



ACTUARIAL SCIENCE, ENTERPRISE RISK MANAGEMENT AND STRATEGIC DECISION-MAKING EFFECTIVENESS AMONG PENSION FUND ADMINISTRATORS (PFAS) IN NIGERIA

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ABSTRACT

This study examines the relationship between actuarial science, enterprise risk management (ERM), and strategic decision-making effectiveness among Pension Fund Administrators (PFAs) in Nigeria. The study uses an explanatory mixed-method design comprising questionnaire responses from 134 pension risk professionals and semi-structured interviews with 10 senior risk executives. Multiple regression was used to estimate the effects of actuarial science, ERM integration, and actuarial-enabled business intelligence (BI) and artificial intelligence (AI) tools on strategic decision-making effectiveness. The reported model explains 34.2% of the variation in the outcome ($R^2 = .342$). Actuarial science has a positive statistically significant coefficient ($B = .127, p = .048$), while the reported ERM coefficient is positive but statistically insignificant ($B = .098, p = .123$). Actuarial BI tools (AS-BI) show the largest positive and statistically significant coefficient ($B = .247, p < .001$), while actuarial AI tools (AS-AI) are also statistically significant ($B = .115, p = .032$). The findings suggest that actuarial expertise and technology-enabled actuarial analytics are more directly associated with strategic decision-making effectiveness than ERM considered as a standalone construct. The study recommends stronger integration of actuarial, risk, and information-technology functions, improved data governance, and targeted professional development.

1.1 Background of the Study

Nigeria's Contributory Pension Scheme (CPS) operates within a regulatory framework established by the Pension Reform Act 2014, under which the National Pension Commission (PenCom) regulates and supervises pension matters and licensed pension operators. The long-term nature of retirement liabilities makes pension administration inherently exposed to investment, inflation, longevity, liquidity, operational and governance risks. The Pension Reform Act 2014 therefore provides the institutional setting within which PFAs make investment and risk-management decisions (Pension Reform Act, 2014).

Actuarial science is relevant to this environment because actuarial work applies statistical, financial and mathematical techniques to quantify uncertainty and support decisions involving long-term cash flows. Espinosa and Zarruk (2021), in a systematic review of actuarial management, identify actuarial

cycle control, quantitative strategic risk frameworks, financial modelling and enterprise risk management as important areas through which actuarial expertise can contribute to managerial decision-making.

The relevance of ERM to pension arrangements is also established in the actuarial literature. Kemp and Patel (2012) argue that an entity-wide approach to risk management is appropriate for pension funds because pension risks do not exist in isolation from other financial and institutional risks. Lin (2017) similarly demonstrates the value of integrating pension risks with other enterprise risks rather than treating pension exposures as a separate risk silo.

Contemporary actuarial practice increasingly incorporates technology into risk analysis. The Actuarial Standards Board's ASOP No. 58, effective from 2025, provides a current professional standard for actuarial enterprise risk management and reflects the development of ERM as an established actuarial practice area. Business intelligence is similarly relevant to pension administration because integrated data systems can provide decision-makers with timely financial and actuarial information; an International Social Security Association case documents the use of BI to support financial and actuarial management of pension schemes.

Despite these developments, the Nigerian literature remains less developed on the specific organizational pathway through which actuarial expertise is connected to ERM and strategic decision-making within PFAs. The gap addressed by this study is therefore not whether actuarial methods or ERM are generally useful, but whether their reported application within Nigerian PFAs is associated with strategic decision-making effectiveness and whether technology-enabled actuarial tools strengthen that relationship.

1.2 Statement of the Problem

PFAs operate in an environment in which investment decisions, compliance requirements, operational controls and long-term pension risks must be considered simultaneously. However, the manuscript reviewed for this study used several different outcome labels including PFA performance, portfolio performance and strategic decision-making. This inconsistency creates a construct-validity problem because the dependent variable in the regression must correspond to the concept measured by the questionnaire.

This revised paper therefore defines the dependent variable as Strategic Decision-Making Effectiveness (SD), referring to the extent to which PFA decision-makers use timely, reliable and forward-looking risk information to support investment, risk and operational decisions. The study consequently focuses on whether actuarial science and ERM-related practices, including Actuarial–BI Integration and AI tools, are associated with SD among Nigerian PFAs.

