International Journal of

Finance

(IJF)

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International Journal of Finance

ISSN 2520-0852 (Online)

Vol. 10, Issue No. 8, pp. 70 - 89, 2025 www.carijournals.org

Machine Learning Adoption and its Effect on Efficiency of Credit Analysis in Tier II Commercial Banks in Kenya

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Abstract

Purpose: The purpose of the study was to examine the Machine Learning Adoption and its Effect on Efficiency of Credit Analysis in Tier II Commercial Banks in Kenya. The study specifically aimed at assessing the effect of regulatory pressure, technological readiness and organizational capacity on efficiency of Credit Analysis.

Methodology: The study adopted a descriptive research design, targeting 48 professionals comprising of credit risk managers, data analysts, loan officers, IT officers, compliance officers, and strategy leads through census sampling technique. Primary data was collected through structured questionnaires using 5-point Likert scales. Data analysis was conducted using SPSS version 28.0, employing both descriptive statistics and inferential statistics.

Findings: Regarding the first objective, results revealed a statistically significant strong positive relationship between regulatory pressure and efficiency of credit analysis, $r(48) = 0.616$, $p < .05$. Multiple regression analysis indicated that regulatory pressure explained 37.9% of variance in credit analysis efficiency, $R^2 = 0.379$, $F(1, 46) = 28.059$, $p < .05$, $\beta = 0.616$, $p < .05$. For the second objective, findings indicated a statistically significant very strong positive relationship between technological readiness and efficiency of credit analysis, $r(48) = 0.819$, $p < .05$. Regression analysis showed that technological readiness explained 67.0% of variance in credit analysis efficiency, $R^2 = 0.670$, $F(1, 46) = 93.375$, $p < .05$, $\beta = 0.819$, $p < .05$. Regarding the third objective, results showed a statistically significant very strong positive relationship between organizational capacity and efficiency of credit analysis, $r(48) = 0.803$, $p < .05$. Multiple regression analysis indicated that organizational capacity explained 64.5% of variance in credit analysis efficiency, $R^2 = 0.645$, $F(1, 46) = 83.527$, $p < .05$, $\beta = 0.803$, $p < .05$.

Unique Contribution to Theory, Practice and Policy: The study recommended that the Central Bank of Kenya should continue refining regulatory frameworks that encourage machine learning adoption. Tier II banks should prioritize systematic investments in digital infrastructure, exploring cloud-based solutions, investing in data quality improvement initiatives, and strengthening cybersecurity frameworks. Banks should also invest systematically in human capital development through competitive recruitment strategies, comprehensive training programs, leadership development, and cultural transformation initiatives.

Key Words: *Regulatory Pressure, Technological Readiness, Organizational Capacity, Efficiency of Credit Analysis*

International Journal of Finance

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Background of the Study

The integration of machine learning technology in Credit Analysis represents a paradigm shift in the global banking sector, fundamentally altering how financial institutions assess, monitor, and manage credit risk. Traditional credit scoring models, predominantly based on linear statistical methods such as logistic regression, have proven inadequate in capturing the complex, multidimensional relationships inherent in modern borrower data (Addy, Ugochukwu, Oyewole, Ofodile, Adeoye, & Okoye, 2024). This inadequacy has manifested in persistently high rates of non-performing loans (NPLs) across various markets, creating an urgent need for more sophisticated analytical approaches that can enhance predictive accuracy and reduce financial losses (Al Zaidanin & Al Zaidanin, 2021). Kenya's financial sector has shown a growing interest in adopting artificial intelligence and machine learning, driven significantly by the Central Bank of Kenya's guidelines that promote digitization and risk-based lending practices (Central Bank of Kenya, 2023). The country's banking sector is stratified into three tiers, with Tier I banks (large institutions with extensive resources) showing significantly higher adoption rates of machine learning technologies compared to their smaller counterparts (Karanja, 2019). Recent studies indicate that over 67% of Tier I banks have either implemented or are piloting ML-based credit risk models, including logistic regression, random forest, and gradient boosting algorithms (Mutembete, 2022).

