ROBOTIC PROCESS AND ENTERPRISE PERFORMANCE: EVIDENCE FROM AN EMERGING ECONOMY

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ABSTRACT

The banking sector has been undergoing a broader digital revolution in recent years, including robotic process automation. Hence, this study examines the impact of the robotic processes on enterprise performance, emphasizing Access Bank of Nigeria as the study's focus. Specifically, the study examined (i) the effect of speed of service on employees' satisfaction. (ii) the influence of the accuracy of data processing on employees' work quality. (iii) the influence of scalability on employees' commitment. A descriptive research approach was adopted, and the staff of Access Bank of Nigeria served as the population. The sample size of 131, calculated through Taro Yamane's (1967) method, was used with simple random sampling to collect primary data from the respondents. A partial least squares structural equation model (PLS-SEM) was adopted to examine the causal relationship through SmartPLS 3.0. The results showed that all robotic process factors substantially predict enterprise performance; employees' satisfaction, employees' work quality, and employees' commitment all have R-squared values larger than 20%, which means that the model of robotic process (speed of service, accuracy of data processing, and scalability) accounts for a substantial amount of the volatility in these dependent variables. The study concluded that the robotic process significantly contributes to high performance in the banking industry in an emerging economy. Bank managers in emerging economies should promote scalability that may help ensure consistency in the outcome during the robotic process.

Keywords: *Robotic Process; Enterprise Performance; Scalability; Accuracy of Data; Speed of Service*

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INTRODUCTION

Patric Geary, the marketing director of Blue Prism, an RPA software business, coined the phrase "robotic process automation" (RPA) in 2012 (Hindle et al.2017). In 2014 and 2015, RPA started to gain traction as businesses reported significant savings from automation. To increase productivity and efficiency, the idea of robotic process automation (RPA) enables computer-generated workers, often known as robots, to perform monotonous, rule-driven operations that do not require human intellect for processing (Geyer-Klingeberg et al., 2018).

Organizations employ robotic process automation (RPA) as an electronic solution to simulate human operations or activities (Lamberton et al., 2017). Technological advancements are changing the nature of jobs, how work is done, and the working environment (Behrend et al., 2024). According to Lacity et al. (2015), RPA programming is often regarded as the best option for replacing people in various procedures and activities, such as transferring data from one system (like email) to another for different uses. Fernandez and Aman (2018) contend that RPA frees humans from laborious, non-value-adding jobs so they may concentrate on picking up new abilities that call for human intelligence.

Enterprises and relationships inside enterprises have evolved due to technology. There is no doubt that our world has undergone a significant digitalisation process during the past several decades. Industries, citizens, and governments have all embraced new digital services and technologies (Sabbaghet al., 2013). Digitalization has emerged as a major global economic force, spurring expansion and generating an enormous number of new employment (Kotarba, 2018). Since the introduction of ATMs in the 1970s, electronic transactions in the 1980s, and Internet banking in the 1990s, the banking sector has been at the epicentre of this digital disruption. It is accustomed to this occurrence (K & Mohan, 2025). The industry hasn't returned to the pattern in the past few years and has continued innovating by utilising new technologies.

Globally, the financial industry has accelerated and improved customer experiences through digital transformation by utilizing smart technologies like RegTech to lower compliance risk, learning machines for anti-money laundering (AML), know your customer (KYC), and RPA (Schueffel, 2017). The financial banking industry's digital transformation aims to better serve clients by meeting their expectations for novel features, openness to market, and a range of customer needs. It is possible to carry out credit card issuing, bogus claims, loan information, and robotic automation integration within the financial business. Specifically, RPA is utilized in the administrative office to handle routine company operations, comply with banking anti-money laundering standards, and so on. Robot advisors, virtual financial assistants, and customer-responsive emotion-detection robots can assist clients in the front office (Samra, 2021)

The banking sector has been undergoing a broader digital revolution in recent years, including the use of RPA (Thekkethil, et al., 2021). Banks may now automate many tasks with RPA, including loan processing, compliance, client onboarding, and KYC. Automation may have an incremental but possibly significant effect on an organisation's culture, as stated by Marek (2019). Employees can be repurposed to higher-value assignments that call for greater creativity and judgment when technology relieves them of repetitive duties. This shift in the scope of employment may impact how employees engage with each other and the organization as a whole. This has provided banks with several benefits, including reduced costs, increased productivity, and improved customer service. Finding a balance between formal learning and job-based instruction is a crucial problem in the context of reskilling and upskilling (Lakshmi, et al., 2024). This study aims to look at how Access Bank's enterprise performance is affected by robotic processes.

Access Bank Nigeria faces challenges balancing operational efficiency, cost reduction, and customer satisfaction amidst increasing regulatory demands and competitive pressures (Ogundele et al., 2025) Emerging economies, including Nigeria, lag in RPA adoption compared to developed nations despite having thriving service industries that can benefit from this technology (Zhu & Kanjanamekanant, 2023). This study aims to fill the gap in empirical evidence on RPA's impact on enterprise performance in emerging markets by examining its influence on Access Bank Nigeria's operations.

