Faculty of Natural and Applied Sciences Journal of Computing and Applications
Print ISSN: 3026-8133
www.fnasjournals.com
Volume 2; Issue 4; December 2025; Page No. 12-21.
DOI: https://doi.org/10.63561/jca.v2i4.1070

Lean Practice Implementation and Firm Competitiveness: An Artificial Intelligence Utilization Perspective

***Joseph, M. A.**
Department of Management, Ignatius Ajuru University of Education, Port Harcourt, Nigeria

***Corresponding author email**:michaelarochi@outlook.com

Abstract
This study investigates the extent to which lean practice implementation in terms of artificial intelligence utilization affects the competitiveness (market share) of commercial banks in Nigeria using a panel data framework. The study involves twelve (13) listed commercial banks and covers the period from March 2018 to March 2021. Specifically, the empirical analysis is based on three conventional panel data methods: pooled regression, fixed effects, and random effects methods. The model selection is based on the Likelihood Ratio test and the Hausman specification test. We find that the specified model is consistent with the random effects' theory. More specifically, our findings indicate that cross-sectional heterogeneity, primarily arising from differences in uniqueness such as organisational culture and philosophies, treated as an error process, is a significant aspect of the relationship between artificial intelligence and bank market share. Further, our analysis shows that market share is persistent and can be predicted on the basis of its own immediate history. Finally, as we control the effects of COVID-19 and corporate governance in our model, we find evidence that artificial intelligence utilisation has a positive but insignificant impact on commercial bank market share.

Keywords: Artificial intelligence, Market share, Lean Practice, Competitiveness, Panel Data

Introduction

In depressed economic situations such as the one caused by the COVID-19 pandemic, business enterprises such as banks today are very interested in strategies and practices that will continuously identify and eliminate waste or non-value-added practices and continuously improve their values and services (Ritamaki, 2017). Accordingly, firms are investing significant resources in practices that would reduce operating costs and increase productivity. Artificial intelligence is a perfect fit in this situation since it is fast, reliable, and more accurate than a human. In general, service sectors lag behind the manufacturing sector in terms of lean principles and implementation (Damrath, 2012). Transferring the lean management idea from the manufacturing sector to the service sector may provide the potential for improvement (Bakri, 2019). Lean practice has evolved from a technical manufacturing system to an all-encompassing organizational philosophy (Halling, 2013; Bhasin, 2015; Helmold, 2020). However, in lean practice, everything that does not provide value to the customer, both in manufacturing and service organisation is considered as waste. It continuously focuses on quality and the elimination of waste at every turn and across the full value stream of a product or service. Although the lack of widely available references for adopting Lean in a service organization is a barrier when it comes to applying lean to services. Although there have been some successful lean practice implementations in service firms in the past, no standardized framework or general guideline for implementing lean practice in service organizations has been established (Bartolotti & Romano, 2012; dos Santos & Cabrita, 2016; Berrhal & Marghoubi, 2016). The application of lean practices has improved many organizations' competitiveness (dos Santos & Cabrita, 2016). However, the benefits of implementing lean management principles in service businesses have not been given the required attention.

Many banks and financial institutions worldwide have had to accelerate their digital transformation initiatives in order to accommodate the shifts in consumer behavior brought about by the commencement of COVID-19. In this study, we are examining how banks are incorporating artificial intelligence into their digitization framework. That mainly is to grant themselves a larger customer base while eliminating waste resulting from non-value manual tasks. More specifically, lean practice implementation helps banks to embrace disruptive technologies and create better experiences for both their customers and employees (Bakari, 2019). Accordingly, artificial intelligence AI is employed to save time that would otherwise be spent by a single human employee processing a large amount of data, and it produces results that are both cheaper and more accurate (Ris et al., 2020). Despite the significant influence of lean practices on bank competitiveness, few studies have examined this relationship in terms of artificial intelligence (Oluwagbemi et al., 2011; Mor & Gupta,2021; Berrahal & Marghoubi, 2016). Additionally, from both a theoretical and an empirical standpoint, little is known about how lean practice affects the performance of banks in terms of artificial intelligence and the various bank-specific effects. As an objective, this study tries to examine the extent to which bank performance; in terms of competitiveness, responds to lean practices implementation in terms of artificial intelligence utilization, focusing on Nigerian listed commercial banks.

Nigerian listed commercial banks offer an appropriate case to investigate, for example, the Central Bank of Nigeria CBN has strongly advised financial institutions to leverage new technology tools to enhance the efficiency and effectiveness of payment systems as customers increasingly opt for the bank's digital services during the 2020 lockdowns (Tokede, 2021). Therefore, commercial bank executives have been recommending lean practices more and more as a way to increase competitive advantage and boost banking business performance in Nigeria. They have also observed that the COVID-19 pandemic has caused many changes in their corporate work practices, including the adoption of virtual communication as the standard. In response to this shift, additional automation of banking procedures was implemented, such as the creation of e-Signature technology, which dramatically reduces the need for paper documents in banks by enabling documents to pass through the approval process electronically. This is consistent with Taylor (1911), in his response to how to improve efficiency and productivity, he thus contended that the greatest possible productivity comes through both the employee's effort and the employer's machines.

