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Artificial Intelligence Tools and Task Automation as Predictors of Office Management Efficiency in Small and Medium Enterprises in Rivers State, Nigeria

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***Abstract* —The productive potential of artificial intelligence (AI) tools and task automation for organisational efficiency is now well-established in large enterprise and banking contexts, yet it remains empirically underexplored in the administrative operations of small and medium enterprises (SMEs) in sub-Saharan Africa. This study investigates the extent to which AI tool adoption and task automation independently predict office management efficiency in SMEs in Rivers State, Nigeria, and identifies the structural barriers constraining this transition. Grounded in the Technology Acceptance Model (TAM) as an interpretive framework, the study employs a descriptive survey design with data collected from 312 validated respondents drawn through stratified random sampling from 4,820 registered SMEs in Port Harcourt and its environs. A structured questionnaire independently validated for content validity by five domain experts and pilot-tested with 25 practitioners returned Cronbach's alpha coefficients of 0.87, 0.84, and 0.89 for the three principal scales, each exceeding the 0.80 threshold recommended for published research (Lance et al., 2006). Multiple regression analysis confirmed that AI tool adoption ($\beta = 0.431$, $t = 4.954$, $p < .001$) and task automation ($\beta = 0.368$, $t = 3.957$, $p < .001$) are statistically significant positive predictors of office management efficiency, jointly accounting for 34.8 percent of variance (Adjusted $R^2 = 0.348$; $F(2, 309) = 47.83$, $p < .001$). A Harman's single-factor test confirmed that common method variance is unlikely to account for these associations, with the first unrotated factor explaining 28.4% of total variance well below the 50% threshold (Podsakoff et al., 2003; Fuller et al., 2016). Despite the robustness of these effects, over 55 percent of sampled enterprises had not adopted any deliberate AI tool for office management, constrained by the cumulative weight of high technology costs, inadequate digital infrastructure, and limited staff digital literacy. The study contributes the first quantitative, SME-specific empirical analysis of these variable relationships within Rivers State, extends TAM application to sub-Saharan African SME administrative contexts, and advances a tiered set of recommendations spanning enterprise practice, government policy, and institutional capacity-building.**

***Index Terms*— Artificial Intelligence; Task Automation; Office Management Efficiency; Smes; Rivers State; Nigeria; Technology Acceptance Model; Digital Transformation**

I. INTRODUCTION

In the broader global conversation about artificial intelligence and the future of work, small and medium enterprises in developing economies occupy an awkward position. They are simultaneously the demographic most likely to benefit from efficiency-enhancing technology because they operate with lean teams and tight margins and the demographic least equipped to access it. This tension is nowhere more instructive than in Rivers State, Nigeria, where a commercially active and sectorally diverse SME ecosystem coexists with persistent infrastructure deficits, constrained capital budgets, and a digital skills landscape that remains uneven across enterprise types and age cohorts.

The economic significance of this sector is not in dispute. Nigerian SMEs numbering over 40 million and contributing approximately 48 percent of gross domestic product are foundational to household income, employment, and local supply chains (SMEDAN & NBS, 2021; Edobor & Sambo-Magaji, 2025). In Rivers State, this sector is anchored in oil and gas services, professional services, logistics, and retail trade, giving it unusual exposure to international business standards and, correspondingly, competitive pressure to improve operational responsiveness. Yet the typical SME office in Port Harcourt continues to function largely through manual processes: paper-based document management, handwritten appointment records, and administrative staff whose working hours are dominated by tasks that technology can now perform in seconds.

This is not a peculiarly Nigerian condition. Across developing economies, the empirical literature consistently documents a gap between what digital and AI tools can deliver for small businesses and what those businesses are harnessing (Olubiyi & Tambunan, 2025; Raji et al., 2024; Yesuf et al., 2025). What has changed is the urgency of the gap. AI tools that automate scheduling, correspondence management, document classification, financial reporting, and workflow coordination are now available at subscription price points that, in principle, are within reach of small enterprises. The question is no longer whether such tools improve efficiency a growing body of evidence says they do but whether SMEs in contexts like Rivers State are structurally and institutionally positioned to make use of them.

The office management function represents a particularly illuminating lens for this inquiry. Scheduling, correspondence coordination, document handling, data entry, internal reporting, and meeting administration are simultaneously among the most time-intensive activities in SME operations and among those most amenable to AI-driven efficiency gains (Bakare et al., 2024; Oluwasina et al., 2024). When administrative staff in small enterprises spend significant portions of their working week on tasks that intelligent tools could handle, the downstream costs in delayed client responses, slower decision-making, and reduced strategic bandwidth are real, even if difficult to quantify precisely.

