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Adoption of Data Analytics and Artificial Intelligence in Ghanaian Enterprises: Implications for Organizational Performance

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Abstract: Despite AI and data analytics' growing importance for competitiveness, empirical evidence in Ghana is scarce. Organizations are urged to adopt digital transformation, but the link to performance is unclear. This study explores AI and analytics adoption in Ghanaian enterprises, assessing its impact on performance and identifying adoption barriers. A cross-sectional survey of 1,107 professionals, including HR managers, business leaders, and C-suite executives, was conducted. Adoption rates were analyzed using descriptive statistics, while correlation and multiple regression were employed to test the relationship between AI, data analytics, and organizational performance. Results show that 67% of enterprises have adopted AI, data analytics, or both, while 33% remain non-adopters. Among adopters, 30.3% integrate AI and analytics, 28.9% use analytics only, and 7.7% use AI only. Sectoral adoption varies, with Financial Services (85%) leading, while Retail and the Public Sector lag at 50%. Both AI and analytics significantly improve performance, with stronger results when integrated. Organizations should prioritize analytics as a foundation for AI, invest in workforce capability, and secure leadership commitment to scale adoption successfully. Wider adoption of AI and data analytics in Ghanaian enterprises has the potential to reshape work and service delivery across sectors contributing to national digital transformation. The findings advance understanding of how digital technologies influence performance in emerging market particularly Ghana. Its findings inform the design of strategies and policies that harness data-driven decision-making to drive organizational performance.

Keywords: Business Intelligence**;** Data Analytics**;** Artificial Intelligence**;** Organizational Performance; ICT; Enterprise systems

I. Introduction

The convergence of Artificial Intelligence (AI) and Data Analytics has emerged as a strategic driver of organizational performance across industries (Morley et al., 2020; Hossain et al., 2024). According to Gartner (2018) this has given rise to what is commonly referred to as augmented or intelligent analytics, where AI technologies work alongside human users to process and interpret data more efficiently. Studies have shown how AI and big data analytics are reshaping performance benchmarks within organizations (Davenport & Ronanki, 2018;Loso Judijanto et al., 2024). Hossain et al. (2024) noted that this combination enables decision-makers ensures that analytics outputs inform strategy.

The integration of AI and analytics in Business Intelligence (BI) has yielded a profound impact, notably through the emergence of self-service analytics. By democratizing access to data, these user-centric tools enable non-technical professionals, such as HR managers, marketers, and operations teams, to independently explore datasets and generate visualizations without requiring extensive technical expertise (Kassa & Worku, 2025). This paradigm shift has facilitated a broader range of stakeholders to engage in evidence-based decision-making, thereby cultivating a culture of data literacy within organizations

Additionally, the incorporation of AI into BI systems has shown tangible results in sectors like healthcare, finance and education. In education, for example, data analytics platforms are being used to personalize learning journeys and improve student outcomes through real-time feedback and adaptive content (Li et al., 2022). AI-powered chatbots and virtual assistants help patients with routine inquiries, freeing up healthcare professionals to focus on complex cases (Adamopoulou, 2020).

However, in African markets, the integration of these technologies remains inconsistent. Some research points to the benefits of AI and analytics in enhancing productivity, innovation and supporting evidence-based decision-making (Apondi & Chege, 2023; Kassa & Worku, 2025). Other studies caution that without proper integration, ethical governance, or cultural alignment, these technologies may deliver suboptimal results (Olayinka, 2022; Aldoseri et al., 2023). Yet, much of this evidence is drawn from advanced economies, raising a further gap in understanding how such risks and benefits manifest in developing contexts such as Ghana (Zong & Guan, 2024; Aderibigbe et al., 2023; Mohammadi, 2025). Consequently, the application of such findings could be limited, given the differences in infrastructure, workforce capacity, and levels of technological and economic development. Therefore, this study contributes to existing literature gap by empirically investigating the adoption impact of artificial intelligence and data analytics on organizational performance in Ghanaian enterprises. First, assess the impact of data analytics on organizational performance across organizations; secondly, examine the effect of artificial intelligence adoption on organizational performance; thirdly, evaluate the impact of artificial intelligence and data analytics on organizational performance; Lastly, identify organizational challenges facing adoption of data analytics and AI in organizations.

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This study is structured into key sections. Following a comprehensive literature review that establishes the foundation of our research, we develop hypotheses to guide our investigation. The methodology section outlines the research design, data collection, and analysis procedures employed to test our hypotheses. The results and discussion section presents our findings and interprets their implications, while the summary and recommendation section synthesizes the key insights and provides actionable recommendations for stakeholders.

