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# A Framework for AI Adoption and Strategic Decision Efficiency in Global Strategy Teams

**Imam Akintomiwa Akinlade, Musili Adeyemi Adebayo, Ahmed Olasunkanmi Tijani, Chiamaka Perpetua Ezenwaka, Grace Fadeyi**

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*Abstract: This paper offers an overall model of artificial intelligence implementation in global strategy teams and analyzes its effect on the efficiency of strategic decision-making in the Nigerian and West African organizational settings. In the more challenging market environments that multinational companies are operating in, particularly in emerging economies, the need to have superior decision-making capacity has never been more eminent. It uses the Technology Organization Environment framework and the Dynamic Capabilities Theory to base its researches on elements that affect the use of AI and the consequential impacts it may have on the quality, speed, and strategic performance of decisions. Using a mixed-methodology, we have surveyed 250 strategy professionals working in multinational companies and conducted an in-depth analysis of five cases of organizations of different AI maturity levels active in Nigeria. Findings indicate that organizational preparations, management dedication, and the quality of data infrastructure are significant predictors of AI adoption achievement, whereas cultural flexibility and the market environment moderate the connection amid AI adoption and decision efficiency. Structural equation modeling proved five out of six hypothesized relationships, where the organization culture is a decisive boundary condition. The qualitative data sheds light on the need to address the African markets uniquely in terms of implementation difficulties such as infrastructure limitations, talent shortage, and the necessity of contextual AI solutions. The suggested framework provides a practical insight into strategy teams in the developing economies who want to take advantage of AI technologies without losing strategic agility and cultural relevance, which adds to the literature on technology adoption and new market research.*

***Keywords**: Artificial Intelligence, Strategic Decision-Making, Global Strategy Teams, Organizational Efficiency, Digital Transformation.*

**Imam Akintomiwa Akinlade***
Harvard Business School, Boston, USA.
**Email: iakinlade@mba2023.hbs.edu**

**Musili Adeyemi Adebayo**
The Sure Chill Company Limited Lekki, Lagos, Nigeria.
**Email: adebayomusili@gmail.com**

**Ahmed Olasunkanmi Tijani**
American University, Kogod School of Business, Washington DC, USA.
**Email: oetijani@gmail.com**

Chiamaka Perpetua Ezenwaka
Department of Marketing Analytics and Insights, Wright State University, Dayton, Ohio. USA.
**Email: chiamakaperpetua9127@gmail.com**

**Grace Fadeyi**
Department of Industrial and Production Engineering, University of Ibadan, Nigeria.
**Email: gfadeyi03@gmail.com**

## 1.0 Introduction

Machine Learning (ML) and Artificial Intelligence (AI) are transforming interdisciplinary fields through precise data analysis, predictive modelling, and automated functionality (Ademilua & Areghan, 2022; Adeyemi, 2023-2024). As cyber threats grow more complex with increased digitization, AI has become vital for strengthening data-driven security mechanisms. AI-based techniques enhance threat detection, predictive analysis, and risk management by enabling cybersecurity professionals to identify trends, forecast vulnerabilities, and mitigate attacks effectively (Aboagye et al., 2022). This introduction highlights AI's central role in addressing modern challenges and frames the discussion on its benefits, applications, and future prospects (Omosunlade, 2024; Ukpe et al., 2023).

Digital transformation is accelerated and this is what has completely changed the way organizations are undertaking strategic decision making, especially in global teams that function in various geographical and cultural settings. Artificial intelligence was initially limited to the research laboratories but now it found its way to the operations of the businesses more than ever before and with sophistication (Lindrianasari, & Kuncoro, 2024; Davenport, 2020; Fountaine, 2019). Predictive analytics anticipating market patterns to natural language processing systems simulating competitive intelligence, AI technologies will supplement human judgment and hasten strategic responsiveness in a manner, which a decade ago, appeared unbelievable. However, there has been a lot of complication on the way forward In terms of technology potential to organizational reality, more so in the emerging markets where infrastructure constraint, skills gap, and institutional uncertainties have added to the barriers to adoption.

Africa is the largest economy and most populous country in the continent, and Nigeria is an especially interesting country when it comes to the further investigation of AI use in the strategic decision-making field. The vibrant business culture of the country with the high rate of digitalization and the ongoing infrastructure issues reflect the greater tension that the organizations all around the developing world experience (Adewale, 2023). MNCs in Nigeria and West Africa have to consider regulatory uncertainty, labour shortage, and market instability in their quest to embrace digital transformation programs that headquarters frequently force them to undertake. Due to this duality, a natural laboratory is formed to learn how global strategy teams fit emerging technologies into local realities.

The current literature on the use of AI has largely dominated in the developed market environments with a lot of gaps in how the interplay between organizational, technological and environmental forces in emerging markets (Balogun, 2022; Chukwuemeka, 2023). Although potentially helpful theoretical frameworks like the Technology Acceptance Model (Davis, 1989) and the Technology-Organization-Environment model (Tornatzky, 1990) are used, their applicability to situations characterized by institutional voids and lack of infrastructure is under-researched. In addition, less attention has been given to strategic decision-making that is characterized by high uncertainty, long-term outlook, and high stakes in an organisation compared to operational AI applications.