The study's significance lies in its potential to provide valuable insights for multiple stakeholders. For Access Bank Nigeria, understanding RPA's impact can inform strategic decisions on technology investment and workforce management. For the broader banking sector in emerging economies, the findings can serve as a reference for other financial institutions considering RPA adoption. This study can also contribute to the academic literature by providing empirical evidence from an emerging market context, which is currently underrepresented. Additionally, the results can guide policymakers in formulating regulations supporting the responsible and effective use of RPA in the financial sector.

The main objective of this research project will be to examine the impact of robotic processes on enterprise performance with an emphasis on Access Bank as a case study. Other specific objectives will include determining the effect of speed of service on employees' satisfaction, investigating the influence of accuracy of data processing on employees' work quality, and examining the influence of scalability on employees' commitment.

LITERATURE REVIEW

Concept of Robotic Process Automation (RPA)

It is crucial to remember that there is not a single, widely recognised definition of robotic processes, often known as robotic process automation (RPA). Unless specifically indicated differently, both phrases have the same meaning. Therefore, they can be used succinctly throughout this book. RPA is a new type of process automation in businesses where one or more software robots carry out a task just like a person would (Aguirre & Rodriguez, 2017). According to him, the phenomenon's robotic component just highlights the notion that a machine may be used in place of a human.

However, according to the Naqvi and Munoz (2020), the idea is the use of technology to set up a robot that can recognize and comprehend existing applications to process a transaction using AI, manipulate data, or interact with other digital systems. According to the institution, there are three main ways that RPA is different from other traditional forms of automation: First, it automates procedures by utilizing already-existing information systems (Enriquez et al., 2020). It interacts with these current systems rather than supplanting or harmonizing with them (Van Der Aalst et al., 2018). Secondly, it can adapt to changes within these underlying Information Systems, making handling exceptions possible (Aguirre & Rodriguez, 2017). Thirdly, traditional automation aims to enhance the workforce, while RPA focuses on virtualizing the workforce (Oyeniyi et al., 2024). The RPA market is growing fast (Le Clair et al., 2017).

The dimensions of RPA are:

1. Speed of service
   RPA and other technologies have improved banking speed of service by speeding up transaction processing, increasing customer happiness, and increasing operational efficiency (Metouole et al., 2023). Automation speeds up processes like audits of compliance and client onboarding, which is advantageous to banks and consumers alike (Alassuli, 2025).
2. Accuracy of Data processing
   According to Dhatchayani et al. (2025), data processing accuracy is essential for making decisions and ensuring operational effectiveness in businesses. Reliable data improves overall business performance by ensuring that findings and insights are true and trustworthy (Ji-fan Ren et al., 2016). Strict authentication and quality control procedures are necessary to guarantee correctness in data processing (Ng et al., 2023).
3. Scalability
   RPA is said to be scalable when it allows for further automation efforts across various business activities and processes while adjusting to differing workloads and levels of complexity (Marek, 2019). It helps businesses effectively manage growing job loads without sacrificing quality or performance, essential for ongoing operational expansion and adaptability (Geyer-Klingeberg et al., 2018).

Enterprise Performance

From the point of view of management, performance refers to the intended outcome of the organization and the efficient output that the organisation exhibits at various levels in order to accomplish its objectives. It encompasses both individual and group performance. Although individual performance realisation should be the foundation for enterprise performance realization, overall performance is not always guaranteed by individual performance realization. Performance management is, therefore, much more crucial for optimising and raising an organisation's total performance (Shet et al., 2019).

The organization's prevailing elements cultivate enterprise performance. Scholars said that as high-performance breeds competitive advantage, all organisations attempt to improve enterprise performance (Mutenyo et al., 2021). According to Bagherzadeh et al. (2019), enhancing corporate performance and fostering innovation inside the company depend on an open exchange of information. The dimensions of enterprise performance are;

1. Employee Satisfaction
   Since employee happiness is correlated with both productivity and retention, it is essential for the success of a business (Robbins & Judge, 2019). Levels of satisfaction are highly influenced by elements like possibilities for growth, work-life balance, and acknowledgment (Maslach & Leiter, 2016). By addressing these factors, staff commitment and morale can increase (Guest, 2017).
2. Employees' Work Quality
   Developing skills, creating a positive work atmosphere, and giving ongoing feedback are all necessary to improve employees' job quality (Febrian, 2023). It is essential to productivity in general, consumer satisfaction, organisational performance, and staff happiness (Cascio & Montealegre, 2016).
3. Employee commitment
   Employee commitment is the devotion and allegiance of staff members to their employer. This is commonly shown by their readiness to put in extra work on the

company's behalf and their desire to stick around. Employee commitment may be divided into three categories, according to Meyer and Allen (1991): emotional, continuance, and normative. Each category has an impact on employee conduct and organisational outcomes.