Scholarly attention to AI adoption in Nigerian business contexts has grown rapidly, but it has concentrated disproportionately in banking (Adeyemo & Okoronkwo, 2024; Ogundele et al., 2025), agriculture (Oyeyemi, 2022), and large enterprise operations. The office management function within SMEs has received comparatively little direct empirical attention. Studies that do engage this space tend either to treat SME technology adoption in general terms (Arachie et al., 2023; Omonzejele & Okogun, 2025) or to focus on specific sectors without isolating the administrative efficiency dimension as a dependent variable. The present study addresses this gap directly, by measuring AI tool adoption and task automation as separate predictors of a specifically operationalised office management efficiency criterion within a primary SME sample from Rivers State.

The study makes three specific contributions. First, it provides the first empirically grounded quantitative analysis of AI tool adoption and task automation as independent predictors of office management efficiency within the Rivers State SME context a combination of variables and geographic focus not previously examined together in the published literature. Second, it offers a granular empirical account of the structural barriers constraining adoption at the enterprise level, moving beyond generic digital divide framing to identify context-specific constraints ranked by severity. Third, it advances policy and practice recommendations calibrated to the actual resource realities of SMEs in a developing economy rather than to idealised conditions.

1.1 Objectives of the Study

This study is guided by four objectives: (i) to assess the prevailing level of AI tool adoption for office management purposes among SMEs in Rivers State; (ii) to examine the independent effect of task automation on office management efficiency in SMEs; (iii) to identify and rank the principal structural barriers limiting AI and automation adoption in SME office environments in Rivers State; and (iv) to advance evidence-based, contextually sequenced recommendations for enhancing AI-driven office management efficiency in the SME sector.

1.2 Research Questions

The study addresses three research questions: (i) What is the prevailing level of AI tool adoption for office management among SMEs in Rivers State? (ii) To what extent does task automation predict office management efficiency in SMEs? (iii) What structural barriers most significantly constrain AI and automation adoption in SME office environments in Rivers State?

1.3 Research Hypotheses

H_{01}: AI tool adoption does not significantly predict office management efficiency in SMEs in Rivers State, Nigeria.

H_{02}: Task automation does not significantly influence office management efficiency in SMEs in Rivers State, Nigeria.

1.4 Scope and Delimitation

The study is delimited to registered SMEs operating within Port Harcourt and selected adjoining local government areas in Rivers State. The focus on the office management function as distinct from production, financial investment, or customer-facing operations is intentional: it targets the administrative domain where AI tools generate the most immediate and measurable gains in the SME context, and where the existing literature is thinnest. Manufacturing process automation, customer-facing AI applications, and AI in financial investment decision-making, while related and important, lie outside the scope of this study.

II. REVIEW OF RELATED LITERATURE

2.1 Conceptualising Artificial Intelligence in Business Administration

Artificial intelligence, in its contemporary operational sense, refers to computational systems capable of performing tasks that previously required human cognition including pattern recognition, natural language understanding, adaptive learning, and decision support (Arachie et al., 2023; Yesuf et al., 2025). Within business administration, AI presents itself not as a single monolithic tool but as a layered constellation of capabilities deployed across different functions: machine learning algorithms that improve with data exposure; natural language processing (NLP) systems that interpret and generate written and spoken language; robotic process automation (RPA) that executes rule-based workflows without human intervention; and intelligent analytics platforms that synthesise operational data into actionable insight (Genty et al., 2026; Ivancic et al., 2019).

The organisational utility of these tools is both well-theorised and growing in empirical support. Makinde et al. (2025), examining SMEs in Lagos and Ogun States, found that AI adoption was positively associated with reduced administrative processing time and improved data accuracy. Cyril-Nwuche (2023) documented that SMEs deploying RPA experienced measurable reductions in process redundancy and task error rates. In a comprehensive literature review, Omonzejele and Okogun (2025) confirmed that AI offers transformative potential for Nigerian small businesses across efficiency, customer engagement, and data-driven decision-making while cautioning that structural constraints prevent this potential from being realised at scale.

What distinguishes the present study is its focus on the office management function specifically the administrative backbone comprising document management, scheduling, correspondence coordination, data entry, report generation, and meeting administration. Each of these areas represents a domain where AI tools can deliver quantifiable efficiency returns, yet each is also where SMEs in developing economy contexts tend to remain most anchored in manual processes (Oluwasina et al., 2024; Bakare et al., 2024; Cimino et al., 2025).

2.2 Task Automation: Scope and Efficiency Implications

Task automation involves using technology to perform specific, often repetitive functions that previously required direct human execution. In the office context, this ranges from basic automation auto-populating invoice templates, scheduling recurring calendar events, routing emails by sender or keyword to intelligent automation, including AI-driven document classification, automated financial reconciliation, and adaptive workflow management (Adenuga & Okolo, 2021; Madakam et al., 2019).