Global team strategic decisions require integrating viewpoints across geographical boundaries, integrating information sources that are miles apart, and resolving conflicting interests among stakeholders and working within time pressure and incomplete information (Eisenhardt, 1999; Mintzberg, 2009). The intellectual load is heavy: the professionals in strategies have to work with large amounts of data, find trends in the noise, compare two situations, and present their findings in a convincing way to various groups of people. Hypothetically, AI technologies are applicable to most of these issues since they provide speed in data processing, recognition of patterns, scenario modeling, and decision support (Agrawal, 2018). But to achieve these advantages there must be change in the organization, building competencies, and cultural adjustment, needs which are especially difficult in resource-locked settings.

This study is filling these gaps through the formulation and empirical validation of an all-inclusive framework of AI adoption among global strategy departments with specific reference to the context of Nigeria and West Africa. We do not think about AI adoption as a specific technological choice but as a multifaceted organizational change with many stakeholder groups, technical infrastructure, human capabilities and cultural adaptation. Using quantitative analysis of surveys alongside qualitative analysis of case studies, we are able to obtain generalisable relations among variables as well as contextual complexity that quantitative studies tend to ignore.

The research has a number of contributions. Ideally, we would generalize the Technology Organization-Environment model by describing how it is applied to AI adoption in strategic situations and what boundary conditions mediate between important relationships. Our input is to the growing body of research on AI in companies by analysing organizational and institutional conditions that influence outcomes of implementation. To the practitioners, the study provides a diagnostic model of organizational preparedness and the adoption strategies that can suit the particular situations. Our results can provide policymakers in Nigeria and the rest of Africa with insight into the infrastructure, regulatory, and skills development priorities that are required to facilitate the digital transformation.

The article flows following a succession of chapters that aimed at developing an all-inclusive insight into the adoption of AI and its implications to the effectiveness of strategic decisions. Our review of the literature will start with the review of the relevant literature, and we will build our theoretical framework based on the findings of the technology adoption research, strategic management literature, and organizational theory. This basis supports certain assumptions on the connections between technological, organizational, and environmental variables and their overall impact on the adoption of AI and efficient decision-making. We also outline our mixed-methods research design telling how quantitative survey research and qualitative case studies are complementary to each other. The results section provides findings of both methodological strands, where the first one describes structural equation modeling results, and the second one provides case studies thematic insights. These results are combined in the discussion in order to suggest an improved framework, reflects the implication and notes down limitations. The conclusion summarizes major findings and lays the foundations of further investigation.

### *1.1 Theoretical Framework*

Technology-Organization-Environment framework, as proposed by Tornatzky, (1990) can provide an adequate starting point when examining AI adoption. According to this framework, the decision to adopt technology is determined by three contextual domains, which include technological nature of the innovation, organizational forces that within the adopting firm, and external environmental factors. In contrast to the earlier models which paid attention to the individual-level adoption, the TOE framework makes specific reference to the organizational-level adoption, which makes it appropriate to analyze the strategic technology investment (Tornatzky, 1990).

Within the technological sphere, AI systems have unique features that define the decisions to adopt them. In contrast to most previous enterprise technologies, AI apps are highly variable in the technical requirements, the difficulty of their implementation, and integration in the organization (Benbya, 2021). Training machine learning systems takes a lot of quality data, and thus, organizations must invest in data infrastructure and data governance, which many organizations, especially in the emerging markets, have not undertaken. The AI algorithms are frequently black-boxed, meaning that their reasoning process is opaque, and because of this, the interpretability and accountability become the issues of particular concern to strategic use ( Abolade, 2024).

Internal factors are included in the organizational domain and allow or limit the use of AI. The core determinant of adoption capacity is the resource availability, which involves the availability of financial resources to invest in the technology, human resources who have the required skills, and organizational slack to allow experimentation (Ransbotham, 2020). Top management support proves to be a frequently critical component of enterprise technology adoption, and it might be even more critical with AI, as it has strategic implications and may necessitate an organizational. The culture of the organizations, especially the orientations to innovation, risk tolerance, and data-driven decision-making impact the readiness to embrace AI and its implementation efficiency (Kiron, 2020). The current IT infrastructure is the basis on which AI systems are constructed; organizations that have proactive data management procedures have fewer obstacles compared to those that need to invest in basic infrastructures.

The external environment presents ”ress’res and limits, which are caused by environmental factors affecting the adoption decisions. Technology adoption is usually stimulated by competitive intensity where organizations strive to keep up or be ahead of their competitors (Cheng, 2022).

The regulatory environments determine the viability and desirability of AI adoption, where a well-defined governance structure can promote AI adoption, whereas a poorly defined regulation can suppress it. Nigeria is another country where there is a lot of regulatory uncertainty regarding the protection of data and the accountability of algorithms, which adds to the problem (Ndubuisi, 2022). Potential value that can be created by adoption of AI is affected by market characteristics such as customer sophistication and demand of data-driven services.