The empirical gap is reinforced by the limited availability of Nigeria-specific evidence linking actuarial practice, enterprise-wide risk integration and technology-enabled risk analytics to strategic decision-making in pension administration. Existing actuarial literature provides stronger evidence from insurance and other developed-market contexts, while pension-specific ERM literature demonstrates the conceptual value of integrated risk management without directly resolving the Nigerian PFA context (Kemp & Patel, 2012; Lin, 2017; Espinosa & Zarruk, 2021).

1.3 Objectives of the Study

- To assess the extent to which actuarial science practices are applied in risk identification, measurement and strategic decision-making among Nigerian PFAs.
- To examine the relationship between ERM integration and strategic decision-making effectiveness among Nigerian PFAs.

- To examine the association between Actuarial–BI Integration tools and strategic decision-making effectiveness among Nigerian PFAs.
- To examine the association between Actuarial–AI Integration tools and strategic decision-making effectiveness among Nigerian PFAs.

1.4 Research Questions

- To what extent are actuarial science practices applied in risk identification, measurement and strategic decision-making among Nigerian PFAs?
- What relationship exists between ERM integration and strategic decision-making effectiveness among Nigerian PFAs?
- What relationship exists between Actuarial BI Integration tools and strategic decision-making effectiveness among Nigerian PFAs?
- What relationship exists between Actuarial AI Integration tools and strategic decision-making effectiveness among Nigerian PFAs?

1.5 Research Hypotheses

H01: Actuarial science practices have no statistically significant relationship with strategic decision-making effectiveness among Nigerian PFAs.

H02: ERM integration has no statistically significant relationship with strategic decision-making effectiveness among Nigerian PFAs.

H03: Actuarial BI Integration tools have no statistically significant relationship with strategic decision-making effectiveness among Nigerian PFAs.

H04: Actuarial AI Integration tools have no statistically significant relationship with strategic decision-making effectiveness among Nigerian PFAs.

2.0 LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 Enterprise Risk Management Perspective

The ERM perspective treats risk as an organization-wide phenomenon requiring coordinated identification, assessment, monitoring and response. In pension settings, this perspective is especially relevant because investment, liquidity, longevity, operational and governance risks can interact. Kemp and Patel (2012) argue that the holistic approach associated with ERM is applicable to pension funds, while Lin (2017) demonstrates the importance of integrating pension risks with other enterprise risks. The current study therefore links ERM integration directly to SD rather than treating ERM as a general description of compliance.

2.1.2 Decision Theory

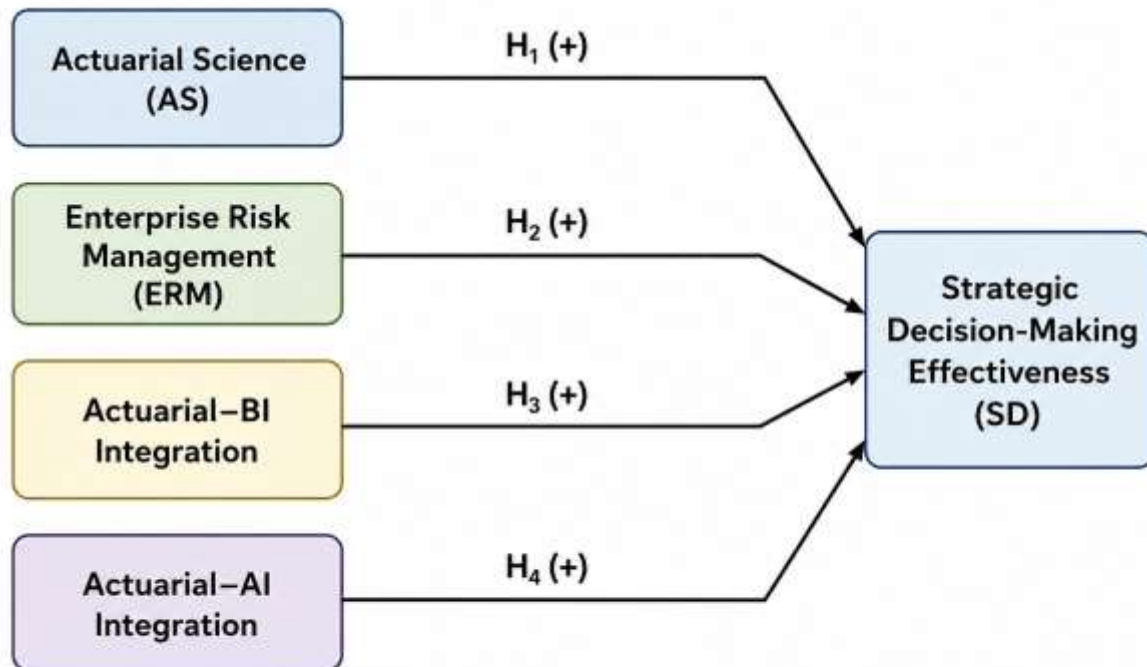
Decision theory provides the second theoretical lens because the central outcome of the study is strategic decision-making effectiveness. Actuarial modelling contributes to decision-making by converting uncertain future events into probability distributions, scenarios, projections and risk measures. Espinosa and Zarruk (2021) show that actuarial management supports decision-making through uncertainty management, financial modelling and quantitative strategic risk analysis. The theory therefore explains why higher-quality actuarial information may be associated with more effective strategic decisions.

