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Effects of Expected Credit Loss on Financial Performance of Listed Insurance Firms

Susan Kaesha[1*], Dr. John Kiarie[2], Dr. Mary Githinji[3]
School of Business and Leadership Studies, St. Paul's University
Corresponding Author's Email: suekaesha1@gmail.com

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Abstract

The purpose of the study was to examine the effects of expected credit loss on the financial performance of insurance firms. This study adopted a descriptive research design. The target population for this study comprised all six insurance firms listed on the Nairobi Securities Exchange (NSE) as of the year 2024. Descriptives and inferential statistics were used in data analysis. The analysis revealed there is a significant correlation between ECL and financial performance (ROA), where the correlation was $r = 0.318$ and the p-value was 0.005. This shows that improvements in the credit loss model help insurers to project exposures more accurately, hence reporting is more likely to project stable earnings and improved returns. In this case, the null hypothesis (H_1) is rejected as the test confirms the significance of ECL on forecasting and financial performance, thus the overall profitability of the firm. The Expected Credit Loss (ECL) model demonstrated the positive correlation and predictive power, anchored in financial Intermediation theory, proved particularly useful in managing credit risks and enhancing predictability in investment portfolios. Its significant influence on ROA affirms that forward-looking credit risk modelling strengthens financial resilience and regulatory compliance, especially under IFRS 9 requirements. Operationalize Expected Credit Loss (ECL) with risk analytics integration. Insurers should embed ECL modelling within their investment and credit risk functions, incorporating tools like machine learning algorithms to forecast default scenarios and macroeconomic stressors. This is vital for compliance with IFRS 9 and will bolster financial resilience against credit shocks.

Keywords: *Financial technologies, expected credit loss, financial performance, insurance firms*

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1. Introduction

The insurance industry is a key instrument of economic growth, which plays a major role in enabling protection, capital growth, creating certainty in investment, ensuring liquidity, and mobilizing savings. The insurers enable other businesses to undertake operations without worrying about risk (Kemboi, 2019). In this regard, the financial stability of insurance companies is crucial for the sustainability of other businesses. However, the financial performance of insurance companies is seldom understood due to complexities in underwriting and models applied when valuing assets (Leslie et al., 2022).

As noted by Feyen et al. (2021), financial Institutions such as banks and insurance companies are adopting financial technologies as an instrument of valuing assets to enhance accuracy in financial performance reporting. This, as a result, has rapidly transmogrified the global financial services setting unprecedented standards of reliability, competitiveness, and efficiency. For instance, the author observed that Fintech has been adopted in financial institutions such as banks in facilitating transactions through Peer-to-Peer lending(P2P) and mobile banking platforms. Feyen et al. (2021) further noted that the integration of financial technology in the financial sector has offered an array of solutions in the banking sector, such as data-driven pricing models and asset valuation models. These integrations have streamlined the operations, enhanced customer service, transparency and sustainability in the increasingly dynamic market. The inclusion of financial technologies by many financial institution firms for competitive advantage in the dynamic market has helped them value their assets in accordance with General Accepted Accounting Principles (GAAP) and International Financial Reporting Standards (IFRS 17) (Otiso, 2020).

Fintech valuation models utilize technology to improve the accuracy and transparency of financial reporting by incorporating predictive analytics, automation, and real-time market data. These models support better risk management and capital allocation while promoting compliance with global financial standards. Feyen et al. (2021) In the context of the insurance industry, four models stand out in their relevance and impact—Expected Credit Loss (ECL), Fair Value Measurement (FVM), Embedded Value (EV), and Discounted Cash Flow (DCF). This paper focused on Expected Credit Loss (ECL).