Teece (2007) has described the Dynamic Capabilities Theory to offer a complementary perspective on the strategic meaning of AI adoption. This school of thought theorizes competitive advantage as being created by the organizational ability to be aware of changes in the environment, capitalize on opportunities and reorganize the resources in reaction to changing environment. All three dimensions can be improved with the help of AI technologies. The abilities of sensing are enhanced by the ability of AI to process a large volume of information and identify weak signals. The ability to take capabilities also has the advantage of using AI to do scenario planning and to evaluate risk. Reconfigurations that may be useful on the basis of AI-enabled supervision of the effectiveness of implementation.

The area that AI Implementation could provide value is made clear through the study of strategic decision-making. Eisenhardt (1999) established that successful organizations in dynamic environments are able to make faster decisions without compromising quality due to real-time information systems, consideration of multiple alternatives simultaneously and two levels advice process. There are AI technologies that may impact every practice. But as Mintzberg (2009) warned, one should not over-rationalize models, as the role played by intuition, political processes, and emergent patterns are significant in the reality of strategic decisions. Any successful use of AI should be able to manage these human facets of strategizing.

The global strategy teams experience specific difficulties that can be tackled by AI and also have their own challenges to adoption. The issue of information asymmetries affects geographically distributed teams because the members in various locations have varying local knowledge (Gibson, 2014). The differences in culture can affect the interpretation of data and the options used by the team members. Coordination issues may be mitigated by the use of AI technologies that offer shared information platforms and processes of making decisions. At the same time, implementing AI in various settings creates implementation complexities since the technologies that are suitable in a specific setting might not be suitable in another setting.

The new market situation presents additional factors. Lack of Infrastructure is a problem that leads to operational difficulties in AI systems that rely on constant power and data availability (Adewale, 2023). The talent issues are particularly acute; whereas large African cities do have rising amounts of data science talent, the demand is much higher than the level of supply (Oyedele, 2023). Institutional voids have a negative impact on the risks to AI investments, especially in cases where they need to enter into partnership with outside entities. Both adoption decisions and implementation are influenced by cultural factors, such as physical discomfort with algorithmic decision-making Effectiveness.

Based on these premises, we will put forward a model that operationalizes AI adoption in the global strategy group as a factor of the influence of technology (AI system characteristics, data infrastructure quality, technical complexity), organizational (leadership commitment, organizational culture, available resources, existing IT capabilities), and environmental (competitive pressure, regulatory clarity, market characteristics) factors. We postulate that these variables will impact AI levels of adoption and subsequently impact the strategic decision efficiency which can be defined in terms of decision speed, decision quality and strategic agility. Organizational culture mediates the relationships between AI adoption and decision efficiency and AI literacy of teams moderate relationships.

Our conceptual model is provided in Fig. 1, and it shows how we expect these constructs to be related.

Figure 1 illustrates how factors influencing AI adoption affect strategic decision efficiency. AI adoption stems from technological, organizational, and environmental contexts. Technological factors include data infrastructure, system compatibility, and complexity; organizational factors involve leadership support, culture, resources, and IT capabilities; environmental factors cover competition, regulation, and external support. AI adoption drives decision speed, quality, and agility. Organizational culture moderates this relationship, while AI competencies mediate it by enabling complementary capabilities that enhance the impact of adoption.