Understanding the link between artificial intelligence and firm competitiveness is important for evaluating the effectiveness of lean practice in the context of commercial bank performance. While lean practice is not, of course, the only influence on the bank competitiveness model, however, it has a major impact on it. This link between lean practice and competitiveness in the service sector, such as banks, has gained prominence, particularly in the major developed economies following the onset of the COVID-19 pandemic. However, it is an under-researched area for underdeveloped economies such as Nigeria. Specifically, this study examines lean practice implementation in terms of adoption and implementation of artificial intelligence utilization as an explanatory factor for firm competitiveness in the listed commercial banks in Nigeria. This study contributes to the empirical literature in two ways. First, we examine the relative impact of lean practice implementation proxied by artificial intelligence utilization on bank competitiveness proxied by market share, focusing on commercial banks in Nigeria. This study employed the dynamic panel data framework that incorporates the unobserved bank-specific effects that reflect the relatively constant differences across banks, such as organizational culture and philosophies, in order to avoid omitted variable bias since they affect the main relationship of interest. This has so far been neglected in empirical works, especially in Nigeria, while it is intuitively appealing.

Antosez et al. (2020) investigate how artificial intelligence techniques can be used to evaluate how well manufacturing companies are using the lean maintenance concept. Rough set theory and decision trees were used in the investigation. Decision trees were developed for the overall equipment effectiveness (OEE) indicator's average value. The rough set theory was used to gauge how much the lean maintenance plan was being used. Rough set theory and decision trees were used in the investigation. For the average value of the overall equipment effectiveness (OEE) indicator, decision trees were created. The degree of usage of the lean maintenance plan was assessed using the rough set theory. This problem not only affects the ability of exploited equipment to achieve high efficiency but also has an impact on the decision-making process and the creation of a company's maintenance strategy. Fares et al. (2020) employed systematic literature review approach to investigate the utilization of artificial intelligence (AI) in the banking sector. The results show how the literature on banking and artificial intelligence encompasses three main research areas: strategy, process, and customer.

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

In India, Mor and Gupta (2021) empirically examined artificial intelligence and technical efficiency. The results showed that the level of technical efficiency, that is, the reduction of technical inefficiency of the sample banks in India, is greatly impacted by AI technologies, chatbots/virtual assistants, and ATMs. In a qualitative study, Mahalakshmi et al. (2022) explore how artificial intelligence AI and machine learning enhance banking industry's quality, efficiency, and productivity. It also reveals that AI delivers higher customer satisfaction through its faster response feature. In a survey study, utilizing a structural equation model, Rabbani et al. (2023) investigate how artificial intelligence (AI) influences the relationship between a bank's market share and its creative financial processes. However, Artificial intelligence was unable to considerably alter the correlation between the bank's market share and its creative financial process.

Aim and Objectives of the Study

The main aim of this study is to examine the effect of lean practice implementation, with particular emphasis on artificial intelligence utilization, on the competitiveness of commercial banks in Nigeria, as measured by market share. The specific objectives of the study are to:

1. Examine the extent of artificial intelligence utilization as a component of lean practice implementation among listed commercial banks in Nigeria.
2. Assess the effect of artificial intelligence utilization on the market share of commercial banks in Nigeria.
3. Determine the role of cross-sectional heterogeneity (such as differences in organisational culture and philosophies) in the relationship between artificial intelligence utilization and bank competitiveness.
4. Evaluate the persistence of market share among commercial banks in Nigeria over the study period.
5. Examine the influence of control variables, particularly COVID-19 and corporate governance, on the relationship between artificial intelligence utilization and market share.

Methods and Materials

Data and Variables

The dataset employed in this comprises 154 quarterly panel observations obtained from 13 listed commercial banks covering a timespan from March - 2018 to March - 2021. The banks include First Bank, Standard IBTC, Sterling Bank, UBN, Wema Bank, Zenith Bank, Fidelity Bank, UBA, Access Bank, FCMB, Ecobank, GTB and Unity Bank. The data were collected from the annual reports and financial statements downloaded from the official websites of the individual banks. Consistent with previous studies, we transform the data into logarithms to allow for data interpretation in terms of percentage.