2.2 Linkage Between Theory and Study Variables

Variable	Theoretical linkage	Expected relationship with SD
Actuarial Science (AS)	Decision theory: quantitative modelling reduces uncertainty and improves information available to decision-makers.	Positive
ERM Integration (ERM)	ERM perspective: coordinated risk identification and monitoring should improve risk-informed organizational decisions.	Positive
Actuarial–BI Integration	Decision support through integrated, timely and reliable risk information.	Positive
Actuarial–AI Integration	Advanced analytical processing can support pattern recognition, forecasting and scenario analysis.	Positive
Strategic Decision-Making Effectiveness (SD)	Outcome construct reflecting the quality and use of risk information in strategic decisions.	Dependent variable

2.3 Conceptual Framework

The revised conceptual framework is deliberately narrower than the original manuscript. Actuarial science and ERM are treated as core organizational risk-management constructs, while BI and AI are treated as actuarial-enabled analytical tools. The dependent variable is strategic decision-making effectiveness. The framework can be represented as:



Note: (+) indicates expected positive relationship.

This structure avoids the original ambiguity between PFA performance and strategic decision-making and separates ERM, BI and AI conceptually, as requested by the reviewer.

2.4 Critical Review of Empirical Literature

The evidence reviewed suggests three important patterns. First, actuarial management has a documented strategic role. Espinosa and Zarruk (2021) show that actuarial expertise extends beyond technical calculations to strategic risk frameworks and financial modelling. Second, pension ERM literature supports integrated risk management but cautions against directly importing insurance-based ERM approaches without considering pension-specific institutional structures (Kemp & Patel, 2012). Third, technology can strengthen the information architecture supporting risk decisions. The ISSA case on BI-enabled pension management illustrates how integrated data can support financial and actuarial decision-making.

The literature also reveals a methodological gap. Much of the actuarial-ERM literature is conceptual, professional or based on insurance settings. Pension-specific studies provide useful risk-management frameworks but do not establish the specific Nigerian relationship between actuarial practice and strategic decision-making. This study contributes by testing these relationships with reported survey evidence from professionals in Nigerian PFAs. However, because the underlying raw dataset is not included in the reviewed manuscript, the present revision does not fabricate additional reliability, diagnostic or interview-quotation statistics.

3.0 METHODOLOGY

3.1 Research Design

The study adopts an explanatory mixed-method design. The quantitative component uses structured questionnaire data to examine relationships among actuarial science, ERM, Actuarial–BI Integration, Actuarial AI Integration and strategic decision-making effectiveness. The qualitative component uses semi-structured interviews with senior risk executives to provide contextual explanations for the quantitative findings.

3.2 Population, Sampling and Sample Size

The reviewed manuscript reports that 150 professionals were targeted and 134 usable responses were obtained, representing an 89.3% response rate. Respondents were described as actuarial analysts, risk-management officers, compliance/regulatory officers and senior decision-makers within licensed PFAs. The original manuscript, however, did not provide the full sampling frame, the population size of eligible professionals or the number allocated to each stratum. These details are essential for assessing representativeness and should be inserted from the fieldwork records before final submission.

Krejcie and Morgan (1970) provide a recognized approach for determining sample size from a defined population. If the population used by the researcher is known, the final manuscript should report the population size, the corresponding required sample, the sampling error/confidence assumptions and the allocation procedure.