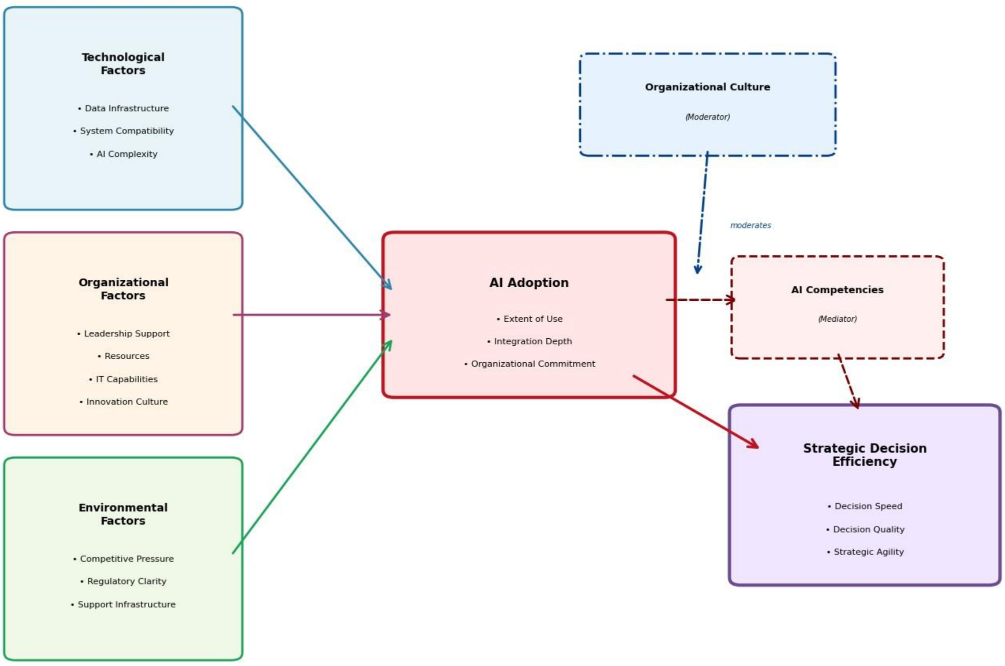


**Fig. 1: Conceptual Framework for AI Adoption and Strategic Decision Efficiency**

Our hypotheses are formalized into six on this framework. The first hypothesis is H1 which holds that technological readiness has a positive impact on the adoption of AI. H2: Organizational factors have a significant impact on the AI adoption success. The third hypothesis is H3, which postulates that the connection between the organizational readiness and adoption is moderated by environmental pressures. H4 anticipates that there is a positive influence of AI adoption on strategic decision efficiency. H5 supposes that, AI-related competencies mediate this relationship. H6 implies that adoption-efficiency relationship is moderated by organizational culture.

## 2.0 Methodology

The study has a mixed-methods design sequential explanatory type, which involves quantitative survey research with qualitative case study research. Its philosophical basis is based on pragmatism, which appreciates various approaches to solving the complicated research questions (Creswell, 2018). We started with the quantitative data collection and analysis to reveal patterns and relationships which was our design sequence and then the qualitative investigation to offer a deeper insight into the way how these patterns were developed.

### *2.1 Study Context and Sample*

The study focused on multinational corporations operating in Nigeria and the broader West African market, targeting individuals in strategic roles. Participants were required to work in strategy, business development, or corporate planning at manager level or above and be involved in strategic decision-making. Eligible firms operated in at least two West African countries and employed 200 or more staff. Stratified sampling by industry sector was followed by purposive sampling to identify suitable organizations, yielding 312 potential respondents, with 250 completing questionnaires (80% response rate). Five organizations were then selected for qualitative case studies, generating 32 semi-structured interviews.

### *2.2 Quantitative Measures*

A designed questionnaire was created based on validated scales adopted by previous studies as well as questions created in this study. There were seven-point Likert scales used on all items. The measurement scales, their source, and important psychometric properties are summarized in Table 1.

**Table 1: Measurement Scales and Key Properties**

| Construct | Items | Source | Cronbach's $\alpha$ |
|---|---|---|---|
| Data Infrastructure Quality | 5 | Adapted from Mikalef (2020) | 0.89 |
| Leadership Commitment | 4 | Chatterjee (2021) | 0.91 |
| Organizational Culture | 6 | Kiron (2020) | 0.87 |
| Competitive Pressure | 4 | Cheng (2022) | 0.85 |
| AI Adoption Level | 8 | Newly developed | 0.92 |
| Decision Efficiency | 7 | Eisenhardt (1999); adapted | 0.88 |
| AI Competencies | 5 | Ransbotham (2020) | 0.90 |

| | | | |
|---|---|---|---|
| Resource Availability | 4 | Chatterjee (2021) | 0.86 |

Table 1 shows that each of the measurement scales possessed good to excellent reliability with the values of Cronbach's alpha at a range of 0.85 and 0.92. Quality of data infrastructure measured the estimates of the respondents concerning data management practices and technical systems of their organization. Leadership commitment was a measure of the top management support of AI initiatives and resource allocation. The culture items at the organization measured the innovation orientation, the willingness to experiment and the level of comfort with the use of data in decision making. The AI adoption scale was a scale that was used to measure the degree of AI utilization across the different strategic processes such as market analysis, competitive intelligence, scenario planning, and risk assessment.

### *2.3 Qualitative Data Collection*

The semi-structured interviews were conducted according to a protocol that would help to evoke detailed accounts of AI adoption processes, implementation difficulties, and perceived effects. Interviews took an average of 55 minutes and were recorded with permission and transcribed word-to-word. Outside of interviewing, we gathered documentary data such as strategy plans and AI project documentation.

#### *2.3.1 Data Analysis*

The quantitative analysis was carried out in a number of steps. Correlation analysis and descriptive statistics gave an initial information. Measures of quality of measurement models were based on confirmatory factor analysis. After the validation of the measurement models, it was estimated that a structural equation model was tested that hypothesizes relationships. Model fit was assessed on several indices such as chi-square statistic, CFI, TLI, RMSEA and SRMR. The mediation analysis involved the bootstrapping procedures and the moderation analysis involved the terms of interaction. IBM SPSS Statistics 28 and AMOS 26 were all used in all the quantitative analysis.

They were followed by qualitative analysis that used thematic analysis steps (Braun, 2006). Analysis started with transcription review and primary noting of an interesting feature, and proceeded to systematic coding review. The first codes were proximate to the data and included the language used by the participants. The further analysis combined similar codes into larger themes. A sub-sample of transcripts was coded in two separate instances by the two researchers, who provided acceptable inter-rater agreement (Cohen kappa = 0.82). Data was managed and coded using NVivo 14 software.

