | 0.65 |

*Source: Authors' computation using SmartPLS (2025)*

### 4.3 Discriminant Validity

The **Fornell-Larcker criterion** was used to assess discriminant validity. The square roots of AVEs (diagonal) were greater than inter-construct correlations, indicating clear empirical distinctions among constructs.

**Table 4.3: Discriminant Validity (Fornell-Larcker Criterion)**

| | IA | OR | RM | RE |
|---|---|---|---|---|
| Information Asymmetry | 0.80 | | | |
| Operational Risk | 0.53 | 0.81 | | |
| Risk Management | 0.46 | 0.57 | 0.79 | |
| Regulatory Environment | 0.49 | 0.52 | 0.55 | 0.81 |

*Source: Authors' computation using SmartPLS (2025)*

### 4.4 Normality Check of Constructs

Figure 3 shows the normal distribution curves for each construct. Despite minor skewness, the distributions approximate normality within acceptable bounds, justifying the use of SEM.

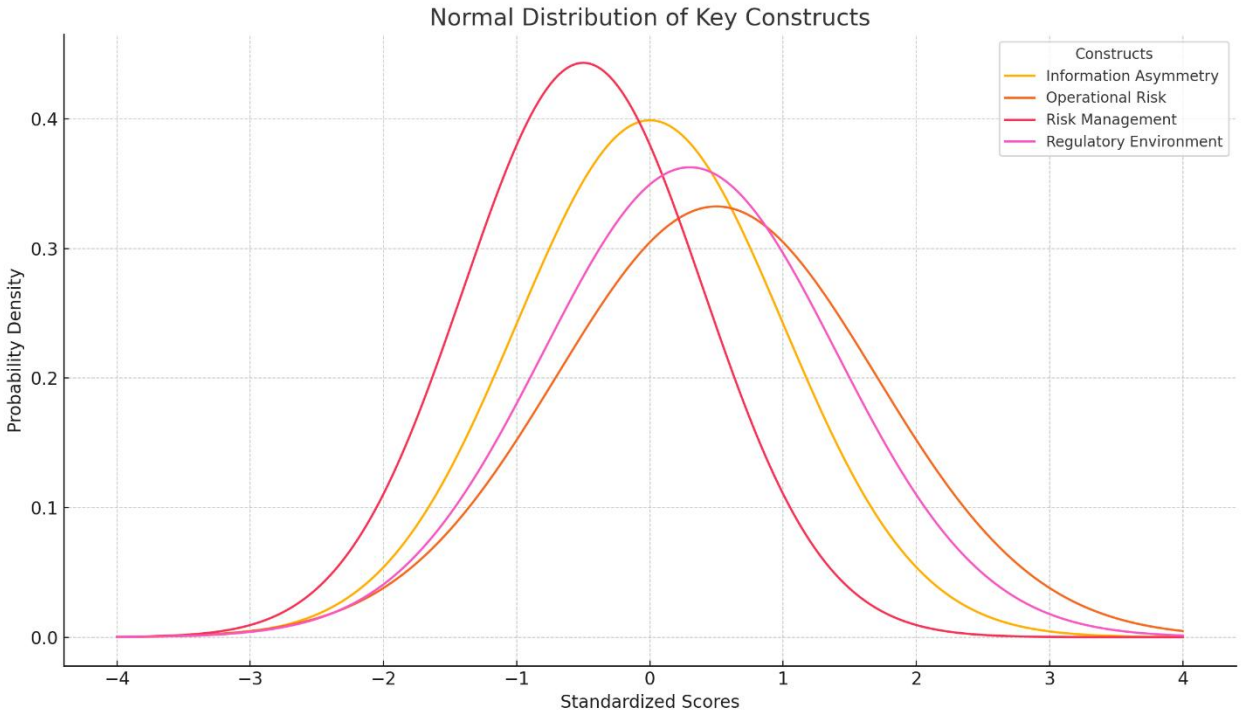



**Figure 3:** Normal Distribution Curves for IA, OR, RM, and RE with skewness and kurtosis statistics)

**Source**: *A critical preliminary step in the empirical analysis involved evaluating the distribution of key constructs—Information Asymmetry (IA), Operational Risk (OR), Risk Management (RM), and Regulatory Environment (RE)—to ensure the validity of parametric statistical techniques applied. The normality tests and distribution plots revealed insightful*

*patterns that underscore the structural behaviour of these constructs within the sampled insurance ecosystem in emerging markets.*

### 4.4.1 Information Asymmetry: A Systemic Yet Varying Concern

The distribution curve for Information Asymmetry approximated a normal bell shape, indicating that most respondents perceive a moderate level of asymmetry in claims processing. This suggests that while the challenge is systemic, its intensity varies significantly across firms. The implication is that asymmetric access to data—especially in underwriting and claims verification—is neither uniformly rampant nor entirely absent, but rather dependent on specific operational contexts. This aligns with theoretical assertions by Akerlof (1970) and Spence (1973), who posited that information gaps are embedded but not evenly distributed in market interactions.