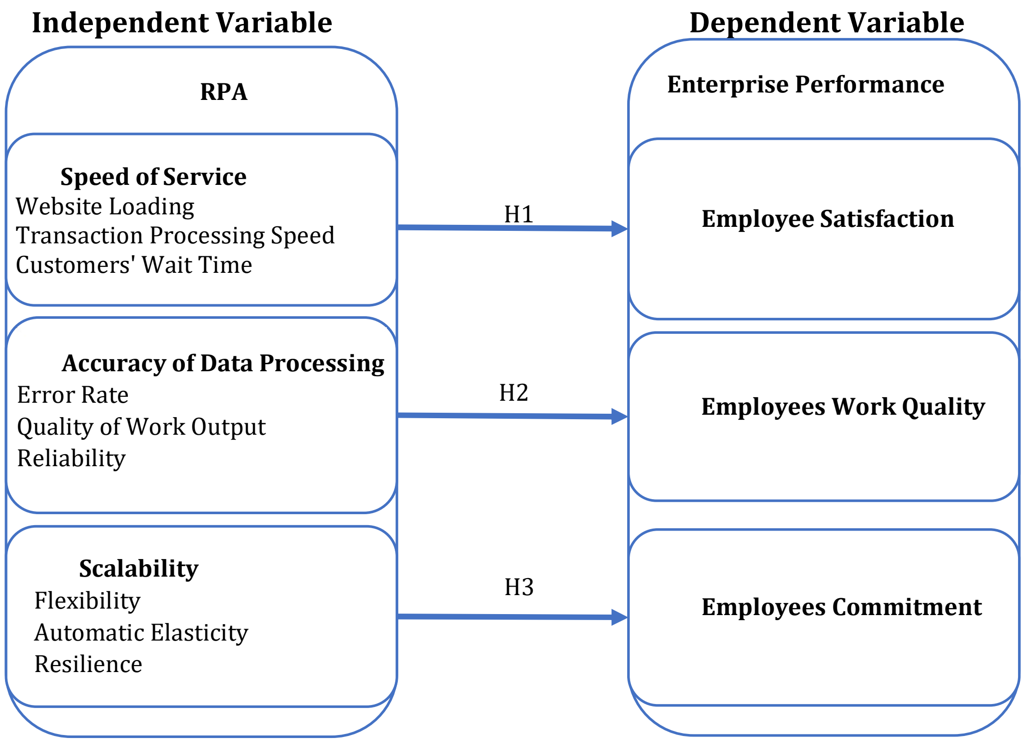
Robotic Process and Enterprise Performance

Because of its possible influence on performance measures, incorporating RPA into business operations has attracted much interest. RPA enables businesses to automate repetitive, rule-based jobs previously completed by people, increasing productivity and cutting expenses (Marek, 2019). Businesses may gain improved workflows and faster turnaround times by implementing software robots to perform repetitive tasks like data input, transaction processing, and customer support questions (Samra, 2021). In addition to increasing operational effectiveness, automation frees up human workers to concentrate on more strategic tasks that call for imagination and judgment.

According to Schueffel (2017), implementing RPA in business settings frequently results in enhanced precision and adherence to regulations, hence enhancing the overall efficacy of the firm. But for RPA to be implemented successfully, some elements must be carefully taken into account, including how well a process can be automated, how well it integrates with current systems, and how staff responsibilities and skills will be affected Marek, (2019). In order to optimise the advantages of automation while minimising possible dangers and problems, companies must strike a balance between technology improvements and effective change management methods, according to research on the link between RPA implementation and corporate performance.

Model of the Study and Hypotheses Development

The Conceptual model for this study is given in Figure 1.



Source: Author's Conceptualization, 2026

Figure 1
Conceptual Model

As shown in Fig. 1, the independent variable is RPA, and the dependent variable is Enterprise Performance. The hypotheses formulated for this study are developed using the relevant factors of RPA that are relevant for the banking industry, as well as the enterprise performance sector that is significant to the banking industry. The research hypotheses developed for this study are:

H1: There is no significant relationship between speed of service and employees' satisfaction.

H2: The Accuracy of data processing has no significant effect on employees' work quality.

H3: Scalability plays no significant role in employees' commitment.

Disruptive Innovation Theory

The disruptive innovation theory introduced by Clayton Christensen in 1997 postulates that easier, more accessible, and less expensive alternatives have the power to completely transform sectors by first catering to niche consumers and then progressively upending more established firms. This theory's broad usefulness for grasping market dynamics has been shown by the substantial research and real-world applications it has spawned across various industries, particularly digital technology, healthcare, and electric cars.

The notion strongly emphasises how flexible and agile organisations can be while dealing with disturbances. While researchers like Sabbagh et al., (2013) highlight dynamic characteristics like seeing and grabbing chances, Kollmann et al., (2017) emphasise the importance of entrepreneurial orientation and strategic adaptability. Chikte and Deshmukh (2022) address the "innovator's dilemma," which states that while successful businesses prioritise retaining their current clientele and competitive advantages above identifying and effectively addressing disruptive innovations, they frequently fall short in these areas.