### *2.5 Integration and Quality Assurance*

Quantitative and qualitative results were integrated at the interpretation stage, with quantitative data identifying significant relationships and qualitative insights explaining underlying mechanisms and context. Quantitative quality was ensured through psychometric and statistical standards, while qualitative rigor followed Lincoln's trustworthiness criteria. The study received institutional ethical approval, and all participants provided informed consent.

## 3.0 Results and Discussion

### *3.1 Descriptive Findings*

The 250 survey respondents who were sampled were of different backgrounds to represent the multinational corporate environment in Nigeria. The greatest sectoral representation of 34 percent was financial services, and the second highest of 23 percent was telecommunications and consumer goods (18 percent) and energy (15 percent) and professional services (10 percent). The size of organization was between 200 and above 50,000 employees. The respondents occupied senior positions: 42 % of them had senior managers positions, 38%, director, and 20 %, general manager or C-suite.

As far as descriptive statistics were concerned, there was a significant variation in terms of AI adoption. The scale had eight items on the AI adoption scale and the mean was equal to 3.87 (SD = 1.52), which indicated moderate adoption levels with a large variance. About 23 % of the respondents said that AI was barely adopted, 41 % of the respondents were in the moderate range of adoption, and 36 % of the respondents said that AI was highly adopted. Table 2 shows the means, standard deviations, and correlations between the important variables of the study

**Table 2: Descriptive Statistics and Correlations**

| Variable | M | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| 1. Data Infrastructure | 4.12 | 1.38 | – | | | | | | |
| 2. Leadership Commitment | 4.45 | 1.52 | .58** | – | | | | | |
| 3. Organizational Culture | 4.23 | 1.29 | .52** | .64** | – | | | | |
| 4. Competitive Pressure | 5.12 | 1.18 | .39** | .42** | .37** | – | | | |
| 5. AI Adoption | 3.87 | 1.52 | .61** | .68** | .54** | .47** | – | | |
| 6. AI Competencies | 3.65 | 1.44 | .49** | .56** | .48** | .38** | .72** | – | |
| 7. Decision Efficiency | 4.34 | 1.26 | .44** | .51** | .58** | .35** | .64** | .59** | – |

**Note: N = 250. ** indicates p < .01**

There are a few interesting patterns that can be noticed in Table 2. There was a positive statistical significance of all the correlations between the predictors and outcomes. Leadership commitment (r =.68) and data infrastructure quality (r =.61) have the strongest correlations with AI adoption, which indicates they have a significant role to play. Decision efficiency was the most strongly correlated with organizational culture (r =.58) which suggested the significance of cultural aspects in converting any strategic initiative into the performance improvements.

The analysis of the case studies showed that there are five overarching themes including organizational readiness as a precondition, leadership as a catalyst, context-specific implementation issues in the context of Nigerian realities, cultural adaptation needs, and the new changes in strategic decision-making practices.

The initial theme was that the AI adoption was subject to conditions of successful adoption that demanded basic capabilities. One of the strategy directors at the commercial bank told us: ”We wasted a year and a half simply getting our data house organised before we could seriously consider the applications of AI. The quality of the data was very bad, systems did not communicate with each other. Companies that tried AI without proper data infrastructure had recurrent failures.

As a catalyst and champion, leadership was born. The strategy leader of the telecommunications firm noted: ”Our CEO was in it since the beginning. She went to protests, posed hard questions and defended the budget when it was under strain. The active participation was in contrast to the situations when only passive support was given by the leadership, where AI initiatives are not successful.

The problems related to the implementation that were peculiar to the situation in Nigeria were especially a problem. The AI systems were affected by power outages. Connection to the Internet was a problem to access real-time data. One IT director moaned: ”We created this beautiful AI solution in the clouds, and then we found out that in three markets, the internet was not even dependable enough to run this solution. The other issue was the lack of talent, as there was a high demand among qualified professionals, which increased cost and turnover.

The fourth theme entailed cultural adaptation requirements. Subjects explained the conflicts between algorithms and manual judgment.

One of the analytics managers said: Strategy people are intelligent and assertive. They do not blindly accept the machine when the algorithm tells them otherwise of what they think. Effective organizations evolved the behavior of combining algorithmic intelligence with human intelligence instead of placing them into the role of rival powers.

Emergent changes in strategic decisions making practices were captured in the fifth theme. There was a higher rate of information synthesis, more systematic planning of scenarios, and better risk assessment in organizations. One of the strategy vice presidents commented: We had a tendency of coming up with three strategic scenarios and evaluating them in a qualitative manner. With this we are able to create dozens of them, subject them to models and find out what factors have the most impact. It does not decide our ultimate choice, but it makes our strategic imagination to grow wretchedly broad.

### *3.1 Measurement and Structural Models*

The quality of measurement model was evaluated using the confirmatory factor analysis. The seven-factor model demonstrated acceptable fit: $\chi^2(545) = 847.33$, p ¡ .001; $\chi^2/df = 1.55$; CFI = .94; TLI = .93; RMSEA = .047; SRMR = .051. Convergent validity was supported by all the factor loadings being.65 or greater and very significant. Composite reliability values ranged from .86 to .93. Average variance extracted for each construct exceeded .60, supporting discriminant validity.