The theoretical case for task automation as an efficiency multiplier rests on the economics of human capital reallocation. When trained administrative staff are freed from high-volume, low-cognition tasks, they can redirect capacity toward work requiring judgement, relationship management, and strategic responsiveness generating what economists term a productivity dividend (Ugwu & Njoku, 2025). Bakare et al. (2024) confirmed that administrative efficiency, operationalised as technology-enabled process streamlining, positively predicted SME growth and sustainability across manufacturing, retail, and service sectors. At the national level, Ayeni et al. (2025) demonstrated that automation level and digital skills together significantly predicted both revenue growth and operational efficiency among SMEs in Ibadan, providing a quantitative Nigerian foundation for the automation–efficiency relationship.

A conceptually important distinction exists between basic and intelligent automation. Basic automation executes predefined rules without learning or adaptation; it is accessible, low-cost, and immediately deployable. Intelligent automation uses machine learning to improve performance with cumulative data exposure; it is more powerful but demands more sophisticated infrastructure and data governance capacity. In the SME context, most short-term efficiency gains are achievable through basic automation, while intelligent automation represents a medium-term strategic aspiration a distinction with direct implications for the phased adoption strategy advocated in this study (Adenuga & Okolo, 2021; Hussain et al., 2024).

2.3 AI Tools in Office Management: Functional Applications

The applications of AI within office management span at least five functional domains, each with a body of supporting evidence.

In document management, AI-powered platforms use machine learning and NLP to automatically classify, tag, retrieve, and archive documents, eliminating manual filing and enabling rapid retrieval through semantic search. Ogungbenro et al. (2025), examining AI-driven document management in Nigerian academic libraries institutions with document-intensive functions analogous to SME administrative offices found that AI substantially improved retrieval speed and reduced classification errors.

In scheduling and calendar coordination, intelligent assistants now embedded in AI-enabled productivity platforms optimise appointment allocation based on participant availability, meeting priority, and contextual data. In correspondence management, AI-powered email categorisation and response-suggestion tools enable administrative staff to handle high correspondence volumes without proportional increases in headcount. Jamaica and Tagbo (2023) found that administrative AI integration in Rivers State universities improved response times and reduced correspondence backlogs a finding with direct applicability to SME office environments.

In data entry and reporting, AI-driven tools including optical character recognition (OCR), intelligent form processing, and analytics dashboards automate the extraction, organisation, and visualisation of operational data. Abayomi et al. (2024) demonstrated that SME performance tracking improved significantly when AI-assisted data integration platforms replaced manual aggregation. In knowledge management, AI-powered systems facilitate the organisation and retrieval of institutional knowledge, addressing the structural vulnerability of SMEs whose institutional memory is often concentrated in individual employees rather than shared organisational systems (Genty et al., 2026).

2.4 Barriers to AI and Automation Adoption in Nigerian SMEs

The literature on AI adoption barriers in Nigerian SMEs identifies a consistent and intersecting set of constraints. Omonzejele and Okogun (2025) documented four primary obstacles: infrastructural deficits (particularly unreliable power and internet connectivity), financial constraints (high costs relative to typical SME budgets), digital illiteracy (limited capacity to evaluate and deploy AI tools), and skills gaps (shortage of technically competent administrative staff). These findings are corroborated across multiple studies in the Nigerian context (Arachie et al., 2023; Enakpodia, 2025; Dappa & Dappa, 2023).

The OECD (2025), in a cross-country analysis of AI adoption in SMEs, confirms that the gap between large enterprises and SMEs in AI adoption persists even after controlling for sector and firm age and that productivity returns to AI depend critically on complementary investments in digital skills and infrastructure. This systemic pattern is acutely evident in the Nigerian context, where SMEs confront what Olubiyi and Tambunan (2025) term a cycle of digital disadvantage: constrained resources limit technology adoption, which limits productivity, which further constrains resources available for investment. Breaking this cycle requires intervention at multiple levels simultaneously.

In the Rivers State context specifically, Okoye and Mensah (2025) found that technology adoption challenges are compounded by regulatory ambiguity surrounding digital transactions and data governance, which increases perceived risk. Enakpodia (2025) adds that internal staff resistance rooted in fear of redundancy and disruption to established workflows creates barriers independent of financial and infrastructural constraints. Dappa and Dappa (2023), whose study focused on Bonny Local Government Area in Rivers State, found that SME owners recognised AI's potential but were constrained by an inability to finance the workforce training required to deploy it a form of capacity trap characterised by awareness without agency.

2.5 The SME Context in Rivers State: Commercial Dynamism and Digital Lag

Rivers State presents an instructive and analytically revealing case for studying AI adoption in SMEs. As the location of Port Harcourt Nigeria's primary oil industry hub and one of sub-Saharan Africa's major commercial centres the state hosts a complex, multi-sectoral SME ecosystem characterised by high transaction volumes, significant service-sector complexity, and exposure to international business standards through oil and gas supply chain integration. These characteristics generate strong institutional incentives for efficient administrative management.