A recent study has extended the idea of disruptive innovation to new settings. Chikte and Deshmukh (2022) investigate how disruptive technologies might transform healthcare by providing more cost-effective, patient-centered solutions. Kotarba (2018) similarly explore the disruptive potential of electric vehicles, showing how traditional automakers need to change to keep up with new technology. These studies highlight how the theory is still relevant today for directing organisational strategies in the face of industry changes, assisting managers in successfully navigating disruptions, and seizing fresh chances for growth.

Empirical Review

Uklanska (2023) focused on articles from 2012 to 2022 obtained from databases such as Web of Science, Scopus, and IEEE Xplore in her bibliometric analysis and literature review on RPA. The study used a cluster approach to pinpoint the main themes in RPA research, focusing on digital transformation and artificial intelligence. It sought to evaluate the accessibility of operational models and provide a more explicit methodological definition for RPA.

Flechsig et al. (2021) conducted a thorough evaluation of the literature on the adoption of RPA. Their study combined data on effective adoption strategies, advantages, organisational difficulties, and traits of RPA-suitable processes. The study's objectives were to draw attention to research gaps and offer organisations useful insights to encourage more investigation into the area.

Atencio et al. (2022) carried out research on the use of RPA for dynamic structural health monitoring (SHM) application performance monitoring. They used the Design Science Research Method (DSRM) to streamline the procedures of error identification and data collection for an inexpensive accelerometer. Their strategy was to improve dependability, lower the need for human labor, and guarantee continuous functioning in SHM applications.

METHOD

This study used a descriptive research approach to collect data from a population of participants to characterize the phenomenon. This approach poses questions concerning respondents' attitudes, values, and perceptions. The 200 participants in the research represent the middle- and upper-level employees of the chosen access banks in Nigeria.

While there are a number of approaches to choosing the right sample size, simple random sampling was employed (Singh, 2003) in this study to choose the right bank employees, particularly those who possess the necessary automation knowledge and are aware of the bank's past financial performance. The ultimate sample size was determined to be 133 using Taro Yamane's method. A questionnaire was the primary instrument used in this study to collect data from participants. It was a literature-based structure (Boone & Boone, 2012; Farh & Cheng, 1997) and used a 5-point Likert scale for data collection.

In order to ascertain the validity of the questionnaire and the accuracy of the instrument for assessing the impact of digital transformation on organizational performance, construct validity was used in this study. The internal consistency items on the questionnaire will be subjected to a Cronbach's Alpha analysis (Karvouniari, 2024).

Structural equation modelling, or SEM, was used to assess how the independent factors affected the dependent variable.

Model Specification

The performance of the enterprise is the dependent variable in this study report, whereas the robotic process is the independent variable. Since structural equation modelling (SEM) will be employed in the report, the following models will be used:

H01: There is no significant relationship between speed of service and employees' satisfaction in the Nigerian banking sector

$$ES = f(WL+TPS+CWT)$$

Where:
ES = Employees' Satisfaction
WL = Website Loading
TPS = Transaction Processing Speed
CWT = Customers' Wait Time

H02: Accuracy of data processing has no significant effect on employees' work quality in the Nigerian banking sector

$$EWQ= f(ER+QWO+R)$$

Where:
EWQ = Employees' Work Quality
ER = Error Rate
QWO = Quality of Work Output
R = Reliability

H03: Scalability plays no significant effect on employees' commitment in the Nigerian banking sector

$$EC= f(F+AE+R)$$

Where:
EC = Employees' Commitment
F = Flexibility
AE = Automatic Elasticity
R = Resilience

The ethical implications of RPA in banking are significant and multifaceted (Dalsaniya et al., 2025). While RPA can enhance efficiency and reduce errors, it raises concerns about job displacement, data privacy, transparency, and accountability (Eulerich et al., 2023). To address these concerns, banks must implement robust data protection measures, prioritize transparency in decision-making processes, and invest in reskilling programs for employees (Asif et al., 2024). Additionally, promoting human-automation collaboration can help mitigate the negative impacts of RPA on job security and enhance overall productivity (Maček, Murg, & Čič, 2020). Ensuring ethical RPA implementation is crucial for building trust with stakeholders and maintaining high social responsibility (Patrício et al., 2024).

RESULTS AND DISCUSSION

Prior to conducting the main analysis, normality tests were performed to ensure the data met the assumptions required for structural equation modeling. According to Hair et al.

(2017), assessing data normality is crucial for valid PLS-SEM results. Table 1 presents the normality assessment results for all variables examined in this study.