The structural model tested hypothesized relationships. Model fit indices suggested good fit: $\chi^2(552) = 879.45$, p ¡ .001; $\chi^2/df$ = 1.59; CFI = .93; TLI = .92; RMSEA = .049; SRMR = .053. Fig. 2 presents the structural model with standardized path coefficients and significance levels.

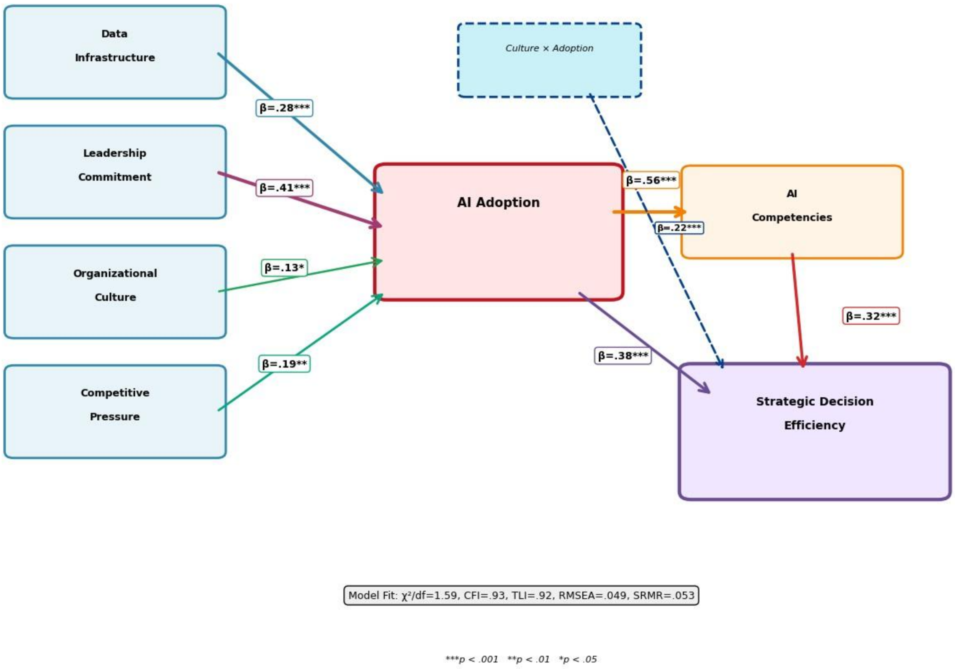


**Fig. 2: Structural Model Results with Standardized Path Coefficients**

Fig. 2 illustrates empirical relationships among framework constructs. Data infrastructure quality demonstrated a significant direct effect on AI adoption ($\beta$ = .28, $p$ < .001), supporting H1. Leadership commitment showed an even stronger effect

($\beta$ = .41, $p$ < .001), confirming H2. Organizational culture's effect on adoption was smaller ($\beta$= .13, $p$ < .05). Competitive pressure significantly predicted adoption ($\beta$ = .19, $p$ < .01).

Testing H3 required examining whether competitive pressure moderated the relationship between organizational readiness and AI adoption. Results indicated that competitive pressure significantly moderated the leadership commitment-adoption relationship ($\beta$ = .16, $p$ < .01) but not other relationships. Simple slopes analysis revealed that leadership commitment's effect on adoption was stronger when competitive pressure was high ($\beta$ = .52, $p$ < .001) compared to when low ($\beta$ = .30, $p$ < .01). Thus H3 received partial support.

AI adoption significantly predicted decision efficiency ($\beta$ = .38, $p$ < .001), supporting H4. H5 proposed that AI competencies mediate the adoption-efficiency relationship.

Bootstrapping procedures confirmed a significant indirect effect (indirect effect = .18,
95% CI [.12, .25]), with AI competencies showing significant paths from adoption ($\beta$ = .56, $p$ < .001) and to efficiency ($\beta$ = .32, $p$ < .001). The direct effect remained significant ($\beta$ = .20, $p$ < .01), indicating partial mediation.

H6 proposed that organizational culture moderates the adoption-efficiency relationship. The interaction term was significant ($\beta$ = .22, $p$ < .001), supporting H6. Simple slopes analysis showed that when organizational culture was highly supportive, AI adoption strongly predicted efficiency ($\beta$ = .56, $p$ < .001); when moderately supportive, the effect was moderate ($\beta$ = .38, $p$ < .001); when unsupportive, the effect was weak and non-significant ($\beta$ = .14, $p$ = .12). Fig. 3 illustrates the impact of culture on the consequences of AI adoption in organizations. These three lines refer to the correlation between decision efficiency and AI adoption on varying levels of culture support.

The highest slope indicates the presence of organizations whose culture is highly supportive and every step towards the adoption of AI would result in significant efficiency improvements. The second level is an average cultural support with good returns but low. The steepest line is the case of the traditional or resistant cultures in which despite the AI investments, the increase in the efficiency is negligible since cultural barriers do not allow utilizing it efficiently. The summary of hypothesis testing results is presented in Table 3.