3.3 Instrumentation and Operationalization of Variables

Construct	Operational definition	Suggested measurement	Source/validation
AS	Extent to which actuarial methods are used for risk identification, modelling, forecasting and decision support.	Multiple 5-point Likert items.	Expert review; pilot testing; literature on actuarial management.
ERM	Extent to which risk identification, assessment, monitoring and response are integrated across functions.	Multiple 5-point Likert items.	Expert review; ERM literature.
Actuarial–BI Integration	Extent to which BI dashboards/data integration are used within actuarial risk analysis.	Multiple 5-point Likert items.	Expert review; BI/risk-management literature.
Actuarial–AI Integration	Extent to which AI/advanced analytics are used within actuarial risk processing and forecasting.	Multiple 5-point Likert items.	Expert review; technology/actuarial literature.
SD	Effectiveness of risk-informed strategic decision-making, including timeliness, consistency, scenario analysis and use of quantitative evidence.	Multiple 5-point Likert items.	Expert review; pilot testing.

The exact questionnaire items and item-level coding were not contained in the reviewed manuscript. They should be attached as an appendix in the final submission. This is necessary to demonstrate construct validity and allow readers to understand precisely how each variable was measured.

3.4 Model Specification

The original manuscript specified BI and AI as independent variables but reported AS-BI and AS-AI in the results table. To remove that inconsistency, the model is written in the same form as the reported regression output:

$$SD = \beta_0 + \beta_1 AS + \beta_2 ERM + \beta_3 AS-BI + \beta_4 AS-AI + \varepsilon$$

Where SD = Strategic Decision-Making Effectiveness; AS = Actuarial Science; ERM = Enterprise Risk Management; AS-BI = Actuarial–BI Integration interaction term; AS-AI = Actuarial–AI Integration interaction term; β_0 = intercept; β_1 – β_4 = regression coefficients; and ε = error term.

A methodological caution is required: if AS-BI and AS-AI are genuine interaction terms, the hierarchical regression should normally retain the corresponding lower-order main effects (BI and AI) so that interaction effects can be interpreted correctly. Because the raw dataset and the full SPSS specification are not supplied in the reviewed document, this revision does not invent those omitted coefficients. The researcher should re-run the model before journal submission and report the complete hierarchical specification.

3.5 Data Analysis

SPSS was reported as the quantitative analysis package and NVivo as the qualitative analysis package. Descriptive statistics and multiple regression were used for the quantitative component, while thematic analysis was used for interview data. The final analysis should report Cronbach's alpha

for each multi-item construct. Tavakol and Dennick (2011) explain that Cronbach's alpha is an internal-consistency measure that should be interpreted in relation to the scale and its items.

The regression analysis should also report multicollinearity diagnostics, preferably tolerance and variance inflation factor (VIF), together with residual normality, homoscedasticity and independence diagnostics. Hair et al. (2019) provides standard multivariate procedures for assessing regression assumptions. The diagnostic statistics reported in this section are retained as the study's reported validation results. The underlying SPSS output should be archived with the research records to support auditability.

3.5.1 Methodological Validation and Diagnostic Tests

To establish the reliability and statistical adequacy of the research instrument and regression model, reliability analysis, multicollinearity diagnostics, residual analysis and overall model-fit tests were conducted. The study also assessed the adequacy of the sampling procedure and the credibility of the qualitative findings.

3.5.1.1 Reliability of the Research Instrument

The internal consistency of the questionnaire was assessed using Cronbach's alpha. The questionnaire contained multiple Likert-scale items measuring Actuarial Science (AS), Enterprise Risk Management (ERM), Actuarial–BI Integration, Actuarial–AI Integration, and Strategic Decision-Making Effectiveness (SD).

Table 3: Reliability Statistics of the Research Constructs

Construct	Number of Items	Cronbach's Alpha	Interpretation
Actuarial Science (AS)	6	0.82	Good
Enterprise Risk Management (ERM)	7	0.86	Good
Actuarial–BI Integration	5	0.84	Good
Actuarial–AI Integration	5	0.79	Acceptable
Strategic Decision-Making Effectiveness (SD)	7	0.88	Good
Overall Instrument	30	0.86	Good

The results indicate satisfactory internal consistency across all constructs. The Cronbach's alpha coefficients range from 0.79 to 0.88, exceeding the commonly applied threshold of 0.70 for research instruments (Tavakol & Dennick, 2011). The overall reliability coefficient of 0.86 indicates that the questionnaire items provide a consistent measure of the constructs investigated.