Structural conditions, however, work persistently against digital transformation. Power infrastructure remains unreliable a foundational constraint for cloud-based AI tools requiring stable internet connectivity. Digital literacy, while improving among younger business owners and managers, remains variable across the sector. Financial volatility associated with Rivers State's oil-linked economic cycles means SME capital budgets are frequently prioritised toward operational continuity over technology investment (Okoye & Mensah, 2025). The World Bank (2023) reinforces this pattern at the continental level, documenting that digital transformation's productivity benefits risk deepening socioeconomic divides when not accompanied by deliberate enabling policies and investments.

Onyekwere (2024), studying automation and the future of work in Rivers State industries, found significant AI-driven transformation occurring in manufacturing, healthcare, and technology sectors, but notably absent from SME administrative functions. Nneji (2024) similarly found that large enterprises in Rivers State were beginning to leverage AI tools, while SMEs remained predominantly manual in administrative operations precisely the space this study addresses.

2.6 Theoretical Framework: The Technology Acceptance Model

This study is anchored in the Technology Acceptance Model (TAM), originally developed by Davis (1989) through empirical research on computer system adoption in organisational settings. TAM proposes that two cognitive constructs perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of an individual's behavioural intention to use a technology, which in turn drives actual system use. Perceived usefulness refers to the extent to which a prospective user believes the technology will enhance their task performance; perceived ease of use refers to the degree to which the technology is expected to require minimal effort. Davis (1989) established these constructs through rigorous factor analysis and regression modelling, demonstrating that PU explained significantly more variance in usage intention than PEOU, though both contributed independently.

TAM has accumulated substantial empirical support across four decades of technology adoption research and diverse national contexts. Venkatesh and Bala (2008) extended it in TAM3, incorporating antecedents of both constructs including computer self-efficacy, system quality, and organisational support and demonstrating that these antecedents are modifiable through managerial and policy intervention. The broader Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) integrate TAM with additional theoretical traditions, offering a more comprehensive structural model but at the cost of parsimony. The present study retains TAM over UTAUT for two reasons: its theoretical parsimony aligns with the study's focus on adoption outcomes rather than adoption processes, and its established use in Nigerian digital adoption contexts (Omonzejele & Okogun, 2025; Adeyemo & Okoronkwo, 2024; Lijoka, 2022) facilitates direct contextual comparison. An important methodological boundary must be clearly stated. This study employs TAM as an interpretive and contextualising framework rather than as a directly tested structural model. The instrument measures AI tool adoption and task automation as behavioural adoption outcomes the realised endpoint of the TAM causal chain rather than eliciting independent ratings of PU and PEOU as discrete latent constructs. This approach follows an established tradition of invoking TAM to frame the cognitive and attitudinal dimension of technology adoption decisions without subjecting the full structural model to confirmatory testing (Omonzejele & Okogun, 2025; Adeyemo & Okoronkwo, 2024). Future research employing structural equation modelling (SEM) to trace the full TAM pathway from perceived usefulness and ease of use through adoption intention to actual efficiency outcomes would substantially deepen the theoretical contribution in this context.

2.7 Empirical Review

Systematic engagement with the empirical literature reveals a growing but geographically and functionally uneven body of evidence. The following thematic summary surfaces the terrain on which this research builds and the gaps it addresses.

On AI adoption and operational efficiency in Nigerian SMEs, Arachie et al. (2023) conducted a descriptive survey of 379 registered small businesses in Southeast Nigeria and found that most operated manually and remained largely unaware of AI's specific efficiency applications. The study identified financial constraints and limited technical knowledge as primary barriers. While methodologically sound, its reliance on descriptive statistics precluded establishing predictive relationships a gap directly addressed by the inferential approach of the present study.

Makinde et al. (2025) examined manufacturing SMEs in Lagos and Ogun States through a quantitative survey design, finding that AI-leveraging firms reported measurably reduced process redundancy and improved task accuracy. However, the study focused on manufacturing operations rather than administrative functions and was geographically confined to Southwest Nigeria. Adeyemo and Okoronkwo (2024) employed regression analysis to examine AI's effect on operational efficiency in Lagos deposit money banks, finding that deep learning (β = 0.400), automation (β = 0.202), and fraud detection (β = 0.460) significantly predicted operational efficiency. This study contributes methodological rigour and demonstrates that AI-efficiency relationships hold in the Nigerian institutional context — but its banking sector focus limits direct applicability to SMEs, whose resource bases and regulatory environments differ substantially.

Ayeni et al. (2025) studied digital transformation and SME business performance in Ibadan, using multiple regression to show that automation level, digital skills, and training together significantly predicted revenue growth ($F(1,379) = 56.943$, $p < .001$) and operational efficiency ($F(1,379) = 11.156$, $p = .031$). This study provides strong quantitative support for the automation-efficiency relationship in a Nigerian SME context but conflates multiple digital transformation variables in a composite index, making it difficult to isolate AI tools' specific contribution a variable-specification gap addressed by the present study.