However, Tier II commercial banks, which serve crucial segments including SMEs and low-income borrowers, face considerable challenges in adopting these technologies. These institutions typically operate with limited resources and face intense competition from both larger banks and agile digital lenders (Nyangena, 2019). A comprehensive study utilizing Metropol credit data from 2014 to 2017 revealed that machine learning models, such as Random Forest, significantly outperformed traditional logistic regression in default classification, achieving an F1-score of 0.307, while emphasizing the critical importance of demographic variables in predicting creditworthiness (Mulwa & Yahya, 2025). Despite these promising results, the study highlighted persistent barriers to adoption, including infrastructural gaps, data governance concerns, and limited availability of skilled personnel (Edunjobi & Odejide, 2024).

The level of machine learning adoption in Credit Analysis represents a multifaceted construct that encompasses the breadth, depth, and sophistication of ML implementation within banking institutions. This variable is characterized by several dimensions, including the types of algorithms employed, the extent of integration with existing systems, and the scope of application across different credit products and customer segments (Hegde, Hegde, Marthanda, & Logu, 2023). Research indicates that the level of adoption significantly influences the effectiveness of credit risk assessment, with higher levels of implementation typically correlating with improved predictive accuracy and reduced operational costs (Sriram, 2025).

The measurement of regulatory pressure impact requires consideration of both quantitative and qualitative factors, including the percentage of compliance requirements implemented, the comprehensiveness of regulatory frameworks adopted, and the degree of automation achieved in regulatory reporting processes. Banks experiencing higher regulatory pressure typically demonstrate greater willingness to invest in advanced compliance technologies, such as regulatory technology (RegTech) solutions, automated monitoring systems, and real-time reporting platforms, for managing complex regulatory requirements (Gatla, 2023). However, the relationship between regulatory pressure and efficiency outcomes is not always linear, as successful compliance implementation depends heavily on organizational readiness, technological infrastructure, and the bank's capacity to integrate regulatory requirements with operational processes (Murugan, 2023).

Statement of the Problem

The global banking sector faces an escalating credit risk crisis, with traditional assessment methods proving increasingly inadequate in today's complex financial landscape. According to the World Bank Global Financial Stability Report (2024), non-performing loans (NPLs) averaged 4.2% globally, with developing economies experiencing significantly higher rates of 7.8%. In Kenya, the Central Bank of Kenya (2023) reports that NPLs among commercial banks stood at 13.4% in 2023, substantially above the regulatory threshold of 5%, resulting in credit losses exceeding KES 180 billion annually. The Economic Survey of Kenya (2024) indicates that credit risk provisioning consumed 2.8% of total banking sector assets, equivalent to KES 156 billion, highlighting the magnitude of inefficient credit analysis systems. Tier II commercial banks specifically recorded NPL ratios of 16.7%, significantly higher than Tier I banks at 9.2% (CBK, 2023), demonstrating acute challenges in credit risk assessment capabilities among mid-tier institutions. Extensive research demonstrates machine learning's transformative potential in Credit Analysis, yet significant implementation gaps persist. Gasmi, Neji, Mansouri, and Soui (2025) in their study on bank credit risk prediction using machine learning models found that ensemble algorithms improved default prediction accuracy by 23% compared to traditional logistic regression models in European banks. Similarly, Shi, Tse, Luo, D'Addona, and Pau (2022) in their systematic review of machine learning-driven credit risk established that Random Forest and Gradient Boosting algorithms achieved 89% accuracy in credit scoring across developed markets.

Nkambule, Twala, and Pretorius (2024) in their study on effective machine learning techniques for dealing with poor credit data demonstrated that institutions with robust digital infrastructure achieved 35% better ML model performance. Leo, Sharma, and Maddulety (2019) in their literature review on machine learning in banking risk management identified technological infrastructure as the primary determinant of successful ML adoption, with 78% of implementation failures attributed to inadequate systems. Mutembete (2022) in his study on credit risk assessment models using machine learning found that Kenyan banks with dedicated data science teams achieved 40% faster ML implementation cycles. Karanja (2019) in her research on credit risk and lending performance of commercial banks in Kenya established that leadership support and staff training programs were critical success factors, with institutions investing in human capital showing 25% higher ML adoption rates.