In this study, we consider lean practice implementation in terms of artificial intelligence utilization. It is indicated by chatbot adoption and utilization, which was observed through content analysis of the annual reports of the included commercial banks. A chatbot is an artificial intelligence (AI) application that can simulate an online human-like or natural language conversation (or chat) with a user or bank customer via text messaging apps, websites, mobile apps, the telephone or text-to-speech instead of direct communication with a real human agent. In this study, artificial intelligence AI utilization is a categorical variable that was used as a dummy variable in the regression analysis. This is useful when a qualitative concept needs to be quantified (Studenmund, 2014). Thus, the data generating process is a dummy variable approach, such that the periods in which the banks adopted AI were set to 1, and the other periods were set to 0. As a result, organizations that use AI will be set to 1, while banks that do not use AI will be set to 0. (Studenmund, 2014; Ottosson & Westling, 2020). We define bank competitiveness in terms of the market share of the individual banks included in the study. According to Genchev (2012), market share of a bank is the ratio of customer deposits in the bank to sector customer deposit. However, we controlled for corporate governance, which is measured in terms of board size (BS). From the annual report, the data-generating process is the number of board members per quarter. We also controlled for the COVID-19 pandemic, and it is measured in terms of a dummy variable, whose value equals 1 for the period of COVID-19 pandemic from 2019Q4 – 2021Q1 or zero for earlier periods of 2018Q1 – 2019Q3.

Table 1: Descriptive Statistics

VARIABLES	$\bar{x}$	σ	CV	S	K	P-value (JB)
BS	13.1598	2.7241	0.207	0.4143	3.2055	0.0769

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

MKS	0.0060	0.0040	0.067	0.2373	1.8645	0.0049

Source: Eviews output based on research data

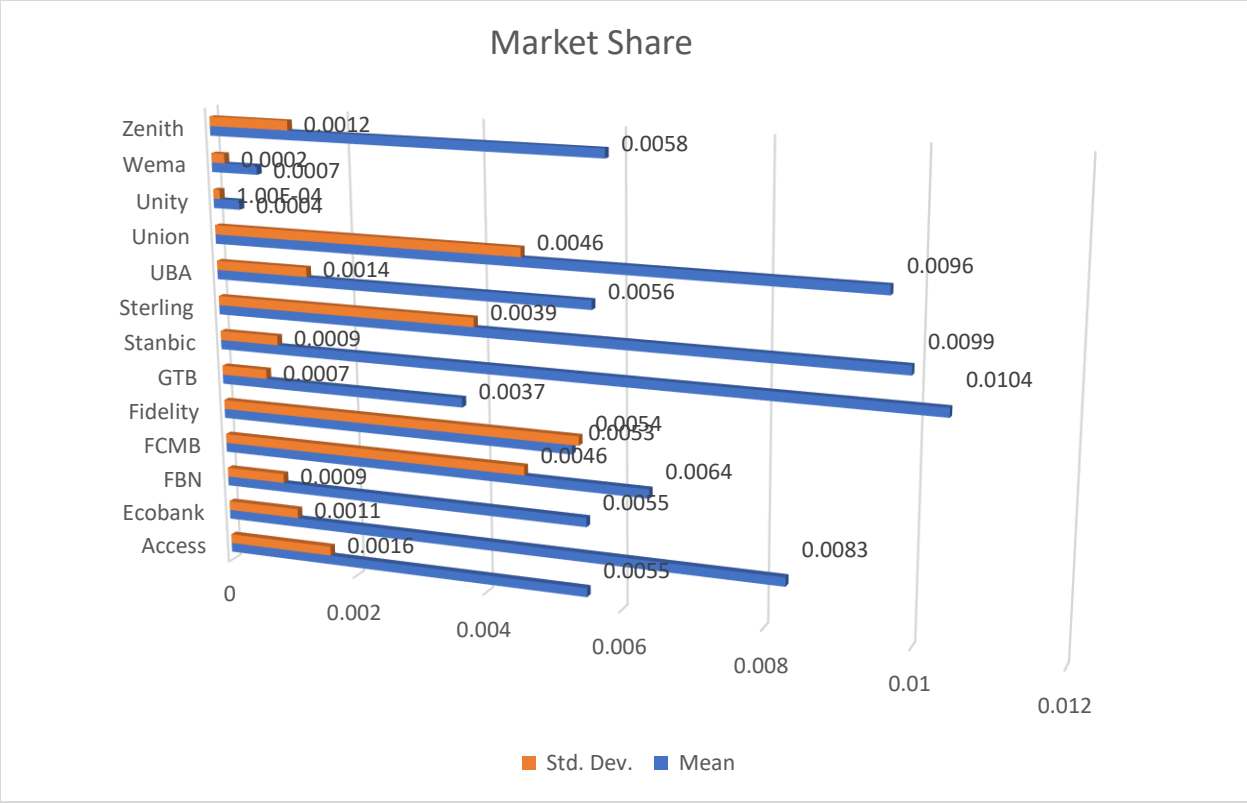

Figure 1: Mean and Standard Deviation for MKS

Figure 1 shows that Stanbic IBTC recorded the highest in terms of market share, as its average or mean point was higher than that of all its competitors. On the other hand, Unity Bank recorded the lowest market share in both mean point and in variability, as Fidelity is the highest in variability, while Unity Bank recorded the lowest variability as it relates to market share for the individual banks.