II. Theoretical and Empirical Review

Resource-Based View (RBV)

The Resource-Based View (RBV), introduced by Wernerfelt (1984) and expanded by Barney (1991), posits that organizations gain sustained competitive advantage through internal resources that are valuable, rare, inimitable and non-substitutable (VRIN). Within this perspective, technologies such as AI and data analytics systems can serve as strategic assets when they enable firms to optimize operations and make data-driven decisions. In the case of Ghana, RBV offers a useful lens to explain how firms adopting AI and analytics can strengthen competitiveness. Organizations that effectively combine advanced analytics infrastructure with supportive systems have reported superior performance outcomes (Darke, 2024). This aligns closely with the present study's focus on assessing the impact of AI and data analytics adoption on organizational performance. However, while RBV underscores the strategic value of technology, it places less emphasis on the human capabilities required to maximize these tools.

Human Capital Theory

Complementing this is Human Capital Theory, which emphasizes the role of employee skills, knowledge, and training in driving productivity and innovation. Originally developed by Schultz (1961) and expanded by Becker (1993), the theory argues that investments in human capabilities, such as education and training, enhance productivity and contribute to economic growth. The theory suggests that workforce competencies are critical enablers of organizational performance and economic development.

For Ghanaian organizations, HCT provides an appropriate framework for understanding barriers to technology adoption. Challenges such as insufficient data literacy, inadequate training, and employee resistance to change hinder the realization of potential performance gains from AI and analytics. In the context of data analytics and artificial intelligence, this theory has gained renewed significance. The successful integration of analytics and AI does not solely depend on technological infrastructure but also on employees' capacity to interpret data insights and apply them strategically (Brynjolfsson & McElheran, 2016). This makes HCT especially relevant to the present study's objective of identifying organizational barriers to adoption.

Technology Acceptance Model (TAM)

According to the Technology Acceptance Model (TAM), developed by Davis (1989), explains a behavioural view for understanding user acceptance of new technologies based on two core perceptions: usefulness and ease of use. Individuals are more likely to adopt technology if they believe it will enhance their job performance and find it intuitive and accessible. When applied to AI-driven performance evaluation systems, TAM suggests that successful implementation in organizations depends not only on the availability of technology but also on how employees and managers perceive its relevance and usability. In practice, tools that support performance feedback, analytics dashboards, or AI-assisted reports are more likely to be used when they align with users' work expectations and minimize complexity (PwC, 2024). The integration of these three theories provides a holistic framework to examine data analytics and AI on organizational performance in the Ghanaian business economy.

Figure 1: Theoretical Model framework

Source: Adapted from literature review Barney (1991), Davis (1989), Becker (1993), Schultz (1961)

Development of Hypothesis

Data Analytics and Organizational Performance (DA-OP)

The relationship between data analytics and organizational performance has received growing attention as firms seek to convert raw data into meaningful insights. The Resource-Based View (RBV) posits that organizations can achieve sustained competitive

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advantage when they possess valuable, rare, inimitable, and non-substitutable (VRIN) data analytics capabilities (Barney, 1991). Such tools improve decision-making processes, identify patterns, and enhance predictive planning, thereby driving organizational efficiency and productivity. Complementing this, Human Capital Theory emphasizes that the benefits of data analytics are maximized when employees possess the skills to interpret insights and apply them strategically (Schultz,1961).

Empirical evidence further supports these theoretical claims. Studies in some emerging economies demonstrate that data-driven decision-making enhances innovation(Brynjolfsson & McElheran, 2016). In Ghana, early research has shown that organizations that integrate data analytics into operations are more likely to report gains in efficiency and competitiveness (Darke, 2024; Asare & Boateng, 2021). However, despite the acknowledged potential, adoption remains uneven, which underscores the need for empirical testing of this relationship in the Ghanaian businesses.

Based on these theoretical and empirical findings, the study proposed the following hypothesis:

H₁: *Data analytics adoption positively and significantly affects organizational performance*.

Artificial Intelligence and Organizational Performance (AI-OP)

The adoption of artificial intelligence (AI) has been increasingly associated with improvements in organizational performance across industries. From the Resource-Based View (RBV), AI constitutes a strategic resource that meets the criteria of being valuable, rare, inimitable, and non-substitutable (Barney's (1991). When embedded within organizational systems and aligned with strategic objectives, AI enhances decision-making, streamlines operations, reduces costs, and fosters innovation. This positions AI as a critical driver of sustained competitive advantage.

Empirical evidence supports these claims. Kassa and Worku (2025) reported that firms adopting AI-driven systems demonstrated significant productivity gains, particularly when AI was integrated into core business processes. Similarly, Badghish and Soomro (2024), studying small and medium-sized enterprises (SMEs), found that organizational acceptance of AI technologies predicted successful adoption, which in turn positively influenced performance outcomes. However, adoption rates remain inconsistent due to infrastructural and skills-related challenges, underscoring the need for further empirical testing in this context.