The Expected Credit Loss model, introduced through the IFRS 9 accounting standard, is a forward-looking tool used to estimate potential credit losses before they occur. Unlike the older incurred loss model, ECL requires institutions to assess possible defaults based on future economic conditions and current exposure levels. It integrates two key components, probability of default and loss given default, to forecast losses on receivables, investments, and counterparties. In insurance firms, this model is particularly significant for managing investment portfolios and policyholder risks. The integration of machine learning and risk analytics has further improved the model's predictive capabilities, enabling insurers to make more informed decisions and build resilience against credit shocks. By anticipating future losses, firms can strengthen their financial buffers, comply with regulatory expectations, and improve overall financial stability

1.1 Problem Statement

The financial performance of insurance firms is essential to the stability of financial markets, investor confidence, and broader economic development. Despite the vital role played by Kenya's insurance sector, recent trends reflect a troubling decline in performance. The Aki Report (2020) noted a drop in GDP contribution from 2.79% in 2015 to 2.30% in 2020, alongside increased regulatory non-compliance cases amounting to Kshs. 94.85 million in fines, which raises critical concerns about financial reporting accuracy and corporate accountability.

Past studies in relation to the valuation of assets in insurance firms have relied on traditional methods such as market, income, and asset-based models. However, these valuation approaches rely on historical data, which are not sufficient in addressing the complexities brought by technological advancements (Tracy, 2022). This study investigated the effects of valuation of assets using fintech models among the insurance listed companies in Kenya.

Similarly, the inability of traditional approaches to account for dynamic market fluctuations and future risk exposure leads to inaccurate asset reporting and hampers sound financial decision-making. This, therefore, creates a contextual gap which the study has filled. By focusing on fintech valuation models such as Expected Credit Loss (ECL), the study seeks to provide a comprehensive understanding of how these models enhance valuation accuracy.

1.2 Objective of the Study

To examine the effects of expected credit loss on the financial performance of insurance firms.

1.3 Research Hypothesis

H_1: Expected Credit Loss does not have a statistically significant effect on the financial performance of insurance firms in Kenya.

2. Literature Review

2.1 Theoretical Review

This study was informed by Prospect Theory. Prospect Theory provides a foundational lens for understanding financial decision-making under uncertainty. Beyond explaining risk preferences, it introduces the concept of loss aversion, where decision-makers feel the impact of losses more acutely than equivalent gains. This often leads to conservative behavior in financial contexts, such as delaying the adoption of new valuation models. In fintech, it helps explain insurers' reluctance to embrace innovations that initially appear risky despite potential long-term advantages.

Prospect Theory was developed by Daniel Kahneman and Amos Tversky in 1979. It is a cognitive psychology theory that explains how individuals and organizations assess potential gains and losses, often becoming risk-averse when faced with potential losses and risk-seeking when expecting gains. In fintech valuation, insurance firms may overestimate or underestimate the financial impact of adopting models such as the Expected Credit Loss (ECL), potentially leading to biased financial decisions. This theory has been applied in studies such as Muthaura, Muguna and Wandiri (2021) to analyze risk behavior in fintech adoption. A key critique is that it overemphasizes behavioral biases and may ignore structured decision-making processes used in financial firms. However, it remains essential for understanding how insurers approach the risks of ECL implementation, helping them make informed, balanced valuation decisions that enhance financial performance while minimizing exposure to potential credit losses.

Prospect Theory has been influential in behavioral finance, yet it faces criticism for lacking predictive precision and for being context dependent. Its focus on individual psychological responses to risk may not fully capture structured, institutional decision-making in firms like insurance companies. Furthermore, critics argue that it overlooks the role of regulatory frameworks and strategic planning in financial choices. Although powerful in explaining biases, its limited applicability to complex corporate financial strategies reduces its effectiveness in forecasting long-term financial behavior.

This theory supports the objective of examining the effects of expected credit loss on financial performance by explaining how insurance firms assess risk in adopting this model, often exhibiting cautious behavior when facing potential losses, which affects valuation outcomes.