Table 1
Normality Results

	Excess Kurtosis	Skewness	Number of Observations Used
Scalability	-0.153	-0.301	103.000
Accuracy of data processing	-0.316	-0.293	103.000
Employees work quality	-0.193	-0.144	103.000
Employees satisfaction	-0.388	-0.055	103.000
Employee commitment	-0.451	0.035	103.000
Speed of service	-0.520	-0.088	103.000
Enterprise performance	-0.526	-0.037	103.000

Source: Field Survey, 2025

Table 1 shows the normality results. The distribution's normality findings showed that the sample size was 103, indicating that the data should be normal if the absolute value of skewness is +1.0 or less. Additionally, an absolute value of +3.0 for kurtosis is anticipated for a typical peak, as any number outside the threshold may be severe and indicate cause for worry. The kurtosis findings were also within the absolute value of ±3.0, and the normality results indicate that all the variables were within the threshold of ±1.0. The results of the normality test imply that all of the data included in the study are normally distributed and suitable for additional analysis and deductions.

To provide a comprehensive overview of the research variables, descriptive statistics were computed for all measurement items. As recommended by Field (2013), examining means and standard deviations helps identify data patterns and potential outliers before conducting advanced statistical analyses. Table 2 displays the descriptive statistics for all questionnaire items used to measure the study's constructs.

Table 2
Descriptive Statistics on Questions Relating to the Study

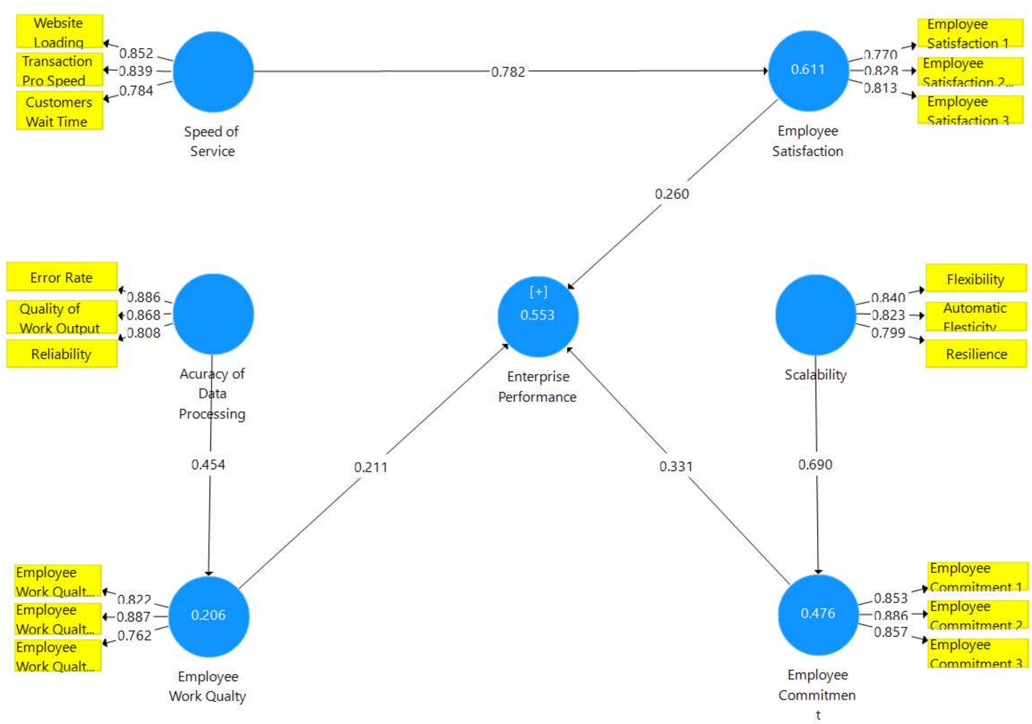
	Mean	Standard Deviation	Number of Observations Used
Automatic_Elesticity	3.978	0.569	103.000
Customers_Wait Time	3.056	0.461	103.000
Employee _Work Qualty 1	3.541	0.647	103.000
Employee _Work Qualty 2	4.091	0.621	103.000
Employee_Commitment 1	3.818	0.638	103.000
Employee_Commitment 2	3.410	0.560	103.000
Employee_Commitment 3	3.443	0.582	103.000
Employee_Satisfaction 1	3.617	0.568	103.000
Employee_Satisfaction 2	3.695	0.522	103.000
Employee_Satisfaction 3	3.260	0.464	103.000
Employee_Work Qualty 3	4.004	0.516	103.000
Error Rate	3.661	0.542	103.000
Flexibility	4.132	0.524	103.000
Quality of_Work Output	3.544	0.544	103.000
Reliability	2.954	0.464	103.000
Resilience	3.921	0.496	103.000
Transaction _Pro Speed	4.127	0.589	103.000
Website_Loading	4.080	0.602	103.000

Source: Field Survey, 2025

The study's variables and indicators, which were obtained via the questionnaire, are displayed in Table 2 with their respective means and standard deviations. A number of important indicators that each shed light on a distinct component of the robotic process and enterprise performance was evaluated as part of the research that looked at the robotic process and enterprise performance. For academics and practitioners, the mean scores, standard deviations, and quantity of data utilized for each indicator offer insightful information and practical consequences. The comparatively high mean scores (over 2.5) for the questions indicate that respondents believe there is a strong correlation between enterprise success and robotic processes. These illustrative findings highlight the complex relationship between robotic processes and business effectiveness. These highlight how crucial it is for an organisation to operate with a good robotic procedure.