Drawing on both theoretical reasoning and prior empirical findings, the study proposed the following hypothesis:

H_2: *Artificial intelligence adoption positively and significantly affects organizational performance.*

Artificial Intelligence and Data Analytics on Organizational Performance (AI+DA-OP)

According to the Resource-Based View (RBV) organizational performance is driven by the acquisition and strategic deployment of unique, valuable, and hard-to-imitate resources. Within this framework, both data analytics and artificial intelligence are seen as knowledge-based assets that enhance competitive advantage. While data analytics enables firms to extract insights ranging from descriptive and diagnostic to predictive and prescriptive, AI amplifies this value by providing adaptive, autonomous, and intelligent decision-making capabilities (Malatji et al., 2020). Through machine learning, automation, and real-time simulation of human reasoning, AI can elevate the impact of analytics by enabling organizations to act proactively and efficiently in dynamic environments.

Empirical research supports this synergistic effect. Naz et al. (2024) found that organizations that combined AI and data analytics capabilities reported superior performance outcomes in terms of innovation and responsiveness. Similarly, Kassa and Worku (2025) highlighted that AI's capacity for continuous learning and evolution transforms it from a supportive tool into a performance catalyst, magnifying the strategic value of analytics systems.

Grounded in this theoretical and empirical evidence, the study proposed the following hypothesis:

H_3: *Artificial Intelligence and data analytics positively and significantly affect organizational performance.*

Organizational Challenges in Adoption of AI and Data Analytics

The adoption of technologies such as artificial intelligence (AI) and data analytics is often constrained by organizational readiness and contextual barriers. The Technology Acceptance Model (TAM) developed by Davis (1989) emphasizes perceived usefulness and ease of use as key determinants of adoption. TAM has been widely used to predict and explain user acceptance of various technologies and its principles have been extended and applied in numerous studies. Research shows that despite the recognized benefits of AI and analytics, challenges related to organizational culture, technical capabilities, and financial investment can hinder adoption (Innovate Africa Network, 2025; Brookings, 2025; IDCA, 2025). For developing economies such as Ghana, these barriers are particularly pronounced given resource constraints and skills gaps.

Conceptual Framework

This conceptual framework illustrates the relationship between data analytics and artificial intelligence on organizational performance, with organizational challenges serving as a moderating variable. The framework provides a structured basis to guide the study's objectives.

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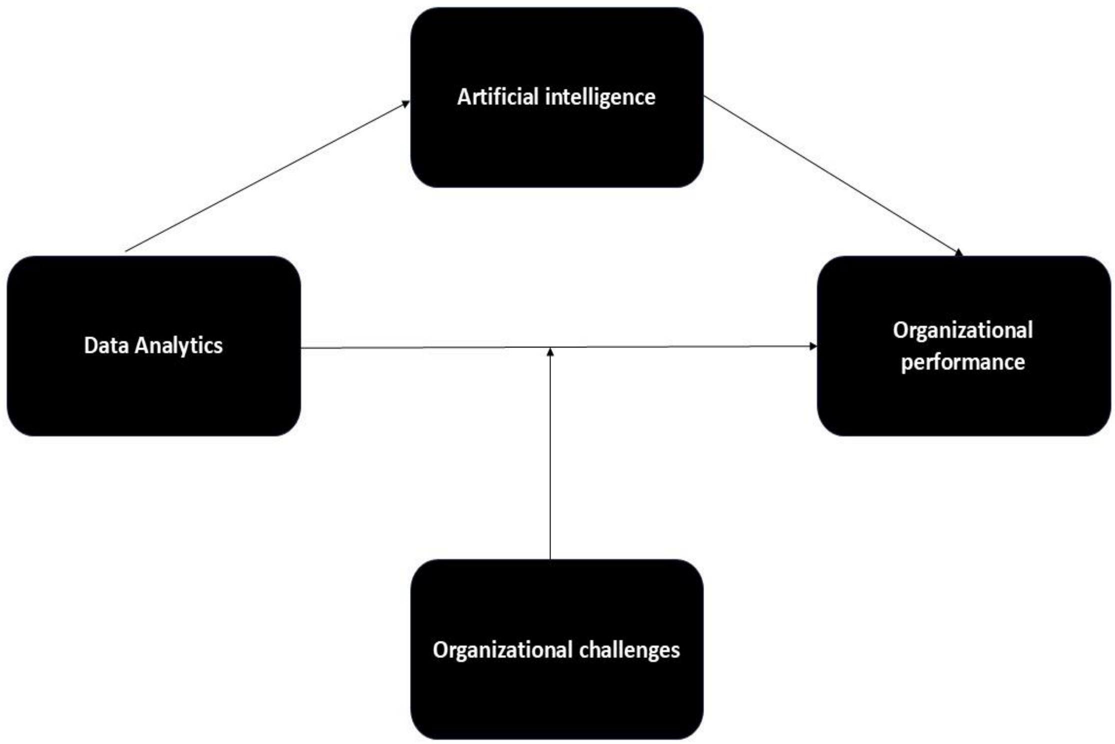
Figure 2: Conceptual model