Model and Methods

To analyze the extent to which lean practice implementation in form of artificial intelligence AI affects bank competitiveness, we employ the conventional panel data framework, including the persistent parameter in the single-equation panel data methods. More specifically, we consider the pooled regression, fixed effects and random effects methods. These methods are employed because panel data literature suggests that they can be used to analyze the relationship of interest while capturing the associated heterogeneity impacts of the individual commercial banks (Brooks, 2014). However, their limitations lie in their inability to capture the endogeneity or simultaneity that may be theoretically inherent in the relationship between lean practice implementation and competitiveness.

The model for the study relationship, which is the impact of lean practice implementation on competitiveness, is specified in functional form as follows.

$$LMKS = f(LAI, COVID, LBS) \quad (1)$$

Where:

LMKS = Log Market Share

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

AI = Artificial Intelligence Utilization

LBS = Log Board Size

COVID = COVID-19 Pandemic

We measure the impact of lean practice implementation on competitiveness of commercial banks through the following econometric equation.

The econometric/empirical specification is as follows:

$$LMKS_{it} = \alpha_0 + \gamma_i + \alpha_1 LMKS_{it-1} + \alpha_2 AI_{it} + \alpha_3 LBS_{it} + \alpha_4 COVID_{it} + \epsilon_{it} \quad (2)$$

The above regression model is dynamic as it incorporates persistence parameter of the dependent variable $\alpha_1 LMKS_{it-1}$ in the model. Persistence is the extent to which a variable is positively related to its previous values. For this model, where ϵ_{it} represents the regression residuals or error disturbances, α_0 is the model intercept, which can be explained as the average value of MKS when zero is the value of all other variables on the right-hand side; γ_i is the parameter of cross-sectional heterogeneity representing the unobserved bank-specific effects or factors such as organizational philosophy and culture, while α_2 is the main regression coefficient, capturing the effects of artificial intelligence. Also, α_3 and α_4 capture the effects of corporate governance and COVID-19 pandemic, respectively, in the model as control variables. Besides, while other variables have both space and time indices it, γ_i has only space index since they represent the constant latent organizational factors, such as organizational culture and philosophy.

In the above specified model, γ_i can be treated using the following competing methods, namely: random effects regression, fixed effects regression, and pooled regression. The pooled regression approach assumes a homogeneity of the cross-sectional factors and while ignoring the heterogeneity effect argument, which argues that γ_i is irrelevant in the market share model. Both random effects and fixed effects methods are different in the way they treat γ_i. The fixed effects method treats γ_i as an important explanatory variable that also correlates with other explanatory variables in the model, while one of the assumptions of the random effects method is that γ_i follows a stochastic process, as a result, correlates with the error term ϵ_{it}.

To ascertain which of these methods follows the data-generating process of our model, we employ the two commonly employed specification tests: namely, the Likelihood Ratio and Hausman tests. Likelihood ratio test compares the outcome of the pooled regression results and the outcome of the fixed effects results. This is employed based on the empirical assumption that γ_i is significantly different from zero. Therefore, if the test is statistically significant, we reject the pooled regression method. Hausman specification test, on the other hand, contrasts the result of the fixed effects results and the outcome of the random effects results based on the empirical assumption that γ_i do not correlate with other included explanatory variables. It therefore follows that if the test result yielded is statistically significant, in favour of the fixed effects method, we reject the random effects method. This implies that, assuming both tests are significant, this suggests that there is empirical evidence that γ_i affects market share both directly and through its association with the included lean practice implementation variable.

Empirical Analysis

In our empirical model, we specify market share to depend on artificial intelligence with board size, and COVID-19 incorporated as a control variable. Our objective is to determine the extent to which the observed changes in market share of the commercial banks are empirically connected to changes in lean practice implementation via artificial intelligence utilization, after controlling for the effects of the COVID-19 period and corporate governance via board size in the model. Panel A displays the major coefficient estimates or regression results, while Panel B displays the goodness of fit statistics. More specifically, we estimate the specified market share model, and the results are displayed in Table 2, with Columns 2, 3, and 4 containing the findings of the pooled regression, fixed effects, and random effects techniques, respectively. Furthermore, Table 3 displays the estimated unobserved organisational-specific effects (cross-sectional heterogeneity) and model specification tests (Hausman and Likelihood Ratio tests), while Figures 2–3 display the residual diagnostic plots.