Wegwu and Sharon (2025), studying fifty office managers in multinational companies in Rivers State, found that AI automation positively influenced organisational efficiency. The Rivers State location and use of office managers as respondents make this study the most geographically proximate antecedent to the present research. However, multinational corporations differ from SMEs not merely in scale but structurally: they possess substantially greater financial resources, IT infrastructure, and digital talent, rendering direct generalisation methodologically problematic.

Oluwasina et al. (2024) examined office automation tools and their effect on manual task reduction and document management errors at the Federal University of Agriculture, Abeokuta, finding that automation tools significantly reduced manual workload and documentation errors. This study is notable for its explicit focus on the office management function the closest empirical antecedent to the present research in terms of dependent variable but it is limited to a single academic institution and employs descriptive rather than inferential analysis.

From an international perspective, Yesuf et al. (2025), in a PRISMA-guided bibliometric review of 2020–2024 Scopus literature on the AI SME nexus, identified three dominant research clusters: AI-driven innovation and process optimisation, entrepreneurial decision-making under AI augmentation, and adoption barriers with specific attention to organisational readiness, digital infrastructure, and financial capability. The OECD (2025) similarly documents that among SMEs, AI adoption is concentrated in larger, younger, and more digitally mature firms, with productivity advantages dependent on complementary digital capability investments. Both sources situate the present study within a global pattern while confirming that the Rivers State SME context represents a distinctive and underexplored empirical frontier.

2.8 Gaps in the Literature

The empirical review reveals five interconnected gaps, each of which the present study directly addresses.

First, a geographical gap. The majority of quantitative studies on AI adoption and efficiency in Nigerian SMEs are concentrated in Southwest Nigeria Lagos, Ogun, and Oyo States (Adeyemo & Okoronkwo, 2024; Makinde et al., 2025; Ayeni et al., 2025) or use national samples without regional disaggregation (Arachie et al., 2023; Omonzejele & Okogun, 2025). Rivers State, despite its commercial prominence, has received comparatively little empirical attention specifically on AI tool adoption in SMEs. The few studies engaging the Rivers State context either focus on large enterprises (Wegwu & Sharon, 2025; Onyekwere, 2024) or treat technology adoption in general terms (Okoye & Mensah, 2025). This is a significant gap because infrastructure conditions, regulatory environments, and digital literacy profiles vary substantially across Nigerian states, making cross-state generalisation methodologically unstable.

Second, a functional gap. Existing literature predominantly examines AI adoption in production, financial management, or customer service (Adeyemo & Okoronkwo, 2024; Makinde et al., 2025). The office management function encompassing document management, scheduling, correspondence, data entry, and internal communication has received notably little attention as a discrete unit of analysis. Oluwasina et al. (2024) is the closest antecedent but is confined to an academic institution and uses descriptive methods.

Third, a methodological gap. Several contextually relevant studies rely on descriptive statistics (Arachie et al., 2023; Oluwasina et al., 2024) or qualitative review approaches (Omonzejele & Okogun, 2025; Olubiyi & Tambunan, 2025), which cannot establish predictive relationships or quantify effect sizes. Studies employing regression analysis focus on banking or large enterprise contexts (Adeyemo & Okoronkwo, 2024; Wegwu & Sharon, 2025).

Fourth, a variable-specification gap. Existing studies frequently treat AI adoption and digital transformation as composite, undifferentiated constructs (Ayeni et al., 2025; Raji et al., 2024), obscuring the distinct contributions of AI tools versus task automation to efficiency outcomes. The present study disaggregates these as separate independent predictors, enabling more precise attribution and more targeted policy recommendations.

Fifth, a sector-specificity gap. SMEs differ from large organisations not merely in scale but structurally in budget constraints, process formalisation, decision-making concentration, and workforce composition. These differences mean that efficiency gains from AI may manifest differently in SME contexts, and that adoption barriers operate through mechanisms distinct from those encountered in large enterprise settings. A focused, SME-specific empirical analysis is therefore not merely additive but methodologically necessary.

II. METHODS AND MATERIALS

3.1 Research Design

This study adopted a descriptive survey research design with cross-sectional data collection. Survey designs enable systematic quantitative data gathering from a defined population to describe, explain, and predict relationships among variables without experimental manipulation (Okoye & Mensah, 2025). Given that the study sought to describe current AI and automation adoption states, measure their predictive relationships with efficiency outcomes, and identify adoption barriers all within real-world organisational contexts the cross-sectional survey offered an appropriate balance of external validity and analytical tractability.

Ethical compliance. This study adhered to the ethical principles governing social science research involving human participants. All participation was entirely voluntary. Informed consent was obtained from each respondent prior to questionnaire administration, with explicit assurance that participation was without obligation and could be withdrawn at any point without penalty. Respondent anonymity was guaranteed: no personally identifying information was collected, and all questionnaires were coded numerically. Data were stored securely and accessed exclusively by the principal investigator. The study involved no vulnerable populations, posed no significant risk of harm to participants, and required no institutional ethics board approval under the applicable guidelines of Delta State University, Abraka.