Source: Author's own construct, 2025

Table 1: Definitions of latent variables

Latent Variable	Indicators	Variable Type	Definition	Author(s)
Data Analytics	Dashboards, Real-Time Reporting, Predictive Analytics	Independent Variable (IV)	Tools and practices used to extract insights from data for timely and informed decision-making.	Dinh et al. (2020); Asare & Boateng (2021)
Artificial Intelligence	Automation Tools, AI-assisted Systems, Machine Learning	Independent Variable (IV)	Technologies that enable intelligent process automation and advanced decision support.	Badghish & Soomro (2024); Kassa & Worku (2025)
Organizational Challenges	Cost Constraints, Leadership Support, Infrastructure Readiness, high cost, unclear benefits, lack of technical expertise		Barriers or enablers that influence the success of AI and analytics implementation.	Brookings, 2025;IDCA, 2025
Organizational Performance	Productivity, Innovation & creativity, Decision making, customer satisfaction, Employee retention, Process efficiency	Dependent Variable (DV)	The tangible and perceived improvements in business outcomes resulting from technology adoption.	Malatji et al. (2020);Naz et al. (2024)

Source: Literature review

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III. Methodology

Research Design

A cross-sectional non-probability sampling strategy was employed. The choice of non-probability methods was guided by the exploratory nature of the research and the difficulty of obtaining a complete sampling frame of all professionals relevant to this study. Non-probability approaches are frequently used in organizational and management research where the population of interest is specialized, dispersed, or difficult to fully enumerate (Ahmad, 2025).

The study primarily used purposive sampling, as the survey targeted specific professionals such as HR managers, business leaders, and C-suite executives whose perspectives were central to the research objectives. However, since the survey was distributed via online platforms (Facebook, LinkedIn, WhatsApp, and one-on-one chats), convenience sampling also occurred often recommended for its dependence on respondents' accessibility and willingness (Makwana et al., 2023). In addition, snowball sampling technique was employed, as some participants shared the survey link within their professional networks, thereby broadening the reach. The integration of purposive, convenience, and snowball techniques enabled the researcher to balance targeted inclusion with wider outreach.

Sample Size

Ghana's business environment is broad and diverse; however, the purpose of this research was to examine specific relationships between data analytics, artificial intelligence, and organizational performance. Therefore, this study adopted an analytical applied research approach focusing on targeted domain. A power analysis using G*Power 3.1 was conducted to determine the minimum required sample size for multiple regression analysis. Using an alpha level of 0.05, a statistical power of 0.80 and a medium effect size ($f^2 = 0.15$) as per Cohen (1988), the recommended minimum sample size was calculated to be 85 participants based on the four predictors (data analytics, artificial intelligence, organizational challenges and performance).

However, using Cochran's formula for large populations (95% confidence, with a conservative proportion of p=0.50, and an achieved sample size of n=1,107) yielded an approximately three (3) percent margin of error for national-level estimates.

Determination of Cochran's Margin of Error (MOE) for large population

$$MOE = \mathrm{z}\frac{\sqrt{\mathrm{p}(1-\mathrm{p})}}{\mathrm{n}}$$

with z=1.96 for 95% confidence level, p=0.50, n=1107

MOE=

$$1.96 \times \sqrt{\frac{0.5(1-0.5)}{1107}}$$

$=1.96 \times \sqrt{0}.000259$

$=1.96 \times 0.01503$

$= 0.0295$

$=2.95\%$

Cochran's required 'n' where e=0.03;

n$_O$=

$$\frac{\boldsymbol{z^2 p(1-p)}}{\boldsymbol{e^2}}$$

$$\frac{\mathbf{1.96^2 \times 0.25}}{\mathbf{0.03^2}}$$

$$\frac{3.8416 \times 0.25}{0.0009}$$

$$\frac{0.09604}{0.0009}$$

$=1067$

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Data Collection and Procedure

The target respondents included HR professionals, business leaders, data users, and executives across diverse sectors (Telecommunications, Financial sectors, Healthcare and Pharmaceuticals, Manufacturing and Supply Chain, Transportation and Logistics, Oil, Gas and Energy, Retail and E-Commerce, Human Resources, and Public Sector) in Ghana.

Data was collected through online survey, distributed through social media channels such as LinkedIn, Facebook, and professional WhatsApp groups. Some participants were reached through one-on-one online chats on these platforms. These platforms were chosen because of the direct access to relevant professionals, especially in the absence of centralized online business directories.