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

Table 2: Estimation Results; LMVS = f(LMKS(-1), AI, LBS, COVID) P-values in Parenthesis

1	2	3	4
Variable/Coefficient	**Pooled Regression**	**Fixed Effect**	**Random Effect**
Panel A: Main Regression results			
Constant (α_0)	-3.5025 (0.0012)	-4.4497 (0.0002)	-3.7018 (0.0008)
LMKS(-1) (α_1)	0.3553 (0.0580)	0.1462 (0.4680)	0.3111 (0.1013)
AI (α_2)	0.2127 (0.3333)	-0.1580 (0.5582)	0.1332 (0.5635)
LBS (α_3)	0.0540 (0.5710)	0.1020 (0.2813)	0.0642 (0.4978)
COVID (α_4)	-0.0705 (0.7644)	-0.2098 (0.3731)	-0.1001 (0.6690)
Panel B: Goodness of Fit and Model Diagnostic Tests			
R^2	0.1684	0.2879	0.1317
$\bar{R}^2$	0.0612	0.1409	0.0196
F-ratio	1.5704 (0.2068)	1.9542 (0.1054)	1.1756 (0.3407)
DW-Statistic	2.5362	2.4051	2.4817
Panel C: Model Specification Tests			
LR Statistic	5.5816 (0.0614)		
Hausman Statistic	0.0000 (1.0000)		