Despite extensive global research, three critical gaps remain unaddressed. First, existing studies predominantly focus on Tier I banks and developed markets, with minimal empirical investigation into ML adoption challenges specific to Tier II banks in emerging economies like Kenya. Second, current research lacks comprehensive examination of the interplay between technological readiness, organizational capacity, and ML adoption levels in determining Credit Analysis efficiency among resource-constrained banking institutions. There is limited studies that have systematically investigated how regulatory pressure influences ML adoption decisions and implementation success in Kenya's Tier II banking sector. This study addresses these gaps by investigating the effect of machine learning adoption on Credit Analysis in Kenya's Tier II commercial banks, specifically examining how technological readiness, organizational capacity, and regulatory pressure collectively influence implementation outcomes and operational performance.

Objectives of the Study

i. To assess the effect of regulatory pressure on efficiency of credit analysis among Tier II commercial banks in Kenya.
ii. To examine the effect of technological readiness on efficiency of credit analysis among Tier II commercial banks in Kenya.
iii. To determine the effect of organizational capacity on efficiency of credit analysis among Tier II commercial banks in Kenya.

Literature Review

Regulatory Pressure and Efficiency of Credit Analysis

The Technology-Organization-Environment (TOE) framework provides the primary theoretical foundation for understanding how regulatory pressure influences technology adoption and operational efficiency in Kenya's banking sector. Tornatzky and Fleischer (1990) conceptualized the environmental context as encompassing external factors including government regulation, industry characteristics, and competitive pressures that influence organizational technology adoption decisions. Baker (2011) demonstrates that regulatory pressure represents a critical environmental factor that can either facilitate or constrain technology adoption, with government regulations serving as external drivers of organizational change. In Kenya's banking context, the Central Bank of Kenya's regulatory guidelines function as environmental pressures that drive institutional change and technology adoption among commercial banks (Kimani & Kibera, 2023).

Diffusion of Innovation (DOI) theory complements TOE by explaining how regulatory pressure influences the rate and pattern of technology adoption across different banking institutions. Rogers (2003) identifies external system factors, including government regulations and policy support, as critical determinants of innovation adoption rates within industries. The theory explains how regulatory pressure can accelerate adoption by reducing perceived risks and providing legitimacy for new technologies (Mutembete, 2022). DOI theory suggests that regulatory frameworks create environmental conditions that influence adopter categories, with clear regulatory support enabling early adoption while regulatory uncertainty may delay implementation (Kanyambu, 2021). The framework explains why regulatory pressure often serves as a catalyst for operational efficiency improvements, as organizations seek to demonstrate compliance while achieving competitive advantages through enhanced capabilities (Central Bank of Kenya, 2023).

Technological Readiness and Efficiency of Credit Analysis

The Technology-Organization-Environment (TOE) framework's technology context provides a comprehensive theoretical foundation for understanding technological readiness in Kenya's Tier II banking sector. Tornatzky and Fleischer (1990) conceptualized the technology context as encompassing both internal and external technologies relevant to the organization, including current practices and available technologies. Parasuraman (2000) extends this concept through the Technology Readiness Index (TRI), which measures an individual's and an organization's propensity to embrace new technologies. In Kenya's banking context, Kimani and Kibera (2023) demonstrate that technological readiness encompasses not only traditional IT infrastructure but also the integration of mobile technology, cloud computing capabilities, and cybersecurity frameworks. The TOE technology context explains why Tier II banks in Kenya exhibit varying levels of technological readiness, with some institutions investing heavily in digital infrastructure while others maintain legacy systems (Central Bank of Kenya, 2023). The technological context in the TOE framework reveals that technological readiness is not merely about having advanced equipment, but about the organization's ability to utilize and integrate new technologies effectively. Mutembete (2022) applies this perspective to show that Kenyan banks with higher technological readiness demonstrate superior ML implementation outcomes, regardless of their size or market position. The framework explains why some Tier II banks achieve competitive ML capabilities despite resource constraints, through strategic technology investments and partnerships (Kanyambu, 2021). Baker (2011) emphasizes that the technology context includes both availability of technologies and the organization's capacity to adopt and implement them effectively. This theoretical foundation suggests that technological readiness in Tier II banks requires alignment between infrastructure investments, technical capabilities, and strategic objectives (Karanja, 2019).