The survey comprised three major sections: background information (job role, industry, experience level and organizational size), AI and analytics adoption on performance impact. A 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree) was adopted, with the neutral option intentionally excluded to promote more decisive responses, in line with Versta Research (2016) recommendations for enhancing the reliability and clarity of business survey data. The survey was in the field between July 4 and August 5, 2025.

Data Processing and Analysis

The collected survey data was first exported into Excel and subsequently processed in Microsoft Power BI for initial cleaning. Data cleaning involved sorting, editing, and the removal of incomplete or erroneous entries generated during questionnaire completion, with blank responses systematically excluded. The cleaned dataset was then coded and imported into IBM SPSS Statistics (version 27) for further analysis. Both descriptive and inferential statistical techniques were applied to examine the data and address the research objectives.

Model Specification

Model specification was formulated to define and test the relationships among the study variables. Based on the review literatures the following regression model was estimated for this study:

$OP=\beta_0+\beta_1(X_1) + \beta_2(X_2) +\epsilon$

Where:

OP = Orgnaizational performance

DA = Data analytics

AI = Artificial intelligence

β = coefficients and

ε = Error Term

Evidence and results

Demographic Profile

A total of 1107 professionals from various enterprises in Ghana participated in the study. The demographic characteristics of the sample are detailed in Table 2.

Table 2: Demographics of respondents

Profile	**Frequency (N)**	**Percentage (%)**
Gender		
Male	572	51.7
Female	535	48.3
Designation		
Business Leader	224	20.2
Executive(C-suite)	280	25.3
HR Managers	603	54.5
Years of work Experience (Current role)		
Less than 1 year	83	7.5

1-3 years	260	23.5
4-6 years	277	25.0
7-10 years	222	20.1
Above 10 years	265	23.9
Organization's size		
Less than 50	224	20.2
50 – 199	280	25.3
200+	603	54.5
Industry		
Financial sector	203	18.3
Healthcare & Pharmaceuticals sector	96	8.7
Human Resources sector	168	15.2
Manufacturing & Supply Chain sector	109	9.8
Oil, Gas & Energy sector	86	7.8
Public sector	193	17.4
Retail & E-commerce sector	84	7.6
Telecommunication sector	79	7.1
Transportation & Logistics sector	89	8.0
Total	**1107**	**100.0**

Source: Field survey (2025)

The sample was characterized by a near-equal distribution of male (51.7%) and female (48.3%) respondents. The largest group of participants were HR Managers (54.5%), followed by (C-suite) Executives (25.3%) and Business Leaders (20.2%). The high participation rate from human resources professionals was noteworthy, as it suggested that the adoption of data-driven technologies is a matter of significant concern within the human capital management domain. This finding reframes the discussion of technology adoption beyond purely technical or operational spheres to include the critical human and organizational change management aspects.

The respondents represent a broad range of experience levels, with a relatively uniform distribution across sectors, with slightly more individuals in the 4-6 years (25.0%) and above 10 years (23.9%). This diversity in experience provided a rich perspective, incorporating both the views of seasoned professionals and those new to their roles. A majority of the participants (54.5%) were from large organizations with more than 200 employees, while the remaining were from small (20.2%) and medium-sized (25.3%) firms. The dominance of large enterprises in the sample implied that the study's conclusions may be more directly applicable to well-resourced, large-scale operations in Ghana rather than an extensive small and medium-sized enterprise (SME) sector, which may face unique constraints not fully captured by this sample.

Adoption of AI and Data Analytics

This study reveals that adoption of AI and data analytics is advancing across Ghanaian enterprises, though unevenly across sectors. Table 3 presents the overall adoption distribution, while figure 3 shows sector-specific adoption levels.

Table 3. Adoption of AI and Data Analytics

Adoption	Frequency(N)	Percentage (%)
AI and Analytics only	336	30.3
Analytics only	320	28.9
AI only	85	7.7
Total Adopters	741	67.0