Source: EViews Output Based on Research Data

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

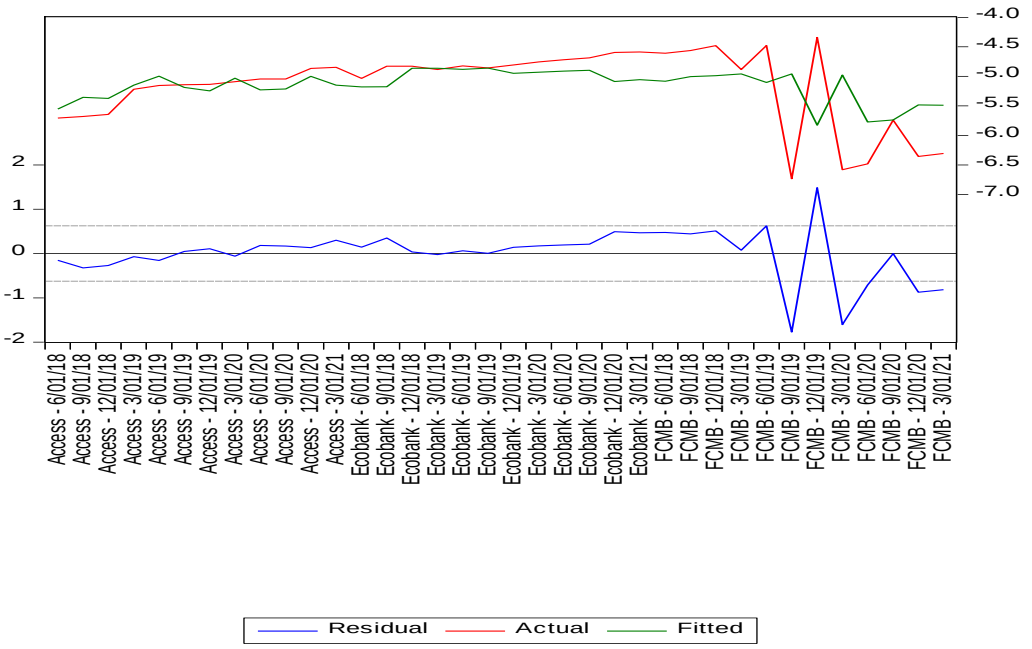

Figure 2: Pooled Regression Residual Diagnostic Plot

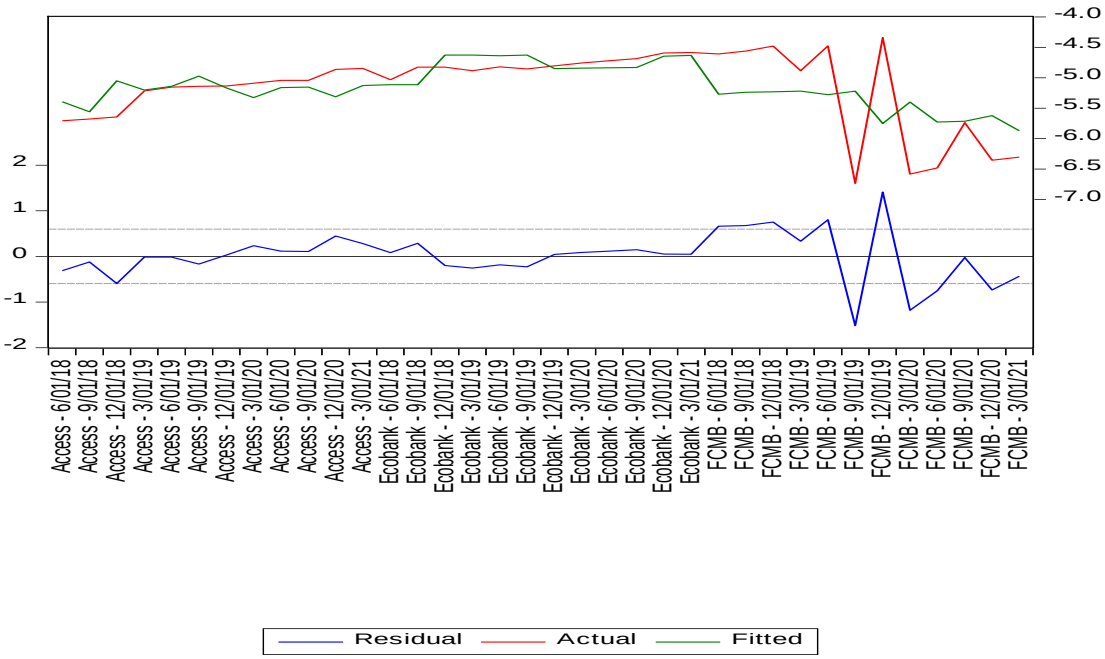

Figure 3: Fixed Effects Residual Diagnostic Plot

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

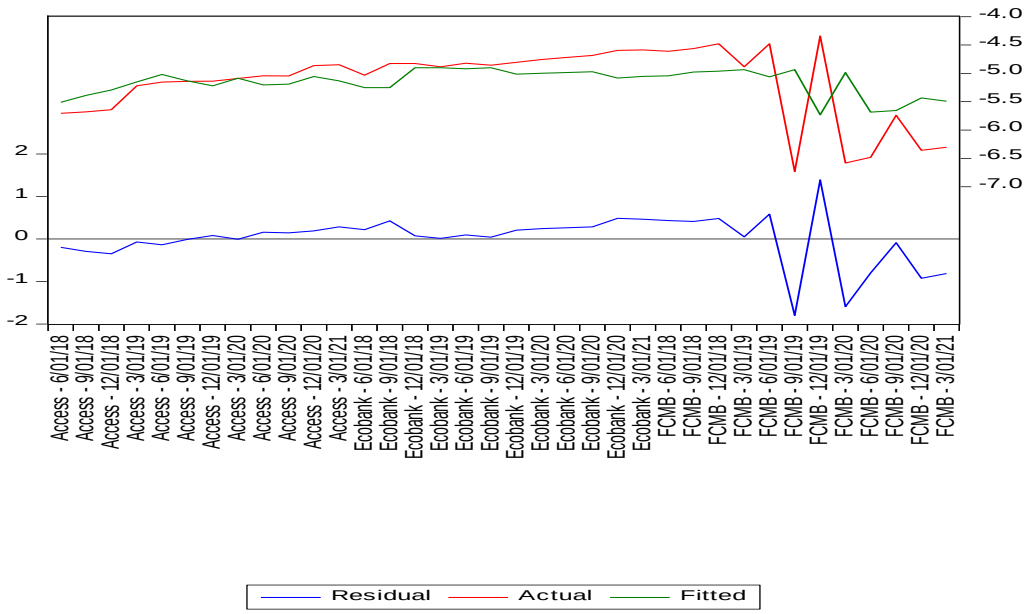

Figure 4: Random Effects Residual Diagnostic Plot

For Table 2, we can see that in Panel A, both the pooled regression, fixed effect and random effects methods produce identical results, in terms of the size, signs and significance for all the estimated coefficients, while the picture is different for the fixed effects method. More specifically, we can see that the intercept terms (α_0) is negative but highly statistical significance for pooled regression, fixed effect and random effect estimation methods, suggesting that market share would, on average, be significantly different from zero keeping all the explanatory variables constant. Also, α_1, which captures the effect of lagged market share on current market share, is consistently positive and has a greater than zero p-value, indicating that market share is not a significant function of its immediate past value. Hence, an increase in market share in the current year would not trigger an increase in market share one year after. Therefore, for commercial banks, market share is not persistent and cannot be predicted based on its own immediate past performance.

Further, for the control variables, board size and COVID, we can see that α_3 is positively signed for pooled regression, fixed effect and random effect methods, indicating that improved corporate governance tends to be associated with higher market share. While for α_4, it is negatively signed for pooled regression, fixed effect and random effect methods, indicating that low or no COVID periods tend to be associated with higher market share. However, α_3 and α_4 coefficients are statistically insignificant for all the panel data methods used. Focusing on the main relationships of interest (AI and bank competitiveness), we can see that the coefficient α_2, capturing the effect of lean practice implementation in terms of AI produces a positive effect for both pooled regression and random effect methods. While the effect is negatively signed for fixed effect. Furthermore, the p-values show that α_2 is statistically insignificant for all methods. However, the conclusion that would be drawn from these results would depend on which of the estimation methods is valid in the context of our data.