Assessment of Measurement Model

The measurement model was evaluated using the partial least squares path modeling approach, which is appropriate for exploratory research examining complex relationships between constructs (Hair et al., 2019). According to Sarstedt et al. (2017), visualizing the path model helps identify the structural relationships between latent variables and their indicators. Figure 2 illustrates the complete path model showing the relationships between robotic process dimensions and enterprise performance indicators.



Source: SmartPLS V3.2.9 Output, 2025

Figure 2
A Path Model of Robotic Process and Enterprise Performance

The route model that shows the connection between robotic process and enterprise performance is seen in Fig. 2. This picture illustrates interaction effects, which occur when many factors work together to create latent variables. The outer weight of this model ranges from zero to a maximum value of somewhat less than 1. It has been found that the maximum outer model weight tends to drop along with a lower average outer model weight when a latent variable includes more indicators.

Weaker loadings in the analysis are justified by the results pertaining to these outer model weights. This is because all loading weights continued to be either over or extremely near the 0.50 threshold. It is also important to remember that these variables are crucial parts of the latent variables, as the literature that has already been published has demonstrated.

Construct reliability and validity are essential for ensuring measurement quality in PLS-SEM analysis (Fornell & Larcker, 1981). According to Hair et al. (2017), Cronbach's Alpha and Composite Reliability values above 0.7 indicate acceptable internal consistency, while Average Variance Extracted (AVE) values above 0.5 demonstrate adequate convergent validity. Table 3 presents the reliability and validity assessment results for all latent constructs in this study.

Table 3
Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Scalability	0.760	0.861	0.674
Accuracy of data processing	0.815	0.890	0.731
Employees work quality	0.770	0.865	0.681
Employees satisfaction	0.727	0.846	0.647
Employee commitment	0.832	0.899	0.748
Speed of service	0.766	0.865	0.681
Enterprise performance	0.836	0.902	0.753

Source: Field Survey, 2025

Table 3 shows how Composite Reliability and Cronbach's Alpha are used to evaluate the construct reliability of latent variables. Internal consistency is measured by Cronbach's Alpha, and all results are higher than the generally recognized cutoff point of 0.7, proving that the items accurately capture the concepts they are meant to measure. The robustness of these variables in reflecting the desired notions is confirmed by Composite Reliability, which shows high values over 0.7 and takes into account both internal consistency and the interactions between items and the latent variable.

Average Variance Extracted (AVE) evaluates every latent variable's convergent validity. Every AVE number is higher than the suggested cutoff point of 0.5, indicating that all variable elements assess the exact same underlying notion. With excellent construct reliability and validity, high internal consistency, robust composite reliability, and good convergent validity, the results support the latent variables' usage as valid and dependable indicators in the research study.

Discriminant validity assesses the extent to which constructs are truly distinct from one another (Henseler et al., 2015). Following the Fornell-Larcker criterion, discriminant validity is established when the square root of each construct's AVE exceeds its correlations with other constructs (Fornell & Larcker, 1981). Table 4 displays the discriminant validity assessment using the Fornell-Larcker criterion, with diagonal values representing the square root of AVE for each construct

Table 4
Discriminant Validity

	Scalability	Accuracy of data processing	Employees work quality	Employees satisfaction	Employee commitment	Speed of service	Enterprise performance
Scalability	0.821						
Accuracy of data processing	0.687	0.855					
Employees work quality	0.648	0.454	0.825				
Employees satisfaction	0.733	0.546	0.740	0.804			
Employee commitment	0.690	0.505	0.787	0.806	0.865		
Speed of service	0.735	0.603	0.657	0.782	0.760	0.825	
Enterprise performance	0.649	0.531	0.665	0.684	0.708	0.666	0.868

Source: Field Survey, (2025)

Strong proof that the latent variables (scalability, speed of service, enterprise performance, employee satisfaction, employee commitment, employee work quality, and accuracy of data processing) are distinct and not highly correlated with one another can be found in Table 4's results of the discriminant validity analysis. The fact that each variable has a stronger correlation with itself than any other suggests that each construct measures a separate part of the entire notion, enhancing its individuality.

Scalability and data processing accuracy show substantial self-correlations compared to their correlations with other factors, as do the other variables. Since the latent variables measure distinct concepts instead of various presentations of the same underlying construct, this demonstrates that the measurement model is adequate for differentiating between these important parts.