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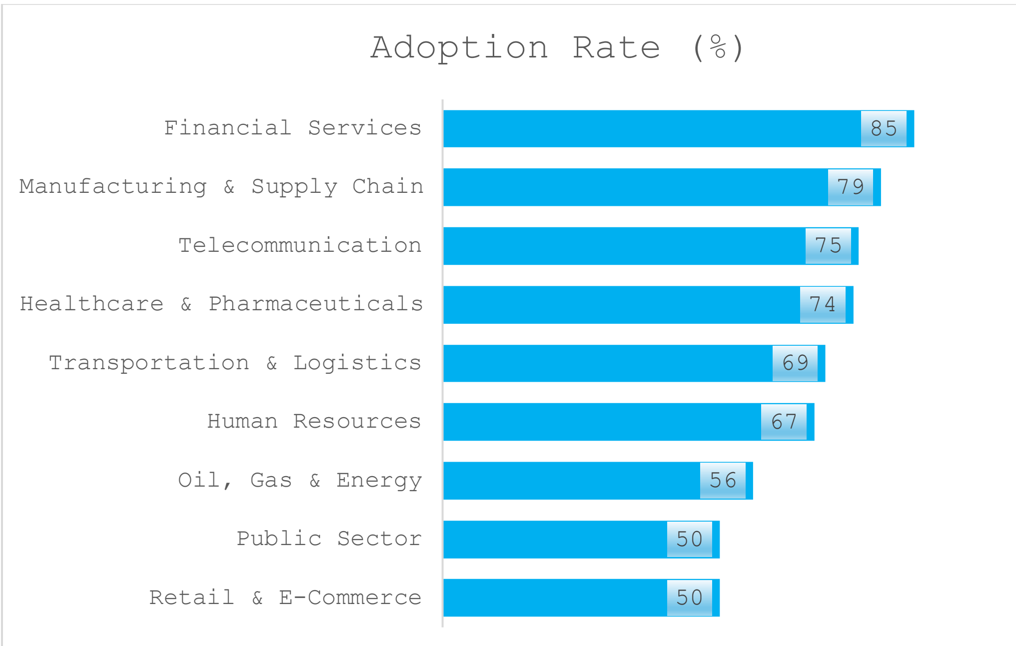
Non-Adopters	366	33.0
Total Respondents	**1,107**	**100.0**

Source: Field survey (2025)

Table 3 presents the overall adoption status of AI and data analytics, indicating that 67 percent of Ghanaian enterprises have adopted either AI, data analytics, or both, while 33 percent remain non-adopters. Among adopters, integrated AI-and-analytics usage (30.3%) slightly exceeds analytics-only adoption (28.9%), whereas AI-only adoption is comparatively lower (7.7%). This pattern reflects a stepwise progression in digital maturity, suggesting that AI only has not yet achieved widespread diffusion as a standalone capability but functions best when layered onto established analytics practices in Ghanaian enterprises.

Figure 3: Sectoral Adoption



Source: Field survey (2025)

Figure 3 presents adoption rates across sectors, revealing a hierarchy of digital readiness. Financial Services (85%), Manufacturing (79%), and Telecommunications (75%) lead adoption. Mid-tier adoption is seen in healthcare (74%) and Transportation (69%), while lagging adoption in Retail (50%) and the Public Sector (50%) is still in experimental phases rather than achieving large-scale deployment. Sectoral variations further underscore uneven readiness, with forthcoming adoption expected to concentrate in human resources, oil and energy, and public sector organizations.

Reliability and validity

Before proceeding with inferential analysis, the reliability of the measurement instruments for each construct was assessed using Cronbach's alpha coefficient. Reliability is a measure of internal consistency, indicating whether the items within a scale are reliably measuring the same underlying construct (Korhonen et al., 2022). As a general rule, a Cronbach's alpha value of 0.70 or higher is considered acceptable.

The results of the reliability analysis, presented in the table 4, indicate that all four constructs demonstrated higher internal consistency.

Table 4: Reliability Results

No	Construct	No. of items	Cronbach's alpha
1	Data analytics	7	.840
2	Artificial Intelligence	6	.925
3	Organizational performance	6	.878
4	Organizational challenges	7	.795

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Source: Field survey (2025)

The data analytics construct with a Cronbach's alpha of 0.840, showed a strong level of internal consistency. The artificial intelligence construct, with a coefficient of 0.925, demonstrated particularly high reliability, suggesting that the items used to measure AI adoption were highly correlated and accurately captured the intended concept. Similarly, the organizational performance and organizational challenges constructs also exhibited strong reliability with alpha values of 0.878 and 0.795, respectively. The high reliability of all constructs provides a firm foundation for the subsequent inferential statistical analysis, strengthening the confidence that the relationships found between the variables are a true reflection of the phenomena.

IV. Correlation Results

The correlation coefficients were interpreted according to Cohen's (1988) guidelines, which provided a framework for understanding the strength of associations. The results are presented in table 5 below:

Table 5: Correlation Analysis

	OP	**DA**	**AI**
OP	1		
DA	.401**	1	
AI	.405**	.456**	1

** Correlation is significant at the 0.01 level (2-tailed).

Source: Field survey (2025)

As shown in Table 5, all pairs of variables are positively and significantly correlated at the 0.01 level. Organizational Performance (OP) has a statistically significant positive correlation with Data Analytics (DA) ($r=0.401$, $p<0.01$) and with Artificial Intelligence (AI) ($r=0.405$, $p<0.01$). These findings provided initial support for the study's hypotheses, indicating that higher levels of DA and AI adoption are associated with organizational performance.

A particularly notable finding is the strong positive correlation between DA and AI ($r=0.456$, $p<0.01$). This relationship is stronger than the correlation of either variable with organizational performance, suggesting a profound symbiotic relationship between these two technologies. The results indicated within Ghanaian enterprises, the adoption of DA and AI is not occurring in isolated silos. Instead, enterprises that invest in one are more likely to be investing in the other, viewing them as complementary components of a unified digital strategy.