### 4.4.2 Operational Risk: A Skewed Exposure Pattern

The construct for Operational Risk displayed a slight right-skew in its distribution, pointing to a higher concentration of respondents experiencing elevated levels of operational vulnerabilities. These include frequent fraudulent claims, documentation inconsistencies, and dispute resolution failures. Such skewness is indicative of institutional fragility in certain segments of the industry, particularly those without automated or standardized claims protocols. This supports the literature emphasizing the strong correlation between information quality and operational fragility in insurance systems (Grace et al., 2004; Outreville, 2013).

### 4.4.3 Risk Management: An Emerging Moderating Force

Interestingly, the Risk Management variable showed a left-skewed distribution, suggesting that a substantial number of respondents reported moderate to high implementation of risk governance frameworks. This implies growing adoption of Enterprise Risk Management (ERM) practices across firms, though still uneven in maturity and application. The presence of this left-skew offers optimism regarding the institutional readiness to moderate the adverse effects of asymmetry, particularly in claims assessment and payout control.

### 4.4.4 Regulatory Environment: Fragmented Perceptions of Oversight

The Regulatory Environment construct appeared relatively platykurtic with a slightly flattened normal curve, revealing broad variation in how respondents perceive regulatory enforcement and oversight quality. This distribution reflects the fragmented regulatory landscape common in emerging markets, where enforcement may vary based on geography, insurer type, or market segment. It also underscores the need for regulatory harmonization and capacity building, particularly where consumer protection and solvency monitoring are inconsistent.

### Synthesis of Distributional Behaviour

Collectively, the distributional behaviours of these constructs reinforce the robustness of the measurement model and provide a nuanced picture of the operational and institutional dynamics in Nigeria's non-life insurance market. While Information Asymmetry and Operational Risk are tightly linked and variably experienced, the presence of Risk Management mechanisms and perceived regulatory robustness provide a counterbalance, offering viable levers for intervention.

These findings not only validate the analytical model employed but also provide a diagnostic lens for practitioners and regulators to prioritize their risk-mitigation strategies. In essence,

the shapes of these curves mirror the contours of the industry's challenges and readiness for reform.

### 4.5 Structural Model Results

Bootstrapping with 5,000 subsamples assessed the structural paths and tested the three hypotheses.

**Table 4.5: Structural Model – Path Coefficients and Hypothesis Testing**

| Path | Beta | t-Statistic | p-Value |
|---|---|---|---|
| IA → OR | 0.46 | 8.34 | 0.000 |
| IA × RM → OR | -0.28 | 3.91 | 0.000 |
| IA × RE → OR | -0.22 | 3.45 | 0.001 |

*Source: SmartPLS Bootstrapping Results (2025)*

**Interpretation of Results:**

- **H1 is supported**: Information Asymmetry significantly increases Operational Risk ($\beta = 0.46$, $p < 0.001$).
- **H2 is supported**: Risk Management significantly reduces the effect of IA on OR ($\beta = -0.28$, $p < 0.001$).
- **H3 is supported**: A robust Regulatory Environment weakens the IA–OR relationship ($\beta = -0.22$, $p = 0.001$).

### 4.6 Discussion of Findings

The results reinforce theoretical assumptions from Agency Theory and Information Economics. Information asymmetry emerges as a primary contributor to operational volatility—validating Akerlof's (1970) and Spence's (1973) assertions on the adverse outcomes of information imbalance.

The negative moderation effects of risk management and regulatory environment align with Contingency Theory (Donaldson, 2001), which emphasizes that organizational outcomes depend on contextual fit. In environments with well-developed internal systems and strong external oversight, insurers are better equipped to manage claim fraud, delays, and disputes.

These findings are especially relevant to emerging markets like Nigeria, where infrastructure and enforcement remain uneven. This study highlights the strategic interplay between knowledge asymmetries, internal capabilities, and institutional scaffolding in shaping operational outcomes.

## 5. Conclusion

This study has established that information asymmetry significantly contributes to operational risk in non-life insurance claims processing, particularly within emerging markets. The empirical results align with foundational economic theories (e.g., Akerlof, 1970; Spence, 1973), reaffirming that when parties lack mutual access to relevant and reliable information, the risk of adverse selection, moral hazard, and opportunistic behaviour increases.