Organizational Capacity and Efficiency of Credit Analysis

The Technology-Organization-Environment (TOE) framework's organizational context provides comprehensive theoretical grounding for understanding organizational capacity in Kenya's Tier II banking sector. Tornatzky and Fleischer (1990) conceptualized the organizational context as encompassing firm size, managerial structure, human resources, and internal communication processes that influence the adoption of technology. Baker (2011) extends this framework to demonstrate how organizational characteristics influence the success of technology adoption, with larger organizations typically having greater resources but potentially more complex decision-making processes. In Kenya's banking context, Kimani and Kibera (2023) show that organizational capacity encompasses not only traditional HR metrics but also learning capabilities, innovation culture, and change management competencies. The TOE organizational context explains why some Tier II banks achieve successful ML implementation despite resource constraints, through superior organizational capabilities and strategic management (Central Bank of Kenya, 2023). Diffusion of Innovation (DOI) theory complements TOE by explaining how organizational characteristics influence the timing and success rates of adoption. Rogers (2003) identifies key adopter characteristics including risk tolerance, resource availability, and network connectivity that determine innovation adoption patterns. Mutembete (2022) applies DOI theory to show that Tier II banks with higher organizational capacity tend to be early adopters of ML technologies, achieving competitive advantages through superior risk management capabilities. The theory explains why organizational capacity development is crucial for successful ML adoption, as institutions must possess adequate resources, expertise, and cultural readiness to implement complex technologies effectively (Kanyambu, 2021). Karanja (2019) demonstrates that organizational capacity acts as a mediating factor between technology availability and adoption success, with banks possessing superior organizational capabilities achieving better ML implementation outcomes regardless of their size or market position.

Research Methodology

This study employed a descriptive research design. The target population for this study comprised of professionals involved in credit risk assessment, technology deployment, and digital transformation initiatives across Tier II commercial banks in Kenya. They included credit risk managers, data analysts, loan and credit officers, IT and digital transformation officers, compliance and regulatory officers, and strategy innovation leads. Given the focused scope of the study, which targets specific professionals across eight Tier II commercial banks, and considering the relatively small population size of 48 respondents, census sampling was deemed most appropriate. The study utilized primary data to be collected through structured questionnaires administered to the target respondents. The collected data was analyzed using both descriptive and inferential statistics to achieve the research objectives. The regression model used was:

$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \varepsilon$

Where: Y = Efficiency of Credit Analysis, X_1 = Level of Machine Learning Adoption, X_2 = Technological Readiness, X_3 = Organizational Capacity, β_0 = Constant term, β_1, β_2, β_3 = Regression coefficients and ε = Error term. Significance levels was set at $p < 0.05$ for all statistical tests. The analyzed data were presented using tables, charts, and graphs.

Results

Effect of Regulatory Pressure on Efficiency of Credit Analysis

Descriptive Statistics

Respondents were requested to indicate their agreement with statements about regulatory pressure and its effect on credit analysis efficiency using a 5-point Likert scale, where: 1-strongly disagree, 2-disagree, 3-neutral, 4-agree and 5-strongly agree. The results in Table 1 indicate that the respondents agreed that their bank has reliable internet connectivity and power backup systems to support ML operations (M = 3.83, SD = 1.10), achieving the highest mean score among all regulatory pressure indicators. It was also agreed that Central Bank of Kenya guidelines encourage their bank to adopt advanced analytics in credit risk management (M = 3.77, SD = 1.17) and that compliance with CBK's ICT guidelines necessitates investment in advanced credit analysis technologies (M = 3.75, SD = 1.00). Additionally, respondents agreed that data protection regulations influence how they design and implement ML-based credit scoring systems (M = 3.67, SD = 1.12) and that regulatory pressure from supervisory authorities motivates their bank to modernize credit analysis processes (M = 3.65, SD = 1.12). The lowest rating was observed for regulatory requirements for risk-based lending driving their bank to implement machine learning solutions (M = 3.60, SD = 1.22), though this still represents agreement with the statement. The relatively high standard deviations across all items (ranging from 1.00 to 1.22) suggest moderate variability in respondents' perceptions regarding regulatory pressure, indicating that while most professionals acknowledge regulatory influence on ML adoption, the intensity of this pressure may vary across different banks or professional roles.