Regression Analyses

In order to estimate relationships between DA and AI on performance, the study employed an ordinary least square (OLS) estimation approach. The general OLS regression model employed was specified as;

$OP=\beta_0+\beta_1(X_1) + \beta_2(X_2) +\epsilon$

The final estimable regression model is stated as follows;

$OP=\beta_0+\beta_1(DA)+\beta_2(AI)+\epsilon$

Where OP is organizational performance, DA as data analytics, AI represents artificial intelligence and β and ϵ indicate coefficient and error term. The results of the regression analysis are presented in Table 6 below;

Table 6: Model summary

Model	**R**	**R Square**	**Adjusted R square**	**Std. Error of the Estimate**	**Durbin Watson**
1	.472[a]	.223	.221	1.51557	2.077

a. Predictors: (Constant), DA, AI

b. Dependent variable: OP

The model summary results in Table 6 revealed that the independent variables (Data Analytics, Artificial Intelligence) collectively account for 22.3% of the variance in Organizational Performance, as indicated by the R-squared value of 0.223. In social science and business research, where organizational performance is influenced by a multitude of complex and often unmeasured factors, explaining over one-fifth of the variance with just two variables is considered a meaningful and substantial finding (Ozili, 2023).

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The adjusted R-squared of 0.221 further confirms the model's explanatory power. The validity of a regression model relies on the absence of autocorrelation and serial correlation in the residuals. According to Turner (2019), a Durbin-Watson statistic ranging from 1.5 to 2.5 indicates satisfactory model performance. The results yielded a Durbin-Watson statistic of 2.077, which approximates the ideal value of 2.0, indicating that the residuals had no autocorrelation, thereby satisfying a key assumption of linear regression.

Table 7: ANOVA[a]

Model		Sum of squares	Df	Mean square	F	Sig
1	Regression	458.902	2	242.951	105.755	.001[b]
	Residual	1695.408	738	2.297		
	Total	2181.310	740			

a. Dependent Variable: OP

b. Predictors:(Constant), DA, AI

The ANOVA results presented in Table 7 show that the regression model is statistically significant ($F = 105.755$, $p < .001$), indicating that the influence of DA and AI has a strong and meaningful explanation of organizational performance. This result further confirms that the predictors, when considered together, significantly enhance the model's explanatory power, thereby validating the general framework of this study.

Table 8: Regression Coefficients[a]

Model	Unstandardized coefficients Beta		Standardized coefficients			95.0% confidence interval for B		Collinearity Statistics	
	B	Std. Error	Beta	T	Sig	Lower bound	Upper bound	Tolerance	VIF
(Constant)	5.879	.249		23.618	<.001	5.390	6.368		
AI	.178	.023	.280	7.685	<.001	.133	.223	.792	1.262
DA	.199	.027	.273	7.487	<.001	.147	.251	.792	1.262

a. Dependent Variable: OP

Table 8 results show that both data analytics and artificial intelligence are statistically significant predictors on organizational performance.

***Hypothesis H_1:** Data analytics adoption positively and significantly affects organizational performance.*

The regression analysis showed that data analytics adoption had a significant positive effect on organizational performance ($\beta = 0.199$, $p < .001$). These findings support H_1, confirming that greater adoption of data analytics is associated with improved organizational performance.

This result aligns with prior studies emphasizing the strategic value of data analytics capabilities. Consistent with the Resource-Based View (RBV), data analytics represents a VRIN resource that enhances operational decision-making and supports predictive planning, thereby improving productivity and performance (Brynjolfsson & McElheran, 2016; Dinh et al., 2020). Similarly, grounded in Human Capital Theory, the ability of employees to interpret and apply analytics effectively has been shown to increase organizational value (Becker, 1993; Barney, 1991). This means the final hypothesis is supported by the study so we fail to reject the hypothesis.

***Hypothesis H_2:** Artificial intelligence adoption positively and significantly affects organizational performance.*

The regression analysis revealed that AI adoption had a significant positive effect on organizational performance, with an unstandardized coefficient ($B = 0.178$, $p < .001$). The standardized beta coefficient ($\beta = 0.280$) indicates a moderate effect size.

This finding is consistent with the Resource-Based View (RBV), which asserts that organizations gain a sustained competitive advantage when they possess valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). AI capabilities qualify as such strategic resources when integrated into organizational systems and aligned with business objectives, as they streamline operations and innovation strategy. Empirical evidence supports this perspective: Kassa and Worku (2025) demonstrated that AI-driven firms experienced productivity gains when AI was embedded into their core processes, while Badghish and Soomro (2024) also opined that successful AI adoption significantly enhanced organizational outcomes through technology acceptance and

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integration. Therefore, findings support H_2, confirming that the adoption of artificial intelligence is also a significant driver of organizational performance.