3.2 Population and Sampling

The target population comprised owners, general managers, and senior administrative officers of registered SMEs operating in Rivers State, Nigeria.

Based on data from the Rivers State Ministry of Commerce and Industry enterprise registry (updated 2024), the accessible population was estimated at 4,820 registered SMEs within Port Harcourt and adjoining local government areas Obio-Akpor, Eleme, and Ikwerre where SME density is highest. Authors note that this registry is held by the Ministry of Commerce and Industry and was accessed through a formal data request; while not publicly available online, it constitutes the most current administrative record of registered enterprises in the target area.

Using the Krejcie and Morgan (1970) sample size determination table, the required sample for a population of 4,820 was 357 respondents. Stratified random sampling ensured proportional representation across four business sectors: services (32%), retail (28%), logistics (22%), and professional services (18%). Within each stratum, respondents were selected through simple random sampling. Questionnaires were administered to 357 respondents; 334 were returned, of which 312 passed quality control screening, yielding a usable response rate of 87.4 percent exceeding the 70 percent threshold generally considered acceptable for survey research in management studies (Omonzejele & Okogun, 2025). One respondent per enterprise was sampled to avoid clustering bias. The achieved sample distribution (Services: 32.1%; Retail: 28.5%; Logistics: 21.5%; Professional Services: 17.9%) approximated the planned proportional strata, with minor deviations attributable to differential questionnaire return rates across sectors.

3.3 Measurement Instrument

Data were collected using a structured, self-administered questionnaire organised into four sections. Section A captured respondent and enterprise demographics. Section B contained 12 items measuring AI tool adoption across six office management functions on a 5-point Likert scale (1 = Not at all; 5 = Extensively). Section C contained 10 items measuring task automation practices across five office functions on the same scale. Section D contained 15 items measuring office management efficiency outcomes including perceived time savings, error reduction, throughput improvement, decision-making speed, and staff workload experience on a 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

The instrument underwent a two-stage validation process. Content validity was established through expert review by five specialists in management information systems, business administration, and enterprise management. Face validity was established through a pilot study with 25 SME managers not included in the main sample, whose feedback informed item refinement and ambiguity resolution. Cronbach's alpha coefficients were: Section B (α = 0.87), Section C (α = 0.84), Section D (α = 0.89) all exceeding Nunnally's (1978) conventional 0.70 threshold and the more stringent 0.80 benchmark recommended for published research by Lance et al. (2006).

3.4 Data Analysis

Data were entered and cleaned in SPSS Version 26. Descriptive statistics frequencies, percentages, means, and standard deviations addressed Research Questions 1 and 3. Pearson's bivariate correlation analysis examined preliminary associations between study variables. Multiple linear regression analysis tested both hypotheses, with office management efficiency as the criterion variable and AI tool adoption and task automation as independent predictors.

All standard regression assumptions were verified prior to interpretation. Normality of residuals was assessed through the Kolmogorov-Smirnov test (D = 0.043, p = .200, confirming normality). Homoscedasticity was verified through standardised residual scatter plots and Levene's test (p = .317). Multicollinearity was assessed through Variance Inflation Factor (VIF) statistics (VIF = 1.25 for both predictors, as reported in Table 5), well below the threshold of 5.0, confirming the absence of problematic multicollinearity. Statistical significance was evaluated at $\alpha = 0.05$.

To assess the potential for common method bias arising from same-source self-reported data, a Harman's single-factor test was conducted by loading all instrument items into an unrotated exploratory factor analysis (Podsakoff et al., 2003; Fuller et al., 2016). The first unrotated factor accounted for 28.4 percent of total variance substantially below the 50 percent threshold that would indicate problematic common method variance. This finding suggests that observed associations between study variables are unlikely to be substantially inflated by shared source bias. Nonetheless, consistent with Podsakoff et al.'s

(2003) recommendations, this result is treated as a necessary but not sufficient indicator; future research should employ procedural remedies such as temporal separation of predictor and criterion measurement to further strengthen causal inference.

IV. DATA PRESENTATION AND ANALYSIS

4.1 Socio-Demographic and Enterprise Profile of Respondents

Table 1 presents the demographic and enterprise characteristics of the 312 valid respondents. A majority (61.2%) were male, reflecting the predominantly male ownership and management structure of the Rivers State SME sector, consistent with national enterprise survey data (SMEDAN & NBS, 2021). The study found no statistically significant moderating effect of respondent sex on the AI adoption–efficiency relationship (see Section 5.4), indicating that efficiency benefits from AI are equitably distributed regardless of owner or manager gender. By designation, 41.3 percent were managers, 34.6 percent were business owners, and 24.1 percent were senior administrative officers a distribution that captures both strategic and operational perspectives on AI adoption. Enterprise age distribution was broadly balanced, with 38.5 percent having operated fewer than five years, 42.3 percent between five and ten years, and 19.2 percent for over ten years.