For the model diagnostics, the F-statistic p-values show that they are insignificant for all the estimation methods, and therefore not fitted for our market share model. However, it is unclear which method produces the most valid results for the relationships under study. As indicated by the $\bar{R}^2$, the proportion of the model variation explained by the joint effect of all regressors is about 6% for the pooled regression method, almost 29% for the fixed effect method and 13% for the random effects method. This implies that there are other factors which our model could not capture that explain the remaining 94% for the pooled regression, 71% for the fixed effect and 87% for the random effect estimation methods.Nevertheless, the Durbin-Watson (DW) statistic in the pooled regression (DW = 2.5362), fixed effects methods (DW = 2.4051), and random effects method (DW = 2.4817), are all around 2, which is the expected value of Durbin-Watson statistic. We can also see from Panel B that the Durbin-Watson statistic (DW = 2.4817) is much higher than R^2(R^2 = 0.1317), indicating that our model is not spurious. Finally, in terms of the residual diagnostic plots

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

shown in Figures 2 - 3, the three estimations, in all cases, perform equally well with the average line being very close to the fitted line for all methods.

For the model specification test, in Panel C, it is clear that the Likelihood Ratio (LR) statistic (p-value = 0.0614) is significant at 10% level, and therefore, did not accept the pooled regression hypothesis that the unobserved factors are insignificant explanatory factors for the observed cross-sectional variations in the firm market share. On the other hand, the Hausman test statistic (p-value = 1.0000) is insignificant, and thereby could not reject the random effects assumption that there is a zero correlation between the unobserved bank-specific effects and the observed independent variables. Hence, there is satisfactory empirical evidence that for commercial banks, the link between lean practice implementation and competitiveness is consistent with the random effects theory. This suggests that our data-generating process is consistent with the random effects method; hence, going forward, our empirical estimation analysis and conclusion shall be based on the random effects results.

Conclusion

This study investigates the extent to which lean practice implementation (in terms of artificial intelligence) affects the competitiveness of listed commercial banks in Nigeria using panel data methods. Specifically, the empirical analysis is based on the three conventional panel data methods: namely, fixed effects, pooled regression and random effects methods. The model selection is based initially on the Likelihood Ratio LR test and finally, the Hausman specification test. We reject the pool regression method because the LR test is significant, although at 10% level. Based on the outcome of the Hausman test statistic presented in Table 2, we find no sufficient evidence to reject the random effects null hypothesis; hence, we proceed with the random effects method estimation result as the most preferred. The findings are stated as follows: Consistent with the random effects hypothesis, our empirical research indicates strong evidence that bank heterogeneity, which is viewed as an error process, is a significant part of the dynamic relationship between lean practice implementation and competitiveness. This result is expected given that the companies in our sample operate in the same industry, however, respond to lean practice at different frequencies, and hence a model that incorporates organisation-specific effects as an error process is more appropriate to account for the observed variations in bank competitiveness. The implication is that the unobserved company-specific factors are not part of the explanatory factors for bank competitiveness, but rather, part of the error terms. There is evidence that artificial intelligence has a positive but insignificant impact on bank competitiveness. This means that increased adoption of artificial intelligence is weakly associated with improved bank competitiveness. More specifically, the artificial intelligence utilization effect on market share, although positive, is low and insignificant. Hence, it would, on average, lead to low competitive impact in terms of bank market share, holding other factors constant. This finding, which is consistent with the previous empirical works of Rabbani et al. (2023), implies that the market share of commercial banks marginally changes upward following an increase in artificial intelligence adoption and utilization. This can be explained as a result of improvements in their financial processes, driven by innovation and greater awareness of artificial intelligence utilization among their employees and banking customers.

In line with our expectations, there is evidence that COVID-19 has a negative but insignificant effect on market share. This indicates that the periods of no or low COVID-19 pandemic are associated with a higher market share. More specifically, keeping other factors constant, COVID would, on average, lead to a low impact on market share of banks. This finding is consistent with the previous work of Almonifi and Gulzar (2021). Hence, this explains why the included commercial banks largely escaped the financial and economic risks associated with the COVID-19 crisis. In contrast, board size yielded a positive but insignificant effect on market share. Specifically, a 1% increase in the board size of the banks leads to about 6% increase in bank market shares, holding other variables in the model constant. This finding is consistent with the previous work of Sarkar and Sarkar (2018). However, this study also, among other limitations, presents a research limitation due to the relatively small number of commercial banks (13) and the period of time covered by the study (March - 2018 to March – 2021). Hence, this study is a challenge for future research in the Nigerian banking sector and beyond. It is expected that future studies would extend the empirical analysis to other non-conventional lean practice-related factors, covering a longer period of time, in order to determine other possible effects on bank competitiveness generated by lean practice implementation. Also, their limitation of inability of our model to capture the endogeneity or simultaneity that may be theoretically inherent in the relationship between lean practice implementation and competitiveness.