Hypothesis H_3**:** *Artificial intelligence and data analytics positively affect organizational performance.*

Artificial Intelligence and data analytics positively affect organizational performance. As confirmed by the overall model's statistical significance ($F = 105.755$, $p<.001$), the combined effect of both DA and AI is a strong predictor of organizational performance. This finding supports H_3 and highlights the synergistic value of adopting both technologies.

The results correlate with the Resource-Based View (RBV), which emphasizes that unique hard-to-imitate resources are critical drivers of sustained competitive advantage (Barney, 1991). Both DA and AI qualify as such resources: DA provides descriptive, diagnostic, predictive, and prescriptive insights, while AI introduces adaptive, autonomous, and intelligent decision-making capabilities that amplify the impact of analytics.

Empirical evidence further supports these findings. Naz et al. (2024) and Kassa and Worku (2025) reported AI's ability to continuously learn and evolve transforms it from a supportive tool into a performance catalyst, significantly enhancing the value of analytics in organizational settings. The synergy between DA and AI, therefore, positions organizations to act proactively, fostering sustainable competitive edge.

Finally, both variables had a significant impact; a comparison of the standardized beta coefficients indicated further relative contributions. Data analytics (Beta = 0.199) had a slightly stronger relative effect on organizational performance than artificial intelligence (Beta = 0.178). This subtle but important difference suggested that, in the Ghanaian business environment, the foundational practices associated with DA may be a more pervasive and immediate driver of performance than the more advanced applications of AI.

Organizational Challenges

This study also investigated the primary reasons for non-adoption of DA and AI within enterprises. The findings are challenges reported by non-adopters, summarized in table 9;

Table 9: Organizational challenges (Non-Adopters)

No	Items	Frequency(N)	Percentage (%)
1	High cost	52	14.2
2	Lack of technical expertise	83	22.7
3	Unclear benefits	25	6.8
4	Low digital infrastructure	46	12.6
5	Leadership not prioritizing it	160	43.7
	Total	**366**	**100**

Source: field survey (2025)

From table 9, the most significant barrier identified was "Leadership not prioritizing it," cited by 43.7% of respondents. This shows that the primary bottleneck to technology adoption is not financial or technological, but rather cultural and strategic. While "High cost" was cited by some, it was far less significant than the lack of a clear strategic mandate from the top.

The second most-cited challenge was "Lack of technical expertise" (22.7%). This is likely a direct consequence of the top-ranking challenge. When leadership does not prioritize technology adoption, it fails to invest in the training, recruitment and talent development necessary to build the required in-house capabilities. The finding that "Unclear benefits" is the least significant barrier (6.8%) suggested that most business leaders are aware of the value proposition of these technologies, yet they fail to translate this awareness into concrete action and investment. This creates a causal chain where strategic inertia is the root cause that gives rise to the other challenges, particularly the human capital gap.

V. Conclusions and Recommendations

Based on the findings of this study, three main conclusions can be drawn. First, the adoption of data analytics and artificial intelligence were proven as significant drivers of improved organizational performance in the Ghanaian business. Enterprises that proactively invest in and integrate these technologies are more likely to achieve superior performance outcomes.

Second, the relationship between data analytics and artificial intelligence is fundamentally synergistic. Digital transformation requires a holistic approach where data analytics capabilities are established first to create the necessary infrastructure and data-driven culture to aid effective deployment and maximization of more advanced AI systems.

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Third, the most critical hurdles to technology adoption are not purely technical or financial. According to the study, the root cause of non-adoption in Ghanaian enterprises is a strategic and human capital issue. A lack of clear, top-down leadership prioritization hinders investment in the necessary training and talent development, which in turn creates a skills gap that becomes a significant barrier. Accordingly, we propose the following recommendations. Business leaders should adopt a value-driven strategy, viewing technology as a strategic investment rather than a cost center. By championing digital transformation and building a robust data analytics infrastructure. Policymakers should support education and training initiatives to build a pipeline of local talent in data analytics and AI, which would drive national competitiveness and socioeconomic development.

Ethics Approval

This study did not require formal ethics review board clearance, as it involved a non-clinical, low-risk organizational survey. No sensitive personal or health-related data were collected. The research was designed to ensure confidentiality and anonymity, with all responses aggregated for analysis.

Consent to Participate

All respondents, who were most HR managers, business leaders, and C-suite executives, participated voluntarily after being informed of the study's purpose. Participation was motivated by professional interest in the findings, and respondents were assured they would receive a copy of the research report upon completion. Informed consent was obtained, and the data collected were used strictly for research and professional knowledge-sharing purposes.

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Competing Interests

The author declares no competing interests.

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