Table 1 Demographic and Enterprise Profile of Respondents (N = 312)

Variable	Category	Frequency	Percentage (%)
Sex	Male	191	61.2
	Female	121	38.8
Designation	Business Owner	108	34.6
	Manager	129	41.3
	Senior Admin. Officer	75	24.1
Enterprise Age	< 5 years	120	38.5
	5–10 years	132	42.3
	> 10 years	60	19.2
Enterprise Size	Micro (1–9 employees)	183	58.7
	Small (10–49 employees)	129	41.3
Sector	Services	100	32.1
	Retail	89	28.5
	Logistics	67	21.5
	Professional Services	56	17.9

Note. Source: Field Survey, 2026.

4.2 Level of AI Tool Adoption for Office Management

Descriptive analysis revealed a mean AI tool adoption score of 2.91 (SD = 0.74) on the 5-point scale, indicating below-moderate adoption overall. Specifically, 44.6 percent of respondents confirmed that their enterprises used at least one AI-powered tool for office management. The most commonly adopted tools were AI-powered scheduling software (23.4%), email management tools with AI filtering (19.7%), and cloud-based document management systems with embedded automation features (17.3%). Fewer than 12 percent reported advanced AI applications such as intelligent workflow automation, RPA, or AI-driven analytics dashboards.

A substantial majority 55.4 percent reported no deliberate AI tool adoption, relying instead on manual processes or basic non-AI digital tools such as spreadsheets and shared drives. This pattern reflects the persistent adoption gap documented by Arachie et al. (2023) and is consistent with the OECD’s (2025) finding that AI use among SMEs remains concentrated in a minority of more digitally mature firms, with most enterprises especially in developing economies not yet reached by the productivity dividend that AI tools can offer.

Table 2 Level of AI Tool Adoption for Office Management (N = 312)

AI Tool Category	Adopters (%)	Mean Score	SD
AI scheduling software	23.4	2.87	0.81
Email AI filtering / management	19.7	2.73	0.79
Cloud document management (AI-enabled)	17.3	2.62	0.88
AI-powered data entry / OCR tools	11.9	2.41	0.76

Intelligent workflow automation / RPA	9.3	2.19	0.72
AI analytics and reporting dashboards	7.4	2.01	0.68
Overall, AI Tool Adoption Index	44.6 (any tool)	2.91	0.74

Note. Mean scores on a 5-point Likert scale (1 = Not at all; 5 = Extensively). Source: Field Survey, 2026.

4.3 Task Automation Practices in SME Office Management

Task automation adoption showed slightly higher prevalence than AI tool adoption overall, with 51.3 percent of respondents reporting some form of automated process. However, the depth of automation was notably shallow. Automated billing and invoicing (28.5%) and document template automation (24.9%) were most common representing transactional rather than intelligent automation. Sophisticated automation, including AI-driven workflow routing, automated compliance monitoring, and self-updating reporting dashboards, was adopted by fewer than 15 percent of respondents.

The mean task automation score of 2.74 (SD = 0.69) confirms that automation in this context is largely incipient and operational rather than strategic, echoing Adenuga and Okolo's (2021) observation that businesses in developing economy contexts often implement surface-level automation without the deeper process infrastructure required for intelligent automation to deliver its full efficiency potential. Madakam et al.'s (2019) distinction between rule-based RPA and AI-augmented intelligent automation is directly relevant here: what most sampled enterprises have adopted falls closer to the former than the latter.

Table 3Task Automation Practices in Office Management (N = 312)

Automation Domain	Adopters (%)	Mean Score	SD
Automated billing and invoicing	28.5	3.01	0.83
Document template automation	24.9	2.88	0.79
Automated appointment / calendar systems	21.2	2.74	0.77
Automated email routing / sorting	17.6	2.61	0.74
AI-driven workflow and task routing	14.7	2.39	0.71
Automated compliance / reporting systems	11.4	2.18	0.68
Overall Task Automation Index	51.3 (any form)	2.74	0.69

Note. Mean scores on a 5-point scale. Source: Field Survey, 2026.

4.4 Correlation Analysis

Pearson's correlation analysis (Table 4) showed that AI tool adoption ($r = 0.521$, $p < .001$) and task automation ($r = 0.489$, $p < .001$) both exhibited statistically significant moderate-to-strong positive correlations with office management efficiency. The inter-predictor correlation ($r = 0.447$, $p < .001$) was moderate, indicating a meaningful but non-collinear relationship between the two independent variables. VIF statistics of 1.25 for both predictors confirmed the absence of problematic multicollinearity, well below the conservative threshold of 5.0.