Table 1 Regulatory Pressure

Descriptive Statistics	N	Mean	Std. Deviation
Central Bank of Kenya guidelines encourage our bank to adopt advanced analytics in credit risk management.	48	3.77	1.17
Regulatory requirements for risk-based lending drive our bank to implement machine learning solutions.	48	3.60	1.22
Compliance with CBK's ICT guidelines necessitates investment in advanced credit analysis technologies.	48	3.75	1.00
Data protection regulations influence how we design and implement ML-based credit scoring systems.	48	3.67	1.12
Regulatory pressure from supervisory authorities motivates our bank to modernize credit analysis processes.	48	3.65	1.12

Correlation Analysis Between Regulatory Pressure and Credit Analysis

To determine the strength and direction of the relationship between regulatory pressure and efficiency of credit analysis in Tier II commercial banks in Kenya, correlational analysis was conducted. Results as presented in Table 2 indicate that there was a statistically significant strong positive relationship between regulatory pressure and efficiency of credit analysis, $r(48) = 0.616$, $p < .05$. This indicates that there is a strong relationship between regulatory pressure and efficiency of credit analysis among Tier II commercial banks in Kenya.

Table 1 Correlation Analysis Between Regulatory Pressure and Credit Analysis

Correlations

		Regulatory Pressure	Credit Analysis Efficiency
Regulatory Pressure	Pearson Correlation	1	.616**
	Sig. (2-tailed)		.000
Credit Analysis Efficiency	Pearson Correlation	.616**	1
	Sig. (2-tailed)	.000	
	N	48	48

*. Correlation is significant at p <.05 level (2-tailed).

Regression Analysis Between Regulatory Pressure and Credit Analysis

Regression Model Summary

The results in Table 3 indicate that 37.9% of the variance in efficiency of credit analysis was explained by regulatory pressure, $R^2 = 0.379$.

Table 3 Model Summary for Regulatory Pressure and Credit Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.616[a]	.379	.365	.69692

a. Predictors: (Constant), Regulatory Pressure

b. Credit Analysis

Regression ANOVA

The regression ANOVA results in Table 4 indicate that regulatory pressure had a significant influence on efficiency of credit analysis, $F(1, 46) = 28.059$, $p < .05$.

Table 4 Regression ANOVA for Regulatory Pressure and Credit Analysis

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.628	1	13.628	28.059	.000[b]
	Residual	22.342	46	.486		
	Total	35.970	47			

a. Dependent Variable: Credit Analysis Efficiency

b. Predictors: (Constant), Regulatory Pressure

Regression Coefficient Between Regulatory Pressure and Credit Analysis

Regression coefficient results in Table 5 indicate that regulatory pressure significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $\beta = 0.616$, $p < .05$.

The regression equation was:

$Y = \beta_0 + \beta_1 X_1$

$Y = 1.592 + 0.579X_1$

The equation implies that an increase in regulatory pressure (X_1) was result in a corresponding increase in efficiency of credit analysis (Y) by 0.579. Based on the multiple linear regression results it was concluded that regulatory pressure significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $R^2 = 0.379$, $F(1, 46) = 28.059$, $p < .05$, $\beta = 0.616$, $p < .05$.

Table 2 Regression Coefficient Between Regulatory Pressure and Credit Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.592	.415		3.834	.000
	Regulatory Pressure	.579	.109	.616	5.297	.000

a. Dependent Variable: Credit Analysis Efficiency

Effect of Technological Readiness on Efficiency of Credit Analysis

Descriptive Statistics

Respondents were requested to indicate their agreement with statements about technological readiness and its effect on credit analysis efficiency using a 5-point Likert scale, where: 1-strongly disagree, 2-disagree, 3-neutral, 4-agree and 5-strongly agree. The results in Table 6 indicate that the respondents agreed that their bank has reliable internet connectivity and power backup systems to support ML operations (M = 3.83, SD = 1.10), which received the highest mean score among all technological readiness indicators. Respondents also agreed that they have adequate cybersecurity frameworks in place to protect ML-based credit analysis systems (M = 3.65, SD = 1.10) and that their core banking systems are well-integrated with analytics platforms for seamless data flow (M = 3.56, SD = 0.99). Furthermore, it was agreed that they have comprehensive, high-quality datasets readily available for training machine learning models (M = 3.50, SD = 1.13). However, the lowest rating was for their bank having robust digital infrastructure such as servers and cloud platforms capable of supporting machine learning applications (M = 3.42, SD = 1.20), though this still indicates agreement rather than neutrality or disagreement. The standard deviations across all items ranged from 0.99 to 1.20, suggesting moderate variability in respondents' perceptions of their institutions' technological readiness. The relatively lower mean score for digital infrastructure compared to other indicators suggests that while Tier II banks have made progress in areas such as connectivity and cybersecurity, there may be room for improvement in fundamental infrastructure components necessary for advanced machine learning implementations.