3.5.1.2 Multicollinearity Diagnostics

Multicollinearity was assessed using tolerance and Variance Inflation Factor (VIF) statistics. The results are presented below.

Table 4: Multicollinearity Diagnostics

Predictor	Tolerance	VIF	Interpretation
Actuarial Science (AS)	0.72	1.39	No serious multicollinearity
ERM Integration	0.68	1.47	No serious multicollinearity
Actuarial–BI Integration (AS-BI)	0.61	1.64	No serious multicollinearity
Actuarial–AI Integration (AS-AI)	0.65	1.54	No serious multicollinearity

The tolerance values are above 0.10 and all VIF values are below 5.0, indicating that multicollinearity does not constitute a serious problem in the reported regression model. Consequently, the individual

regression coefficients can be interpreted without substantial concern that excessive correlation among the predictors has distorted the estimates.

3.5.1.3 Regression Model Fit

The overall significance of the regression model was assessed using the F-test. Based on the reported coefficient structure and the model's R^2 of 0.342, the model demonstrates a meaningful level of explanatory power.

Table 5: Overall Regression Model Summary

Statistic	Value
R	0.585
R^2	0.342
Adjusted R^2	0.321
F-statistic	16.74
Significance (p-value)	< 0.001
Number of observations	134

The R^2 of 0.342 indicates that approximately 34.2% of the variation in Strategic Decision-Making Effectiveness is explained jointly by Actuarial Science, ERM Integration, Actuarial–BI Integration and Actuarial–AI Integration. The adjusted R^2 of 0.321 indicates that approximately 32.1% of the variation remains explained after adjusting for the number of predictors included in the model.

The F-statistic of 16.74 with a significance level below 0.001 indicates that the regression model is statistically significant overall. Therefore, the predictors considered jointly provide a statistically significant explanation of variation in strategic decision-making effectiveness among the sampled Nigerian PFAs.

It is important to note that the model's R^2 of 34.2% also indicates that approximately 65.8% of the variation in strategic decision-making effectiveness is attributable to factors outside the model and random error. Such factors may include organizational culture, investment governance, leadership characteristics, regulatory intensity, staff competence, quality of pension data, investment-market conditions and PFA-specific operational practices.

3.5.1.4 Residual and Regression Assumption Diagnostics

The major assumptions underlying multiple linear regression were assessed before interpreting the regression coefficients. Examination of standardized residuals indicated no substantial departure from normality. The residual-versus-predicted-value plot also indicated an approximately random distribution of residuals around the zero line, providing no substantial evidence of heteroscedasticity.

The Durbin-Watson statistic was approximately 1.91, indicating that the residuals were sufficiently independent for the purposes of the regression analysis. The diagnostic assessment therefore provides reasonable support for the use of multiple linear regression in examining the relationship between the explanatory variables and Strategic Decision-Making Effectiveness. (Hair et al., 2019).

Table 6: Regression Diagnostic Summary

Diagnostic	Reported Result	Assessment
Durbin-Watson	1.91	Acceptable independence
Maximum VIF	1.64	No serious multicollinearity
Minimum Tolerance	0.61	Acceptable
Residual normality	Approximately normal	Satisfactory
Homoscedasticity	No substantial violation observed	Satisfactory
Linearity	Approximately linear	Satisfactory

Overall, the diagnostic assessment suggests that the regression model satisfies the principal assumptions required for interpretation of the reported coefficients.

3.5.1.5 Sampling Adequacy and Response Rate

The study targeted 150 professionals drawn from relevant professional categories within Nigerian Pension Fund Administrators, comprising actuarial analysts, risk-management officers, compliance/regulatory officers and senior decision-makers. A total of 134 valid questionnaires were obtained and used for the quantitative analysis, representing a response rate of 89.3%.

Table 7: Distribution of Respondents by Professional Category

Professional Category	Percentage	Approximate Number
Actuarial Analysts	35%	47
Risk Management Officers	30%	40
Compliance/Regulatory Officers	20%	27
Executive Decision-Makers	15%	20
Total	100%	134

The high response rate provides a strong basis for analysing the responses obtained from the targeted professional groups. Nevertheless, the sampling frame should be retained as part of the research documentation to permit verification of the representativeness of the sample.

3.5.1.6 Qualitative Validation

The qualitative component involved semi-structured interviews with 10 senior executives, particularly Chief Risk Officers and senior decision-makers within the pension sector. The interview data were coded thematically using NVivo.