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2.2 Empirical Review

Johnson and Lee (2021) conducted a comprehensive study that focused on evaluating how macroeconomic indicators affect the precision of ECL estimations within Kenyan insurance firms. The independent variables examined in their study included GDP growth, inflation rate, and interest rate fluctuations, while the dependent variable was ECL estimation accuracy. The study analysed the data using a panel data regression analysis model, drawing from quarterly data spanning five years across ten Kenyan insurance firms. The findings revealed that macroeconomic volatility had a significant effect on the accuracy of ECL estimations, thereby influencing the firms' ability to provision for credit risk effectively. Despite the robust methodology and insightful results, the study did not evaluate the direct relationship between ECL estimations and financial performance indicators such as Return on Assets (ROA). This omission presents a crucial gap, which the current study seeks to address by examining how ECL models influence the profitability of listed insurance firms in Kenya.

Feyen et al. (2021) explored the broader context of digital transformation in financial services, including the adoption of ECL models. The independent variable in their study was the adoption of fintech tools, particularly the implementation of ECL models for credit risk assessment. Using a descriptive research design combined with case study analysis, they investigated fintech adoption in several Sub-Saharan African financial institutions, including banks and insurers. The key focus was on fintech tools' role in risk assessment and compliance, with ECL implementation as one of the core areas analysed. Their findings indicated that ECL models enhance transparency and risk management by allowing insurers to predict and provision for credit losses more accurately. However, their study lacked a quantitative analysis of how ECL adoption influences firm-level financial performance metrics such as ROA or profitability ratios. The current research fills this void by empirically linking ECL adoption to financial outcomes in the Kenyan insurance sector, thereby demonstrating the tangible benefits of this fintech model beyond risk assessment.

Mashamba (2023), in his study, utilised empirical econometric models, particularly generalised method of moments (GMM) regression analysis, to evaluate the impact of fintech adoption on bank funding and economic performance. The independent variable was fintech adoption, while the dependent variables included funding efficiency and GDP growth. Although the study demonstrated that fintech solutions improve financial efficiency and resource allocation, it did not isolate the role of ECL models within insurance firms, nor did it assess their impact on firm-level profitability. Consequently, Mashamba's research provides a regional fintech context but leaves an empirical gap regarding ECL's effect on the profitability of insurance firms, a gap this study intends to bridge.

Chirairo and Molele (2024), in their study, analysed how intellectual capital, as an intangible fintech-related asset, influences firm value. The independent variables in their study were human capital, structural capital, and relational capital, while the dependent variable was firm value, measured using Tobin's Q and ROA. Using multiple regression analysis, they found a positive correlation between fintech-driven intellectual capital and firm value. Although their work underlined fintech's contribution to asset quality and valuation, it did not address ECL models or explore their relevance within insurance firms. Nonetheless, the study offers valuable valuation logic that supports the rationale for examining ECL as a fintech valuation model capable of enhancing the financial performance of insurers.

Kou and Lu (2025), in their comprehensive literature review, assessed various fintech applications, including ECL models. Their study utilised systematic review methods, focusing on variables such as adoption barriers, regulatory challenges, and implementation costs associated with fintech solutions. They highlighted the technical and organisational challenges of ECL adoption, including data quality issues, compliance complexities, and integration with legacy systems. However, Kou and Lu did not conduct an empirical analysis to assess the financial performance impact of ECL models, nor did they explore the insurance sector specifically. The current study builds upon their findings by empirically analysing the relationship between ECL adoption and profitability outcomes (ROA) in Kenya's listed insurance firms, thus offering quantitative insights into the financial implications of overcoming ECL implementation challenges.