Table 3 Technological Readiness

Descriptive Statistics	N	M	S.D
Our bank has robust digital infrastructure (servers, cloud platforms) capable of supporting machine learning applications.	48	3.42	1.20
We have comprehensive, high-quality datasets readily available for training machine learning models.	48	3.50	1.13
Our core banking systems are well-integrated with analytics platforms for seamless data flow.	48	3.56	0.99
Our bank has reliable internet connectivity and power backup systems to support ML operations.	48	3.83	1.10
We have adequate cybersecurity frameworks in place to protect ML-based credit analysis systems.	48	3.65	1.10

Correlation Analysis Between Technological Readiness and Credit Analysis

To determine the strength and direction of the relationship between technological readiness and efficiency of credit analysis in Tier II commercial banks in Kenya, correlational analysis was conducted. Results as presented in Table 7, indicate that there was a statistically significant very strong positive relationship between technological readiness and efficiency of credit analysis, r (48) = 0.819, $p < .05$. This indicates that there is a significant very strong relationship between technological readiness and efficiency of credit analysis among Tier II commercial banks in Kenya.

Table 4 Correlation Analysis Between Technological Readiness and Credit Analysis

Correlations

		Technological Readiness	Credit Analysis Efficiency
Technological Readiness	Pearson Correlation	1	.819**
	Sig. (2-tailed)		.000
Credit Analysis Efficiency	Pearson Correlation	.819**	1
	Sig. (2-tailed)	.000	
	N	48	48

*. Correlation is significant at $p < .05$ level (2-tailed).

Regression Analysis Between Technological Readiness and Credit Analysis

Regression Model Summary

The results in Table 8 indicate that 67.0% of the variance in efficiency of credit analysis was explained by technological readiness, $R^2 = 0.670$.

Table 5 Model Summary for Linear Relationship Between Technological Readiness and Credit Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.819[a]	.670	.663	.50802

a. Predictors: (Constant), Technological Readiness

b. Credit Analysis

Regression ANOVA

Multiple linear regression ANOVA results shown in Table 9 indicate that technological readiness statistically and significantly affected efficiency of credit analysis, $F(1, 46) = 93.375$, $p < .05$.

Table 6 ANOVA Analysis of Technological Readiness and Credit Analysis

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.098	1	24.098	93.375	.000[b]
	Residual	11.872	46	.258		
	Total	35.970	47			

a. Dependent Variable: Credit Analysis Efficiency

b. Predictors: (Constant), Technological Readiness

Regression Coefficient Between Technological Readiness and Credit Analysis

Regression coefficient in Table 10 indicate that technological readiness significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $\beta = 0.819$, $p < .05$.

The regression equation was:

$Y = \beta_0 + \beta_2 X_2$

$Y = 0.708 + 0.840 X_2$

The equation implies that an increase in technological readiness (X_2) will result in a corresponding increase in efficiency of credit analysis (Y) by 0.840. Based on the regression results, it was concluded that technological readiness significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $R^2 = 0.670$, $F(1, 46) = 93.375$, $p < .05$, $\beta = 0.819$, $p < .05$.

Table 7 Regression Coefficient Between Technological Readiness and Credit Analysis Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.708	.321		2.208	.032
	Technological Readiness	.840	.087	.819	9.663	.000