Multicollinearity assessment is critical in structural models to ensure that predictor variables are not highly correlated, which could affect the stability of path coefficient estimates (Hair et al., 2019). According to Kock and Lynn (2012), VIF values below 5 are acceptable, though values below 3 are preferable. Table 5 presents the inner VIF values for all predictor variables in the structural model.

Table 5
Inner VIF Values

	Employees work quality	Employees satisfaction	Employee commitment	Enterprise performance
Scalability			1.000	
Accuracy of data processing	1.000			
Employees work quality				2.865
Employees satisfaction				3.119
Employee commitment				3.702
Speed of service		1.000		

Source: Field Survey, 2025

The Variance Inflation Factor (VIF) values for latent variables associated with enterprise performance are displayed in Table 5. Regression analysis uses the VIF table to evaluate the multicollinearity across predictor variables. A high level of multicollinearity makes it more difficult to isolate individual effects on the dependent variable.

The predictor factors in this VIF table that are assessed for multicollinearity include scalability, accuracy of data processing, and speed of service. To find issues, VIF readings are compared to a standard of 10. There is no discernible multicollinearity because the VIF values of any predictor variable are much lower than 10.

The predictor variables' low VIF values imply that they have low correlation and that it is possible to evaluate each one separately for its impact on the dependent variable. This suggests that the estimates of the associations between the dependent variable and the predictors provided by the model are trustworthy and steady.

Test of Hypotheses

The coefficient of determination (R^2) measures the model's explanatory power, indicating the proportion of variance in dependent variables explained by predictor variables (Chin, 1998). Hair et al. (2017) suggest that R^2 values of 0.75, 0.50, and 0.25 represent substantial, moderate, and weak explanatory power, respectively. Table 6 presents the R^2 and adjusted R^2 values for all endogenous constructs in the research model.

Table 6
Coefficient of Determination Score

	R Square	R Square Adjusted
Employees work quality	0.206	0.202
Employees satisfaction	0.611	0.609
Employee commitment	0.476	0.473
Enterprise performance	0.553	0.546

Source: Field Survey, 2025

The models pertaining to employees' dedication, job quality, and satisfaction all have R-squared values of more than 20%, which suggests that they account for a substantial amount of the variability in the dependent variables. This implies that the observed changes in these employee-related characteristics are well captured by the models.

A strong goodness of fit is shown by the adjusted R-squared values for company performance, workers' commitment, workers' job quality, and workers' satisfaction, all of which are over 20%. The models adequately describe the variability in enterprise performance without being unduly complicated, as indicated by the near values of adjusted R-squared and regular R-squared, which also indicate that the models do not suffer from overfitting.

Effect size (f^2) measures the substantive impact of predictor variables on endogenous constructs beyond statistical significance (Cohen, 1988). According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Table 7 displays the effect sizes for all relationships in the structural model.

Table 7
Assessment of the Effect Size (f2)

	Employees work quality	Employees satisfaction	Employee commitment	Enterprise performance
Scalability			0.909	
Accuracy of data processing	0.260			
Employees work quality				0.035
Employees satisfaction				0.049
Employee commitment				0.066
Speed of service		1.571		

Source: Field Survey, 2025

Table 7 shows the effect size, also known as the F-squared, which is a statistical measure of the strength of the link or influence of independent variables on a dependent variable. This research evaluates the impact sizes of many latent factors on "Enterprise performance." A 0.02 effect size is considered minor, a 0.15 effect size as medium, and a 0.35 effect size as high. Since all of the f-square values are more than 0.35, the effects of scalability, accuracy of data processing, and speed of service are all considerable.

This demonstrates that each independent variable has a significant impact on the other independent variables separately. The impact sizes indicate that employee commitment, job quality, and satisfaction are comparatively more strongly influenced by scalability, accuracy of data processing, and speed of service.

Hypothesis testing in PLS-SEM involves examining path coefficients, their statistical significance through bootstrapping procedures, and the direction of relationships (Hair et al., 2017). Following standard conventions, hypotheses are supported when t-values exceed 1.96 and p-values are below 0.05 for a 95% confidence level (Sarstedt et al., 2017). Table 8 presents the bootstrapping results showing path coefficients, standard errors, t-statistics, and p-values for all hypothesized relationships.

Table 8
Bootstrapping Results Showing Path Coefficient for Structural Model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Hypotheses
Scalability -> Employee commitment	0.690	0.692	0.039	17.569	0.000	Supported
Accuracy of data processing -> Employees work quality	0.454	0.456	0.055	8.200	0.000	Supported
Employees work quality -> Enterprise performance	0.211	0.213	0.079	2.675	0.008	Supported
Employees satisfaction -> Enterprise performance	0.260	0.262	0.087	2.983	0.003	Supported

Employee commitment -> Enterprise performance	0.331	0.330	0.096	3.443	0.001	Supported
Speed of service -> Employees satisfaction	0.782	0.783	0.031	25.127	0.000	Supported

Source: Field Survey, 2025

Table 8 presents statistical correlations between latent variables and examines direct null hypotheses. With regard to "Speed of service -> Employees satisfaction," the hypothesis is supported by the high beta value, T statistic over 1.96, and p-value below 0.05, which all demonstrate a statistically significant link.