2.3 Conceptual Framework

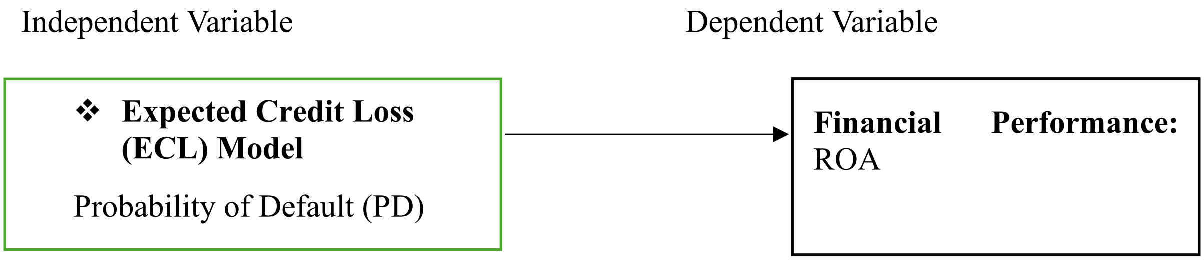

Figure 1: Conceptual Framework

3. Methodology

This study adopted a descriptive research design that examined the relationship between fintech valuation models and the financial performance of listed insurance firms in Kenya. Descriptive design was appropriate for this research as it allowed for the collection of detailed information through observation and analysis, which enabled a comprehensive understanding of the influence of fintech valuation models on Return on Assets (ROA). The quantitative approach enabled the collection of numerical data that gave a statistical relationship between the variables, thus making it reliable in providing quantifiable feedback on the accuracy level of the models, complexity, decision-making, and the overall overview of the influence of the models on financial performance. This was successful as the use of questionnaires with 5 Likert scale gave room to perform standardization, correlation, and regression, which helped in coming up with the findings, conclusions, and recommendations.

The target population for this study comprised all six insurance firms listed on the Nairobi Securities Exchange (NSE) as of the year 2024. These firms were selected due to the availability of audited financial statements and their regulatory obligation to disclose financial data to both the Insurance Regulatory Authority (IRA) and the NSE, ensuring consistency, transparency, and comparability. As fintech adoption varies across the sector, focusing on listed firms that allow for examination of how fintech valuation models are implemented in well-regulated and publicly accountable environments. Additionally, the study targeted 30 key personnel within these insurance firms who are directly involved in the implementation and management of fintech valuation models, based on prior evidence from Otiso (2020) and Mwangi (2021), who confirmed that listed insurers in Kenya have increasingly adopted fintech tools in core financial functions, including asset valuation. These individuals, through purposive sampling, were selected based on their roles in finance, risk, and actuarial departments, as they possess relevant knowledge and experience with the valuation models under investigation.

The sample included 12 participants from finance departments, 10 from risk management units, and 8 from actuarial teams, ensuring broad functional representation. Furthermore, selection also considered academic and professional qualifications, with a preference for individuals holding at least a bachelor's degree in finance, actuarial science, accounting, or economics, and/or professional certifications such as CPA, CFA, or actuarial credentials. These individuals provided primary data through structured questionnaires and a survey aimed at capturing firm-specific insights on fintech adoption and usage. As of 2024, there are approximately 6 listed insurance firms on the NSE, and these formed the entire population for the study. Given this manageable size, a census approach was adopted, whereby data collected from all listed firms. This study employed the use of closed-ended questionnaires that were designed with an ordinal value of the Likert scale. This primary data ensured comprehensive and accurate findings from 30 key personnel in listed insurance firms, including finance officers, risk officers, and actuarial analysts. The questionnaires and the survey were designed in a way where the respondent would give their demographic information, such as age, gender, level of education, the organization they are in and years of service in the organization. The demographic was key as it helped understand the socioeconomic status of the respondents. The subsequent section captured detailed information on the adoption, implementation, and perceived impact of fintech valuation models, specifically Expected Credit Loss (ECL), Fair Value Measurement (FVM), Embedded Value (EV), and Discounted Cash Flow (DCF), where every model was rated alongside the financial performance that was in line with the objectives of the study.

The data collected through questionnaires and survey was cleaned, coded and entered into Excel, where descriptive statistics such as means, frequencies, percentages, and standard deviations were calculated to summarize responses and identify trends in the adoption of fintech valuation models. Descriptive statistics were done to summarize the variables of the study and to explore the relationship among variables and the impacts of the models on the financial performance.

Regression analysis was also conducted, where the ANOVA was employed as it helped determine if the model explains the variation between the variables, as well as evaluating if the combined effects of all independent variables offer a perfect fit.