a. Dependent Variable: Credit Analysis Efficiency

Effect of Organizational Capacity on Efficiency of Credit Analysis

Descriptive Statistics

Respondents were requested to indicate their agreement with statements about organizational capacity and its effect on credit analysis efficiency using a 5-point Likert scale, where: 1-strongly disagree, 2-disagree, 3-neutral, 4-agree and 5-strongly agree. The results in Table 11 indicate that the respondents agreed on two organizational capacity indicators with equal highest mean scores: that senior management actively supports and champions the adoption of machine learning in credit risk management (M = 3.69, SD = 1.03), and that their organizational culture embraces innovation and is receptive to adopting new technologies like machine learning (M = 3.69, SD = 0.99). It was also agreed that their bank allocates adequate financial resources for machine learning technology investments and training (M = 3.58, SD = 1.07) and that their bank has sufficient staff with technical expertise to develop and manage machine learning models (M = 3.54, SD = 1.20). The lowest rating was for having comprehensive training programs to build internal machine learning capabilities among staff (M = 3.52, SD = 1.15), though this still represents agreement with the statement. The standard deviations across all organizational capacity items ranged from 0.99 to 1.20, indicating moderate variability in respondents' perceptions. The relatively high scores for management support and organizational culture suggest that Tier II banks have established a favorable environment for machine learning adoption at the strategic and cultural levels. However, the comparatively lower scores for technical expertise and training programs indicate that while leadership support exists, there may be challenges in translating this support into tangible human capital development and technical capability building, which are critical for successful machine learning implementation in credit analysis.

International Journal of Finance

ISSN 2520-0852 (Online)

Vol. 10, Issue No. 8, pp. 70 - 89, 2025 www.carijournals.org

Table 8 Organizational Capacity

Descriptive Statistics			
	N	M	S.D
Our bank has sufficient staff with technical expertise to develop and manage machine learning models.	48	3.54	1.20
Senior management actively supports and champions the adoption of machine learning in credit risk management.	48	3.69	1.03
Our bank allocates adequate financial resources for machine learning technology investments and training.	48	3.58	1.07
We have comprehensive training programs to build internal machine learning capabilities among staff.	48	3.52	1.15
Our organizational culture embraces innovation and is receptive to adopting new technologies like machine learning.	48	3.69	0.99

Correlation Analysis Between Organizational Capacity and Credit Analysis

A Pearson correlation coefficient was calculated to examine the relationship between organizational capacity and efficiency of credit analysis among Tier II commercial banks in Kenya. The results indicate a statistically significant very strong positive correlation, $r(48) = 0.803$, $p < .05$. This suggests that as organizational capacity increases, efficiency of credit analysis tends to improve substantially. The strength of the correlation is very strong.

Table 9 Correlation Analysis Between Organizational Capacity and Credit Analysis

Correlations

		Organizational Capacity	Credit Analysis Efficiency
Organizational Capacity	Pearson Correlation	1	.803**
	Sig. (2-tailed)		.000
Credit Analysis Efficiency	Pearson Correlation	.803**	1
	Sig. (2-tailed)	.000	
	N	48	48

*. Correlation is significant at p <.05 level (2-tailed).

Regression Analysis Between Organizational Capacity and Credit Analysis

Regression Model Summary

The results in Table 13 indicate that 64.5% of the variance in efficiency of credit analysis was explained by organizational capacity, $R^2 = 0.645$.

Table 10 Regression Model Summary for Organizational Capacity and Credit Analysis

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.803[a]	.645	.637	.52697

a. Predictors: (Constant), Organizational Capacity
b. Credit Analysis

Regression ANOVA

Multiple linear regression ANOVA results shown in Table 14 indicate that organizational capacity statistically and significantly affected efficiency of credit analysis, $F(1, 46) = 83.527$, $p < .05$.

Table 11 ANOVA Analysis of Organizational Capacity and Credit Analysis

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23.196	1	23.196	83.527	.000[b]
	Residual	12.774	46	.278		
	Total	35.970	47			

a. Dependent Variable: Credit Analysis Efficiency
b. Predictors: (Constant), Organizational Capacity

Regression Coefficient Between Organizational Capacity and Credit Analysis

Regression coefficient in Table 15 indicate that organizational capacity significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $\beta = 0.803$, $p < .05$.

The regression equation was:

$Y = \beta_0 + \beta_3 X_3$

$Y = 0.807 + 0.809X_3$

The equation implies that an increase in organizational capacity (X_3) will result in a corresponding increase in efficiency of credit analysis (Y) by 0.809. Based on multiple linear regression results, it was concluded that organizational capacity significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $R^2 = 0.645$, $F(1, 46) = 83.527$, $p < .05$, $\beta = 0.803$, $p < .05$.