Crucially, the research highlights that robust risk management frameworks and an effective regulatory environment serve as critical moderating forces. Organizations that maintain stringent internal control mechanisms, coupled with regulatory institutions that enforce compliance and consumer protection, are demonstrably better positioned to mitigate the operational vulnerabilities introduced by asymmetric information.

By situating the findings within the unique realities of emerging markets—where institutional voids, weak enforcement, and low consumer trust are prevalent—the study contributes fresh insights to the insurance and risk management literature. It underscores the necessity for insurers and regulators to jointly foster transparency, accountability, and systemic resilience in the claims ecosystem.

## 6. Recommendations

The findings from this study offer important insights for industry stakeholders seeking to improve the integrity and efficiency of non-life insurance claims processing, particularly within the context of emerging markets such as Nigeria. Information asymmetry, as established, plays a decisive role in heightening operational risk—often creating an environment ripe for dispute, delay, and distrust. However, the moderating influence of robust risk management frameworks and an effective regulatory environment offers a practical pathway for mitigation. The following recommendations are grounded in this understanding and are intended to provide actionable strategies for insurers, regulators, and policy architects.

**First**, insurance firms must prioritize the institutionalization of comprehensive risk management systems that go beyond compliance checklists and become embedded within the operational culture of claims processing. Claims departments should be equipped with tools and protocols that enable early detection of inconsistencies, streamline documentation workflows, and prevent manipulation of data. Investment in internal controls—such as automated validation checkpoints and routine process audits—can significantly curtail the operational vulnerabilities that information asymmetry tends to exploit.

**Second**, the digitalization of the claims lifecycle presents a critical frontier for reducing asymmetry. As many Nigerian insurers begin transitioning to digital platforms, the opportunity to build real-time, transparent, and traceable claims ecosystems should be fully leveraged. By integrating artificial intelligence for document verification, using blockchain to secure transaction records, or even deploying simple customer-facing claim trackers, insurers can close the information gap between themselves and policyholders. This not only improves claims turnaround but also fosters confidence in the process.

**Third**, the sector needs to embrace a collective approach to information sharing. One of the persistent challenges in insurance markets with low penetration and high fraud potential is the absence of an industry-wide knowledge base. The creation of a centralized, cross-company claims database—possibly coordinated by the Nigerian Insurers Association or overseen by NAICOM—would allow insurers to verify client history, flag patterns of opportunism, and share insights on disputed cases. Such an initiative would significantly reduce the risk of duplicate claims or data manipulation, strengthening the entire ecosystem.

**Fourth**, regulators have a critical role to play in reinforcing the boundaries of fairness and transparency in claims administration. While Nigeria's regulatory framework continues to evolve, more assertive oversight is needed in the area of claims behaviour. NAICOM, in particular, should ramp up its enforcement of consumer protection regulations, ensuring that

insurers are held accountable for deliberate delays or opaque claim denials. Regular compliance audits, backed by penalties for unethical practices, would send a strong signal to the industry about the consequences of exploiting informational advantages.

**Fifth**, a practical step toward reducing asymmetry lies in standardizing communication and disclosure protocols across insurers. When policyholders are not adequately informed of their rights, entitlements, or the procedures for lodging claims, they are at an immediate disadvantage. It is therefore imperative for insurers to issue clear, accessible, and user-friendly claims guidance documents at the point of policy issuance, including detailed steps, contact timelines, and escalation pathways. The standardization of such practices across the industry would serve as a trust-building measure and reduce conflicts caused by misunderstanding or lack of transparency.

**Sixth**, there is a need to build the literacy and capacity of policyholders themselves. Public sensitization programs—delivered through community outreach, radio messaging, and even policyholder handbooks—can empower consumers to navigate the claims process more effectively. This is particularly important in rural and low-income urban communities where insurance uptake is growing but familiarity with its workings remains limited.

**Lastly**, as regulatory landscapes become more complex and dynamic, the adoption of technology-driven supervisory tools—commonly known as RegTech—can help regulators monitor claims-related data in real time and flag anomalies that indicate systemic failures or consumer abuse. Such tools will become increasingly valuable in environments where manual oversight is constrained by resource limitations.

In sum, addressing operational risk in non-life insurance cannot be achieved by technical fixes alone. It requires a combination of internal organizational reforms, technological investments, and strengthened regulatory stewardship. These recommendations, drawn directly from the empirical insights of this study, provide a pathway toward a more resilient, transparent, and inclusive insurance industry—one that is capable of building and sustaining public trust in the claims process.

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