4. Results and Discussion

4.1 Descriptive Statistics

The section on descriptive statistics serves as a basis for subsequent inferential analyses that provide a detailed summary of the measures of central tendency such as such as frequencies, mean, median, mode, standard deviation, variance, Kurtosis, skewness, maximum, and minimum (Min) and a significant level of 95% or 0.05 for each construct and variability across the constructs. The study specifically analyzed the fintech valuation models: Expected Credit Loss (ECL), alongside the Return on Assets (ROA) as the dependent variable.

Table 1: Descriptive Statistics

Statistic	*Expected credit Loss(ECL)*	*Financial Performance (ROA)*
Mean	3.83	3.41
Median	3.8	3.28
Mode	4	3.28
Standard Deviation	0.41	0.22
Sample Variance	0.17	0.05
Minimum	3	3
Maximum	5	5
Count(N)	155	155
Kurtosis	-0.55	0.81
Skewness	-0.3	1.44
Confidence Level (95%)	0.03	0.03

4.1.1 Return on Assets (ROA) –Financial Performance

The findings from the 155 respondents on the ROA as the financial performance metrics showed a mean of 3.41, a median and mode of 3.28, a standard deviation of 0.22, which shows low variability among the listed firms. The results pustules a minimum of 3 and a maximum of 4, indicating that all the firms use this metric to value their financial performance. For the skewness was 1.44, this positively skewed distribution with non-normal tails this implies that the responses spread around the mean, which shows an even and flatter distribution than normal and a kurtosis of 0.81 and a confidence level of 0.03, that is below the threshold of 95% level of confidence revealing that ROA is the most adopted metric of financial performance.

4.1.2 Expected Credit Loss (ECL)

Expected credit loss had a mean of 3.83, while the mode and median were 4.00 and 3.8, respectively. This signified that values were symmetrical. The standard deviation of 0.41 was low, this showed the consistent usage as this stipulated in the regulatory frameworks and accounting standards IFRS 17 and 9, as well as low variability among the listed insurance firms. The negative skewness of -0.30 showed that the insurance firms selected this model above the mean. A peaked distribution was observed as kurtosis of -0.587 recorded which was consistent with the concentrated responses. The confidence level of 95% attained, where the internal width of 0.03 signifies that the Model influences financial performance.

4.2 Diagnostic Tests

Before estimating the regression model, a series of diagnostic tests was done to ensure that the assumptions of Ordinary Least Squares (OLS) regression were not violated. These tests validated the robustness of the model, explaining the influence of fintech valuation models on the financial performance of listed insurance companies in Kenya. These tests involved: Multicollinearity test through the use of VIF, Normality test through the Shapiro-Wilk test.

Table 2: Diagnostic Tests

Test	*Variable / Model*	*Statistic*	df	*Sig. (p)*	*Interpretation*
Multicollinearity (Collinearity Statistics)	ECL_score	Tolerance = 0.732; VIF = 1.366	–	–	Low multicollinearity
Normality (Shapiro–Wilk)	ECL_score	W = 0.962	155	0.031*	Violates normality

4.2.1 Multicollinearity test

The Variance Inflation Factor (VIF) of ECL was 1.366. These findings, therefore, imply that multicollinearity was not a challenge in the regression model and that the items in the construct were correlated; therefore, each model contributed unique explanatory power to the analysis.

4.2.2 Normality test

Normality of residuals is a fundamental diagnostic requirement in regression analysis, as it underpins the validity of the classical linear regression model (CLRM) assumptions it also provides for statistical inferences. The Shapiro–Wilk test for normality returned W≈<1) where values close to 1 signify that the distribution is approximately normal, where Expected credit loss (ECL) had W≈0.962, p=0.031. These results collectively imply that the residuals violate normality; thus, the null hypothesis was rejected despite the deviations from normality, the regression results remain valid.

4.3 Inferential statistics

The inferential statistics were conducted to understand the relationship between the dependent variable (ROA) and the independent variable (Expected Credit Loss (ECL). The inferential statistics employed were Pearson correlation and multiple linear regression, which showed the relationship between the fintech valuation models and financial performance.