International Journal of Finance

ISSN 2520-0852 (Online)

Vol. 10, Issue No. 8, pp. 70 - 89, 2025 www.carijournals.org

Table 12 Regression Coefficient Between Organizational Capacity and Credit Analysis

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	.807	.328		2.461	.018
	Organizational Capacity	.809	.089	.803	9.139	.000

a. Dependent Variable: Credit Analysis Efficiency

Combined Multiple Regression Analysis

Regression Model Summary

The results in Table 16 indicate that 73.3% of the variance in efficiency of credit analysis was explained by organizational capacity, regulatory pressure, and technological readiness, $R^2 = 0.733$. The adjusted R^2 value of 0.715 suggests that the model is well-fitted, accounting for the number of predictors in the model. The correlation coefficient ($R = 0.856$) demonstrates a strong positive relationship between the predictor variables and efficiency of credit analysis. The standard error of the estimate was 0.467.

Table 13 Combined Regression Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.856[a]	.733	.715	.46703

a. Predictors: (Constant), Organizational Capacity, Regulatory Pressure, Technological Readiness

b. Credit Analysis

Regression ANOVA

Multiple linear regression ANOVA results shown in Table 17 indicate that organizational capacity, regulatory pressure, and technological readiness statistically and significantly affected efficiency of credit analysis, $F(3, 44) = 40.305$, $p < .05$.

Table 14 Combined Regression ANOVA

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	26.373	3	8.791	40.305	.000[b]
	Residual	9.597	44	.218		
	Total	35.970	47			

a. Dependent Variable: Credit Analysis Efficiency

b. Predictors: (Constant), Organizational Capacity, Regulatory Pressure, Technological Readiness

Combined Regression Coefficient

Regression coefficients in Table 18 indicate that organizational capacity significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $\beta = 0.478$, $p < .05$. However, regulatory pressure ($\beta = 0.137$, $p = .286$) and technological readiness ($\beta = 0.329$, $p = .124$) did not significantly predict efficiency of credit analysis.

The regression equation was:

$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$

$Y = 0.314 + 0.137X_1 + 0.329X_2 + 0.478X_3$

The equation implies that an increase in organizational capacity (X_3) will result in a corresponding increase in efficiency of credit analysis (Y) by 0.478, while holding regulatory pressure (X_1) and technological readiness (X_2) constant. Similarly, increases in regulatory pressure and technological readiness would result in increases of 0.137 and 0.329 respectively, though these effects were not statistically significant. Based on multiple linear regression results, it was concluded that organizational capacity significantly predicted efficiency of credit analysis among Tier II commercial banks in Kenya, $R^2 = 0.733$, $F(3, 44) = 40.305$, $p < .05$, $\beta = 0.478$, $p < .05$. Regulatory pressure and technological readiness did not significantly predict efficiency of credit analysis.

International Journal of Finance

ISSN 2520-0852 (Online)

Vol. 10, Issue No. 8, pp. 70 - 89, 2025 www.carijournals.org

Table 15 Combined Regression Coefficient

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	T	Sig.
1	(Constant)	.314	.331		.948	.348
	Regulatory Pressure	.137	.127	.146	1.081	.286
	Technological Readiness	.329	.210	.321	1.569	.124
	Organizational Capacity	.478	.149	.474	3.214	.002

a. Dependent Variable: Credit Analysis Efficiency

Conclusion

It was concluded that regulatory pressure from the Central Bank of Kenya enhances efficiency of credit analysis in Tier II commercial banks through creating compliance frameworks that drive technological investment and process standardization. In addition, technological readiness represented the strongest determinant of credit analysis efficiency, with infrastructure capabilities serving as critical enablers of machine learning implementation success. In addition, organizational capacity enhanced credit analysis efficiency through technical expertise, leadership support, and innovation-embracing cultures.

Recommendations

The study found that regulatory pressure significantly influenced efficiency of credit analysis among Tier II commercial banks in Kenya. It is therefore recommended that CBK should develop comprehensive AI guidelines, establish regulatory sandboxes for innovation, and implement tiered regulatory approaches that recognize Tier II banks' unique constraints.

Similarly, the study recommends that Tier II banks should prioritize systematic investments in digital infrastructure as the primary pathway to improving credit analysis efficiency. Lastly, banks should invest systematically in human capital development through competitive recruitment strategies, comprehensive training programs, enhanced retention initiatives, and leadership development.

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