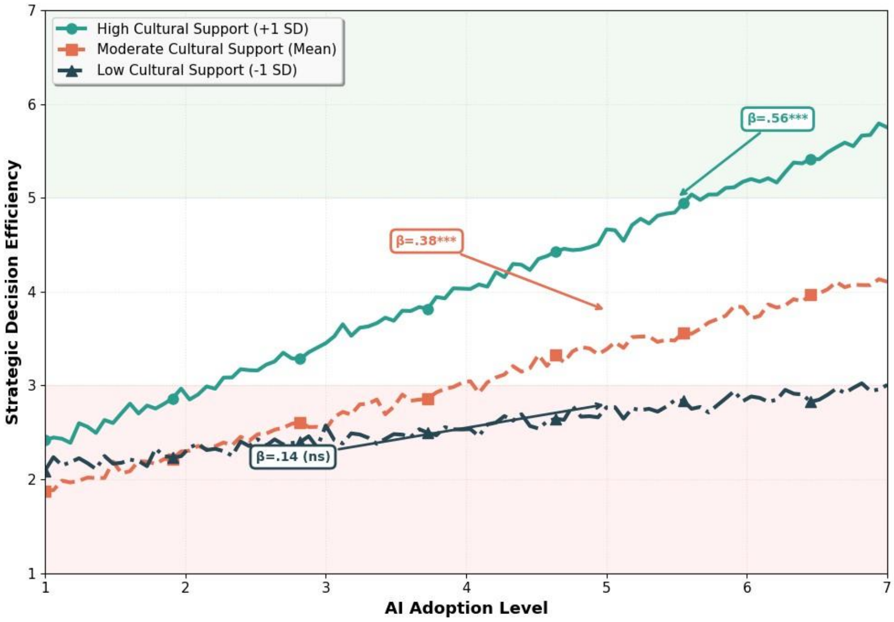

**Fig. 3: Moderating Effect of Organizational Culture on AI Adoption-Decision Efficiency Relationship**

**Table 3: Summary of Hypothesis Testing Results**

| **Hypothesis** | **Result** | **Evidence** |
|---|---|---|
| H1: Technological readiness positively influences AI adoption | Supported | $\beta = .28$, $p < .001$ |
| H2: Organizational factors predict AI adoption | Supported | $\beta$s range .13-.41, $p < .05$ |
| H3: Competitive pressure moderates organizational readiness-adoption relationship | Partially Supported | Moderates leadership effect ($\beta = .16$, $p < .01$) |
| H4: AI adoption positively impacts decision efficiency | Supported | $\beta = .38$, $p < .001$ |
| H5: AI competencies mediate adoptionefficiency relationship | Supported | Indirect effect = .18, 95% CI [.12, .25] |
| H6: Organizational culture moderates adoptionefficiency relationship | Supported | $\beta = .22$, $p < .001$ |

### *3.1 Qualitative Insights*

The case studies revealed five overarching themes: organizational readiness, leadership as a catalyst, context-specific implementation challenges in Nigeria, cultural adaptation needs, and changes in strategic decision-making. First, AI adoption required foundational capabilities, particularly strong data infrastructure. As a strategy director noted, poor data quality and disconnected systems delayed meaningful AI use, and firms attempting adoption without this base experienced repeated failures. Leadership also proved essential. A telecommunications strategy leader explained that their CEO's active involvement—asking difficult questions and defending budgets—was crucial, contrasting with organizations where passive leadership led to unsuccessful AI initiatives.

Implementation challenges specific to Nigeria further shaped adoption. Power outages, unreliable internet connectivity, and shortages of skilled AI professionals hindered real-time data access and increased operational costs. Cultural adaptation formed the fourth theme, with tensions emerging between algorithmic outputs and expert judgment. Managers emphasized that strategic professionals resist blindly following AI and instead combine human insight with algorithmic recommendations.Table 4 summarizes key characteristics across the five case organizations.

### *3.2 Integrated Discussion and Framework Refinement*

The combination of quantitative and qualitative results will help us to suggest a perfect framework. This combined framework is shown in Fig. 4.

The adoption efficiency relationship is not only direct, but also mediated, which indicates partial mediations. The role of organizational culture changes to critical moderator. Feedback loops consider the dynamism of processes in which the efficiency itself is acquired by AI as a means of acquiring resources to be further adopted. The framework specifically adds contextual aspects that are unique to emerging markets: reliability of infrastructure, access to talent, clarity of regulation and maturity of vendor ecosystems.