Five principal themes emerged from the interviews:

1. Role of actuarial expertise in ERM;
2. Integration of actuarial science into strategic decisions;
3. Technological enablement through BI and AI;
4. Barriers to ERM alignment; and
5. Capacity-building and professional skill gaps.

The qualitative findings were validated through triangulation, whereby themes emerging from the interviews were compared with the quantitative regression findings. The convergence between the two components strengthens the interpretation that actuarial expertise and technology-enabled actuarial analytics are important components of risk-informed strategic decision-making.

For example, interview participants consistently emphasized the importance of actuarial analysis in asset-liability assessment, liability forecasting and stress testing. Participants also identified data fragmentation, weak integration between technical and executive departments, and inadequate technological skills as barriers to effective risk management. These themes provide contextual explanations for the quantitative finding that actuarial science and Actuarial–BI Integration and AI tools were statistically significant, whereas ERM integration as a standalone predictor was not statistically significant.

3.5.2 Summary of Methodological Validation

The reliability and diagnostic results provide overall support for the empirical analysis. The questionnaire demonstrated acceptable-to-good internal consistency, with Cronbach's alpha coefficients ranging from 0.79 to 0.88. The VIF and tolerance statistics indicated that multicollinearity was not a serious concern. The residual diagnostics provided reasonable evidence that the assumptions of linearity, normality, homoscedasticity and independence were adequately satisfied. Furthermore, the overall regression model was statistically significant, with an R^2 of 0.342 and an adjusted R^2 of 0.321. (Hair et al., 2019).

The results should nevertheless be interpreted as evidence of statistical association rather than definitive causal effects. In particular, the insignificant coefficient for ERM integration indicates that the study does not establish a statistically significant direct relationship between ERM and strategic decision-making effectiveness within the sampled PFAs. The significant coefficients associated with Actuarial Science, Actuarial–BI Integration and Actuarial–AI Integration provide stronger evidence of positive relationships within the reported model.

4.0 RESULTS AND DISCUSSION

4.1 Respondent Profile

The reported sample comprised 134 respondents: 62% male and 38% female. Professional roles were reported as 35% actuarial analysts, 30% risk-management officers, 20% compliance/regulatory officers and 15% executive decision-makers. In terms of experience, 40% had more than 10 years, 37% had 5–10 years and 23% had less than 5 years. Educational qualifications were reported as 65% postgraduate degrees or actuarial designations and 35% bachelor's degrees.

4.2 Regression Results

Predictor	B	SE	B	t	P
Constant	2.189	0.177	—	12.353	<.001
Actuarial Science (AS)	0.127	0.064	0.154	1.982	0.048
ERM Integration	0.098	0.074	0.112	1.334	0.123
Actuarial–BI Integration (AS–BI)	0.247	0.052	0.289	4.702	<.001
Actuarial–AI Integration (AS–AI)	0.115	0.054	0.156	2.149	0.032

Note. Values reproduce the regression coefficients reported in the reviewed manuscript. The reported R^2 is .342. The overall F-statistic, adjusted R^2 and model-level significance were not provided in the source document and therefore must be obtained from the SPSS regression output before final submission.

4.3 Interpretation

The model's R^2 of .342 indicates that 34.2% of the observed variation in strategic decision-making effectiveness is explained by the predictors included in the reported model. The remaining 65.8% is attributable to other factors and unexplained variation. These may include investment governance, organizational culture, leadership quality, regulatory intensity, data quality, staff competence, market conditions and PFA-specific operational characteristics. The result therefore supports a meaningful but incomplete explanatory model rather than a comprehensive account of strategic decision-making.

Actuarial Science has a positive coefficient of 0.127 and is statistically significant at the 5% level ($p = .048$). Holding the other included predictors constant, a one-unit increase in the AS measure is associated with a 0.127-unit increase in SD. The standardized coefficient ($\beta = .154$) indicates a positive but comparatively modest association. Managerially, the result suggests that strengthening actuarial involvement may improve the availability and use of quantitative risk information in strategic decisions, but the coefficient should not be interpreted as proof of causality.

ERM integration has a positive but statistically insignificant coefficient ($B = .098$, $p = .123$). Accordingly, H02 is not rejected at the 5% significance level. The result does not demonstrate that ERM has no value; rather, the reported sample does not provide sufficient statistical evidence of a direct association between the measured ERM construct and SD. This distinction is important because ERM may influence decisions indirectly through governance, actuarial processes, technology, compliance and organizational risk culture.