The hypothesis is supported by the high beta value, T statistic over 1.96, and p-value below 0.05 for "Accuracy of data processing -> Employees work quality," which all demonstrate statistical significance.

The hypothesis is supported by the high beta value, T statistic over 1.96, and p-value below 0.05 in the association "Scalability -> Employees commitment," demonstrating statistical significance. The statistical analysis of the table provides strong evidence for the proposed linkages, suggesting that they are not random connections but rather statistically meaningful associations.

The effect of speed of service on employees' satisfaction

The results relating to the first objective revealed that employee happiness and service speed are significantly correlated, with all proxies displaying positive weights over the threshold. This lends credence to the idea that transaction processing speed, wait times for customers, and the speed at which websites load may all be used to forecast employee happiness, affecting company performance, especially at Access Bank. This aligns with earlier studies that emphasize the importance of service efficiency in enhancing employee morale and satisfaction. For instance, research by Somda et al., (2023) found that employee satisfaction is closely tied to workplace efficiency, including the speed at which tasks are completed.

The influence of accuracy of data processing on employees' work quality

The results relating to the second objective indicate a substantial correlation between employee work quality and data processing accuracy as evaluated by error rate, reliability, and quality of work output, with all proxies displaying positive weights over the threshold. These results imply that these characteristics can predict the caliber of work produced by employees, improving overall company performance, particularly for Access Bank. This is supported by the study of Ji-fan Ren et al., (2016), which emphasizes the critical role of high-quality data in decision-making and operational efficiency

The influence of scalability on employees' commitment

The results of objective three suggest a considerable correlation between employee commitment and scalability, with all proxies displaying positive weights above the threshold. This suggests that resilience, automatic elasticity, and flexibility may all be used to predict employee commitment, which affects business success. These findings particularly apply to Access Bank. This aligns with earlier research, such as the study by Geyer-Klingeberg et al. 2018, which highlights the importance of organizational flexibility and resilience in maintaining high employee performance and engagement

CONCLUSION AND SUGGESTIONS

The study on robotic processes and enterprise performance in the Banking industry yielded several significant conclusions. The study came to the conclusion that workers' happiness in the banking business was positively impacted by the speed of service, which included client wait times, transaction processing speeds, and how quickly websites loaded.

The study also found that there is a favorable correlation between dependability, quality of work output, error rate of data processing, and the caliber of work produced by workers at Access Bank, which in turn improves company performance.

According to the study's further findings, scalability, which is defined by durability, automated elasticity, and flexibility, was found to be a key factor in Access Bank workers' commitment, which, in turn, improved organizational performance.

Overall, the study rigorously finds that robotic processes significantly impact corporate performance.

The following recommendations are given to Access Bank, the banking sector, and other participants, including the government and other researchers, in light of the conclusions reached from the research's numerous findings:

- To increase employee satisfaction, Banks and other stakeholders should implement measures to enhance service speed. This may be accomplished by the creative manner in which the website loads, the pace at which transactions are processed, and the duration of consumer wait times.
- To increase enterprise performance in the banks and improve workers' work quality, banks should boost their accuracy of data processing by developing appealing and content-based Error rates, delivering quality work Output, and having well-structured and thorough reliability.
- In order to improve the enterprise quality of service delivery, Banks and other stakeholders should promote scalability. This may be accomplished by utilizing resilience, digital payment platforms, and flexibility. These can guarantee that its services are of the highest caliber and assist in establishing solid relationships with clients.

Limitations and Future Research Directions

While this study provides valuable insights into RPA's impact on enterprise performance, several limitations should be acknowledged. First, the study focused solely on Access Bank Nigeria, which may limit the generalizability of findings to other banks or industries. Future research should examine RPA implementation across multiple banks and sectors in emerging economies to validate these findings (Flechsig et al., 2021).

Second, this study examined only three dimensions of RPA (speed of service, accuracy of data processing, and scalability) and three dimensions of enterprise performance (employee satisfaction, work quality, and commitment). Future studies should investigate additional variables such as cost reduction, customer satisfaction, innovation capability, and competitive advantage to provide a more comprehensive understanding of RPA's organizational impact (Enriquez et al., 2020).

Third, the cross-sectional nature of this research limits causal inferences. Longitudinal studies tracking RPA implementation over time would provide deeper insights into how robotic processes evolve and their long-term effects on organizational performance (Eulerich et al., 2023). Additionally, future research could employ mixed-methods approaches, combining quantitative analysis with qualitative case studies to capture the nuanced experiences of employees adapting to RPA technologies (Atencio et al., 2022).

Therefore, given the rapid advancement of AI and machine learning integration with RPA, future research should examine how intelligent automation differs from traditional RPA in affecting enterprise performance outcomes (Patrício et al., 2024).

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