**Table 4: Cross-Case Summary of AI Adoption Characteristics**

| Organization | AI Maturity Level | Key Success Factors | Major Challenges | Strategic Impact |
|---|---|---|---|---|
| Bank | Early exploration | Strong leadership support; external partnerships | Data quality issues; regulatory uncertainty | Limited; mostly pilots |
| Telecom | Moderate adoption | Existing IT capabilities; competitive pressure | Cultural resistance; talent retention | Moderate; improved analysis |
| Consumer Goods | Moderate adoption | Innovation culture; resources | Infrastructure constraints; vendor dependence | Significant; enhanced forecasting |
| Energy | High (operational) Low (strategic) | Technical expertise | Siloed implementation; limited strategic integration | Minimal for strategy |
| Prof. Services | High adoption | Client demand; analytical culture | Change management | Substantial; transformed insights |

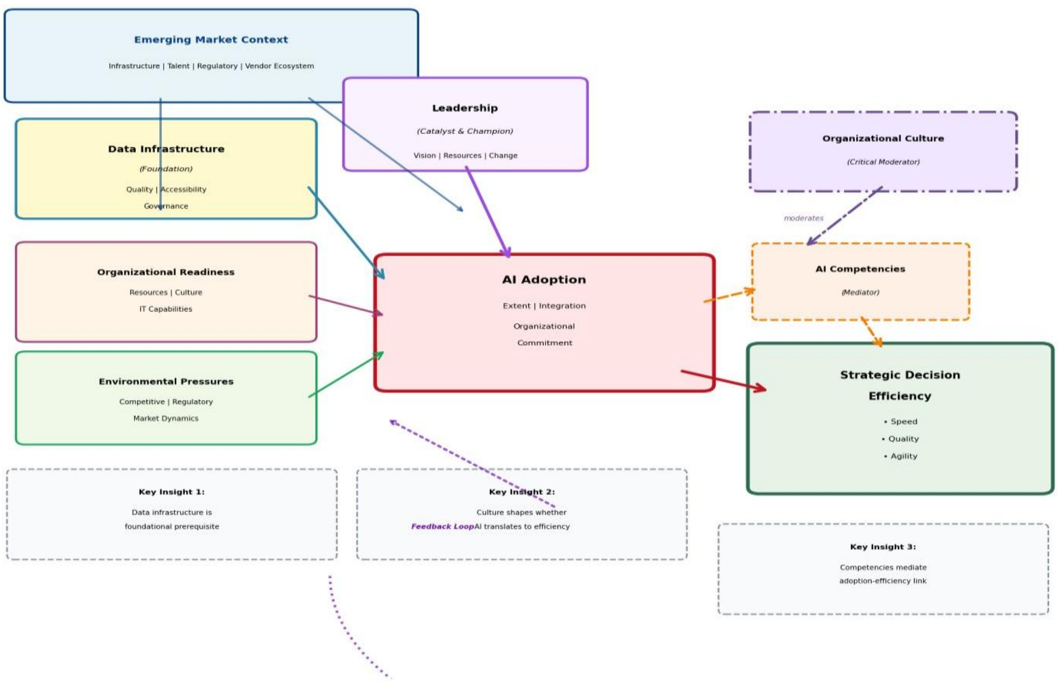


**Fig. 4: Integrated Framework for AI Adoption and Strategic Decision Efficiency**

Theoretical contributions range in various disciplines. In the case of technology adoption scholarship, we show that the TOE framework is applicable to AI though it should be narrowed to include the peculiarities of AI. To strategic management literature, we demonstrate that the effect of AI is dramatically based on organizational culture. In the case of emerging market research, we determine that there are certain contextual variables that influence the use of technology in environments with limited resources.

These have practical implications to various stakeholders. The leaders of the strategies are to understand that the use of AI needs to be accompanied by paying attention to data infrastructure, executive sponsorship, cultural adaptation, and capacity building. Before making serious investments in AI, organizations need to evaluate their readiness on various levels. Infrastructure limitation and lack of talents can be solved via innovative adaptation and strategic alliances of organizations in the Nigerian and African market. Findings are a priority to the policymakers, specifically, infrastructure development, regulatory clarity, and talent development. In the case of technology vendors, the study focuses on contextual adaptation, which are solutions developed in developed markets, which need alteration.

## 4.0 Conclusion

The study formed and tested an overall theory of adoption of AI in global strategy teams and its implications on the strategic decision efficiency of Nigerian and West African settings. Mixed-methods exploration allowed us to establish technological, organizational and environmental success factors to adoption and to show that the role of adoption is vital to both organizational culture and supplementary capabilities. The paper advances the TOE framework to the definition of AI usage as the strategic context, establishes the role of organizational culture as the critical moderator of the implemented AI, and adds to the emergent market literature by shedding light on contextual factors unique to African business contexts. The limitations are cross-sectional design, which does not allow causal inference, the study was based on Nigeria, and self-reported measures. Longitudinal designs that monitor the progression of AI adoption, a wider range of emerging markets, and how organizational culture can influence AI efficacy should be used in future studies.

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**Declarations**

**Ethics and Consent to Participate**

Not applicable.

**Consent to Publish**

Not applicable

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**Authors' Contributions**

Imam Akintomiwa Akinlade conceived the study, developed the theoretical framework, and supervised the overall research design. Musili Adeyemi Adebayo coordinated data collection and contributed to the analysis. Ahmed Olasunkanmi Tijani performed the quantitative modeling and interpretation. Chiamaka Perpetua Ezenwaka conducted the qualitative case studies and synthesis. Grace Fadeyi drafted the manuscript and refined the final submission.