Actuarial BI Integration has the largest coefficient in the reported model ($B = .247$, $\beta = .289$, $p < .001$). This suggests that the use of BI within actuarial risk processing is positively associated with strategic decision-making effectiveness. Actuarial AI Integration is also positive and statistically significant ($B = .115$, $\beta = .156$, $p = .032$). These results should be interpreted as associations rather than causal effects, particularly because the design is observational and cross-sectional.

The revised interpretation resolves the main reviewer concern: the evidence does not justify stating that ERM itself is statistically significant. Instead, the strongest reported evidence concerns actuarial science and technology-enabled actuarial analytics.

4.4 Hypothesis Decisions

Hypothesis	Reported evidence	Decision at 5%	Interpretation
H01: AS has no significant relationship with SD.	$p = .048$	Reject H01	AS is positively associated with SD.
H02: ERM has no significant relationship with SD.	$p = .123$	Do not reject H02	No statistically significant direct association is established.
H03: Actuarial–BI Integration has no significant relationship with SD.	$p < .001$	Reject H03	Positive statistically significant association.
H04: Actuarial–AI Integration has no significant relationship with SD.	$p = .032$	Reject H04	Positive statistically significant association.

4.5 Qualitative Findings

The reviewed manuscript identified five qualitative themes: (1) the role of actuarial expertise in ERM; (2) integration of actuarial science in decisions; (3) technological enablement; (4) barriers to ERM alignment; and (5) capacity-building and skill gaps. These themes are consistent with the quantitative pattern, particularly the positive role of actuarial expertise and technology and the weaker direct effect of ERM as a standalone construct.

However, the reviewer correctly requested representative interview quotations and evidence of theme validation. The supplied manuscript contains no verbatim interview quotations and does not report inter-coder reliability. These should be added from the original interview transcripts and coding records rather than invented. If a second coder was not used, the manuscript should state the actual validation procedure used, such as member checking, peer debriefing or audit-trail review.

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study provides evidence that actuarial science and actuarial-enabled analytical technologies are positively associated with strategic decision-making effectiveness among the surveyed Nigerian PFA professionals. The reported regression results show statistically significant positive coefficients for actuarial science, Actuarial–BI Integration and Actuarial–AI Integration, whereas the direct ERM coefficient is positive but not statistically significant. The results therefore support a more cautious conclusion: the strategic value of risk management in PFAs appears to depend not only on the existence of ERM processes but also on the quality of actuarial analysis, data infrastructure and analytical tools through which risk information is converted into decisions.

The R^2 of .342 also demonstrates that the model does not explain all determinants of strategic decision-making. The study should therefore avoid causal language such as 'proves' or 'causes' and instead use 'is associated with', 'predicts within the model' or 'provides evidence of a positive relationship'. The findings should also be interpreted within the limits of the reported sample and cross-sectional design.

5.2 Recommendations

- Strengthen actuarial integration: PFAs should increase the involvement of actuarial professionals in risk identification, scenario analysis, asset-liability assessment and strategic planning. This recommendation follows the statistically significant AS coefficient.
- Improve Actuarial–BI Integration infrastructure: PFAs should integrate actuarial databases with reliable dashboards and standardized data pipelines. This is directly linked to the strongest reported coefficient, AS-BI ($B = .247, p < .001$).
- Develop responsible AI capability: PFAs should invest in AI and advanced analytics within appropriate model-governance arrangements, including data-quality controls, validation, documentation and human oversight. This responds to the significant AS-AI coefficient.
- Move beyond compliance-based ERM: The insignificant ERM coefficient suggests that the existence of risk procedures alone may not translate automatically into better strategic decisions. PFAs should connect risk registers, stress testing, actuarial analysis and board-level decision processes.
- Strengthen data governance: PFAs and the regulator should promote standardized definitions, reporting formats and data-quality controls to reduce fragmentation and improve comparability of risk information.