4.3.1 Pearson correlation

Table 3: Pearson Correlation

Pearson Correlation	ROA
ROA	1
ECL	0.318**

ECL demonstrated a positive and significant correlation with ROA, where it had an $r = 0.318$ and a $p < 0.01$. This suggests that as the expected credit loss rises, the financial performance also increases, thus the overall profitability of the firm, as they are ready for credit exposures, which therefore enhances the financial outcomes

4.3.2 Simple Linear Regression

This is an inferential statistical tool that is employed to show the relationship between one dependent variable and various independent variables. From Table 8, multiple linear regression analysis was used to test the fintech valuation models and financial performance of insurance firms: a case of listed insurance firms in Kenya.

Table 3: Regression Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Expected Credit Loss (ECL)	0.441	0.060	-7.295	0.004

From the findings, there was a significant effect of Expected Credit Loss (ECL) on insurance financial performance in terms of ROA ($\beta=0.441$, $p=0.004$).

4.4 Hypothesis Testing

This research hypothesis, i.e. H_1: Expected Credit Loss does not have a statistically significant effect on the financial performance of insurance firms in Kenya, was tested. Reference is made to tables 1 and 2, where the hypothesis testing was conducted and reported as follows where if $r<1$ and $p<0.05$, you reject the hypothesis.

Table 4: Hypothesis test results

	Hypothesis Statement	Correlation Result (r, p-value)	Decision	Interpretation
H_1	Expected Credit Loss (ECL) does not have a statistically significant effect on the financial performance of insurance firms in Kenya.	$r = 0.318$, $p= 0.004$	Rejected	ECL has a significant positive effect on financial performance.

The analysis revealed there is a significant correlation between ECL and financial performance (ROA), where the correlation was $r = 0.318$ and the p-value was 0.004873. This shows that improvements in the credit loss model help insurers to project exposures more accurately, hence reporting is more likely to project stable earnings and improved returns. In this case, the null hypothesis (H_1) is rejected as the test confirms the significance of ECL on forecasting and financial performance, thus the overall profitability of the firm.

4.5 Discussion of Empirical Findings

The findings of the regression analysis showed that ECL and financial performance (ROA) were positively and significantly correlated. The prudential regulatory system, which prioritizes forward-looking loss recognition to enhance firm stability, is consistent with this. According to empirical evidence, the findings are consistent with other research mentioned in the literature review, where recent studies, such as Johnson & Lee (2021) and Kou & Lu (2025), emphasized that robust credit risk recognition mitigates default shocks and sustains profitability in volatile markets. While some authors note that stricter provisioning may suppress short-term profits (Mashamba, 2023) but the current results support the stabilizing impact on insurers over the long run.

5. Conclusion

The Expected Credit Loss (ECL) model demonstrated the positive correlation and predictive power, anchored in financial Intermediation theory, proved particularly useful in managing credit risks and enhancing predictability in investment portfolios. Its significant influence on ROA affirms that forward-looking credit risk modelling strengthens financial resilience and regulatory compliance, especially under IFRS 9 requirements.

6. Recommendations

Operationalise Expected Credit Loss (ECL) with risk analytics integration Insurers should embed ECL modelling within their investment and credit risk functions, incorporating tools like machine learning algorithms to forecast default scenarios and macroeconomic stressors. This is vital for compliance with IFRS 9 and will bolster financial resilience against credit shocks.

Policy makers should develop a National Framework for Fintech Valuation Standards, where the Ministry of Finance and the Capital Markets Authority (CMA) should collaborate with stakeholders to create a unified fintech valuation policy framework that mandates or encourages the use of models like FVM, EV, and ECL across the insurance and wider financial sector.

Industry regulators should expand regulatory sandboxes such as Bima Lab and Bima Box IRA, should scale up their innovation programs to include fintech valuation tools, allowing firms to test digital asset valuation platforms under regulatory supervision. This would reduce transition risks and support model standardization across the industry.

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