References

Cite this article as:
Joseph, M. A. (2025). Lean practice implementation and firm competitiveness: an artificial intelligence utilization perspective. *FNAS Journal of Computing and Applications, 2*(4), 12-21. https://doi.org/10.63561/jca.v2i4.1070

Almonifi, Y. S. A., & Gulzar, R. (2021). The COVID-19 pandemic effect on the performance of the Islamic banking sector in KSA: an empirical study of Al Rajhi bank. *Available at SSRN 3834859*.

Antosez, K., Pasko, L., & Gola, A. (2020). The use of artificial intelligence methods to assess the effectiveness of lean maintenance concept implementation in manufacturing enterprises. *Applied Sciences*, 10(21), 7922.

Bakri, M. (2019). Implementing Lean tools to streamline banking operations: A case study of a small Lebanese bank. *Management Studies and Economic Systems*, *4*(2), 131-144.

Berrahal, W., & Marghoubi, R. (2016, March). Lean continuous improvement to information technology service management implementation: Projection of ITIL framework. In *2016 International Conference on Information Technology for Organizations Development* (IT4OD) (pp. 1-6). IEEE. DOI: 10.1109/IT4OD.2016.7479279

Bhasin, S. (2015). *Lean management beyond manufacturing* (Vol. 10). New York, NY: Springer.

Bortolotti, T., & Romano, P. (2012). 'Lean first, then automate': a framework for process improvement in pure service companies. A case study. *Production Planning & Control*, *23*(7), 513-522.

Brooks, C. (2014). Modelling long-run relationships in finance. *Introductory Econometrics for Finance (3rd edition). Cambridge: Cambridge University Press. Search in*.

dos Santos, J. X., & Cabrita, M. (2016, July). Lean Banking: Application of lean concepts and tools to the banking industry. In *The 2016 International Conference on Systematic Innovation*. Lisbon, Portugal. Retrieved from https://www.researchgate.net/publication/308294242.

Damrath, F. (2012). Increasing competitiveness of service companies: developing conceptual models for implementing Lean Management in service companies. performance impacts. *International Journal of Management Letters*, *4*(4), 132-151.

Fares, O. H., Butt, I., & Lee, S. H. M. (2022). Utilization of artificial intelligence in the banking sector: A systematic literature review. *Journal of Financial Services Marketing*, 1-18.

Genchev, E. (2012). Effects of market share on the bank's profitability. *Review of Applied Socio-Economic Research*, *3*(1), 87-95.

Halling, B. (2013). *Lean Implementation: the significance of people and dualism* (Doctoral dissertation, KTH Royal Institute of Technology).

Helmold, M. (2020). *Lean management and Kaizen*. Springer international publishing.

Mahalakshmi, V., Kulkarni, N., Kumar, K. P., Kumar, K. S., Sree, D. N., & Durga, S. (2022). The Role of implementing Artificial Intelligence and Machine Learning Technologies in the financial services Industry for creating Competitive Intelligence. *Materials Today: Proceedings*, *56*, 2252-2255.

Mor, S., & Gupta, G. (2021). Artificial intelligence and technical efficiency: the case of Indian commercial banks. *Strategic Change*, *30*(3), 235-245.

Oluwagbemi, O., Abah, J., & Achimugu, P. (2011). The impact of information technology in Nigeria's banking industry. *Journal of computer science and engineering*, *7*(2), 63-67.

Ottosson, F., & Westling, M. (2020). Artificial Intelligence and its Breakthrough in the Nordics: A Study of the Relationship Between AI Usage and Financial Performance in the Nordic Market. [Masters Thesis, UMEA UNIVERSITET].

Rabbani, M. R., Lutfi, A., Ashraf, M. A., Nawaz, N., & Ahmad Watto, W. (2023). Role of artificial intelligence in moderating the innovative financial process of the banking sector: a research based on structural equation modeling. *Frontiers in Environmental Science*, *10*, 2083.

Ris, K., Stankovic, Z., & Avramovic, Z. (2020). Implications of Implementation of Artificial Intelligence in the Banking Business with Correlation to the Human Factor. *Journal of Computer and Communications*, *8*(11), 130.

Ritamaki, A. (2017). Applying Continuous Improvement in Order to Reach Operational Excellence. (Hame University of Applied Science). Visamaki Spring.

Sarkar, J., & Sarkar, S. (2018). *Bank Ownership, Board Characteristics and Performance: Evidence from Commercial Banks in India. International Journal of Financial Studies, 6(1), 17.* doi:10.3390/ijfs6010017

Studenmund, A. H. (2014). *Using Econometrics: A Practical Guide*. 6th edition. Harlow: Pearson Education Limited.

Taylor, F. W. (1911). *The Principles of Scientific Management*, 1998 edition. Dover.

Tokedo, K. (2021) CBN urges banks to leverage on technology to drive payment systems. *News Direct: Nigeria.*https://nigeriannewsdirect.com/cbn-urges-banks-to-leverage-on-technology-to-drive-payment-systems/