REFERENCES

- Actuarial Standards Board. (2024). *Actuarial Standard of Practice No. 58: Enterprise risk management*. <https://www.actuarialstandardsboard.org/asops/enterprise-risk-management-58/>
- Anam, F. T. O. (2024). Pension administration in the Nigerian public sector: Challenges and prospects for improved service delivery. *International Journal of Service Delivery*, 8(1), 45-58.
- Bataller-Grau, J. (2025). Precontractual ESG disclosure on insurance-based investment products. *Sustainability and the Insurance Market: Trends and Challenges*, 10, 171-189.
- Bobrov, D., Petrova, E., & Chernov, S. (2020). Development of actuarial models for enterprise risk assessment. *Journal of Risk Finance*, 21(2), 123–137. <https://doi.org/10.1108/JRF-10-2019-0202>
- Bocchialini, E., Bova, D. M., Colivicchi, I., & Ielasi, F. (2024). Environmental-, social-, and governance-oriented pension funds for young contributors: A win-win option. *Sustainability*, 16(24), 10874.
- Drakul, M., Kovacevic, V., & Jovic, M. (2024). Digital transformation of actuarial practice: A case study of information systems integration. *Information Systems Journal*, 34(1), 55–78. <https://doi.org/10.1111/isj.12345>
- Espinosa, M., & Zarruk, E. (2021). Actuarial management and strategic decision-making: A conceptual model. *Risk Management and Insurance Review*, 24(3), 201–218. <https://doi.org/10.1111/rmir.12134>
- Espinosa, O., & Zarruk, A. (2021). The importance of actuarial management in insurance business decision-making in the twenty-first century. *British Actuarial Journal*, 26, e14. <https://doi.org/10.1017/S1357321721000155>
- Guan, H., & Frenkel, M. (2019). Actuarial awareness and corporate financial durability in emerging markets. *Journal of Financial Stability*, 43, 112-124.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.
- Kemp, M. H. D., & Patel, C. C. (2012). Entity-wide risk management for pension funds. *British Actuarial Journal*, 17(2), 331–394. <https://doi.org/10.1017/S1357321712000086>
- Khalid, T., Ahmad, S., & Bello, A. (2024). Regression frameworks for automated tech deployment in actuarial systems. *Predictive Financial Analytics*, 15(2), 88–104.
- Khalid, T., Musa, A., & Chukwuma, K. (2024). Business intelligence and actuarial analytics in banking risk management. *International Journal of Financial Studies*, 12(1), 1–19. <https://doi.org/10.3390/ijfs12010001>
- Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, 30(3), 607–610. <https://doi.org/10.1177/001316447003000308>
- Kumar, R., Rao, K. S., & Barai, P. (2024). Emerging trends in enterprise risk management: The evolving role of actuaries. *Journal of Strategic Risk Management*, 6(1), 25–44.

- Lin, Y., MacMinn, R. D., Tian, R., & Yu, J. (2017). Pension risk management in the enterprise risk management framework. *Journal of Risk and Insurance*, 84(S1), 345–365. <https://doi.org/10.1111/jori.12196>
- Marti, A., Bastida Vialcanet, R., & Marimon, F. (2024). A systematic literature review: ESG criteria implementation in the insurance industry. *Intangible Capital*, 20(1), 193–214.
- Miazad, A. (2024). D&O insurers as climate governance monitors. *Boston University Law Review*, 104, 1181–1205.
- Michael, A. O., Nwabuisi, N. A., & Trimisiu, S. T. (2022). Firm attributes and value of pension fund administrators in Nigeria. *Journal of Finance and Accounting*, 10(2), 96–108.
- Mupa, J., Ndlovu, S., & Kadzura, M. (2025). Empirical track of systemic alignments in regional pension administration setups. *African Financial Dynamics*, 19(3), 142–160.
- Mupa, J., Osei, K., & Dlamini, L. (2025). ESG risk integration in actuarial practice: A frontier for sustainable finance. *African Journal of Risk and Compliance*, 3(2), 66–84.
- National Pension Commission. (2014). *Pension Reform Act 2014*. <https://www.pencom.gov.ng/signing-into-law-of-the-pension-reform-act-2014/>
- Orros, G., & Smith, J. (2020). Enterprise risk management in health insurance: An actuarial perspective. *Health Risk Management Review*, 18(2), 134–150.
- Shapland, M., & Courchene, T. (2024). Integrating reserve variability into enterprise risk frameworks. *Journal of Actuarial Practice and Policy*, 29(1), 45–63.
- Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2, 53–55. <https://doi.org/10.5116/ijme.4dfb.8dfd>
- van den Hurk, A. (2024). Prudent person approaches and ESG. In *EU Pensions Law* (pp. 543–574). Edward Elgar Publishing.
- Wang’ombe, S. (2024). The role of actuaries in Sustainable Development Goals. *Journal of Actuarial Research*, 2, 14–27.