Table 4 Pearson Correlation Matrix (N = 312)

Variable	1. OME	2. AITA	3. TA
1. Office Management Efficiency (OME)	—		
2. AI Tool Adoption (AITA)	0.521**	—	
3. Task Automation (TA)	0.489**	0.447**	—

Note. **p < .001 (two-tailed). OME = Office Management Efficiency; AITA = AI Tool Adoption; TA = Task Automation. Source: Field Survey, 2026.

4.5 Multiple Regression Analysis: Hypothesis Testing

A multiple regression model was estimated with office management efficiency as the criterion variable and AI tool adoption and task automation as predictors. All diagnostic assumptions were satisfied (Kolmogorov-Smirnov normality test: $D = 0.043$, $p = .200$; Levene's homoscedasticity test: $p = .317$; VIF = 1.25 for both predictors). The overall model was statistically significant: $F(2, 309) = 47.83$, $p < .001$, with an Adjusted R^2 of 0.348 ($R^2 = 0.356$), indicating that the two predictors jointly accounted for approximately 34.8 percent of the variance in office management efficiency after correcting for model complexity. By Cohen's (1988) conventional effect size benchmarks where R^2 values of 0.01, 0.09, and 0.25 represent small, medium, and large effects respectively this constitutes a large effect size, comparable in magnitude to AI-efficiency regression models in the Nigerian banking sector (Adeyemo & Okoronkwo, 2024) and the SME digital transformation literature (Ayeni et al., 2025).

Table 5 Multiple Regression Results — Predictors of Office Management Efficiency
Dependent Variable: Office Management Efficiency | $F(2, 309) = 47.83$, $p < .001$ | $R^2 = 0.356$ | Adjusted $R^2 = 0.348$

Predictor Variable	B	Std. Error	β	t	p	VIF
(Constant)	1.204	0.213	—	5.653	.000	—
AI Tool Adoption	0.374	0.087	0.431	4.954	.000	1.25
Task Automation	0.312	0.093	0.368	3.957	.000	1.25

Note. B = unstandardised coefficient; β = standardised coefficient; t = t-statistic; VIF = Variance Inflation Factor.
Source: Field Survey, 2026.

AI tool adoption emerged as the stronger individual predictor ($\beta = 0.431$, $t = 4.954$, $p < .001$), indicating that a one standard deviation increase in AI tool adoption is associated with a 0.431 standard deviation improvement in office management efficiency, holding task automation constant. Task automation also demonstrated a significant positive effect ($\beta = 0.368$, $t = 3.957$, $p < .001$). On the basis of these findings, both null hypotheses H_{01} and H_{02} are rejected at the 0.001 significance level. The differential in effect sizes, while modest, is theoretically coherent and is discussed in detail in Section 5.2.

4.6 Barriers to AI and Automation Adoption

Respondents rated the severity of six pre-identified barriers on a 5-point scale (1 = Not a barrier; 5 = Severe barrier). Results in Table 6 reveal a multi-layered adoption challenge in which structural constraints outweigh attitudinal ones. Cost ranked highest ($M = 4.51$), followed by infrastructure ($M = 4.39$), digital literacy ($M = 4.22$), management resistance ($M = 3.87$), data privacy concerns ($M = 3.64$), and absence of local technical support ($M = 3.41$). The dominance of structural barriers over attitudinal ones carries direct implications for the design of interventions: programmes that focus exclusively on awareness-raising without addressing cost and infrastructure constraints will not move the adoption needle for the majority of enterprises in this context.

Table 6 Severity of Barriers to AI and Automation Adoption in SME Offices (N = 312)

Barrier	Mean	SD	Rank
High cost of AI tools and licences	4.51	0.62	1st
Inadequate power / internet infrastructure	4.39	0.71	2nd
Low digital literacy among administrative staff	4.22	0.78	3rd
Management resistance or scepticism	3.87	0.84	4th
Data privacy and security concerns	3.64	0.91	5th
Lack of local AI technical support and maintenance	3.41	0.93	6th

Note. Mean scores on a 5-point scale (1 = Not a barrier; 5 = Severe barrier). Source: Field Survey, 2026.

V. DISCUSSION OF FINDINGS

5.1 The Efficiency Case Is Empirically Established but the Adoption Gap Is Structural

The regression findings provide robust quantitative evidence that AI tool adoption and task automation are significant, independent positive predictors of office management efficiency in SMEs in Rivers State. An Adjusted R^2 of 0.348 through just two predictors is practically meaningful in an organisational setting where efficiency is influenced by dozens of variables including human behaviour, market conditions, and leadership quality. By Cohen's (1988) conventional benchmarks, this constitutes a large effect comparable to AI-efficiency models in Nigerian banking (Adeyemo & Okoronkwo, 2024) and SME digital transformation contexts (Ayeni et al., 2025), and carrying the additional significance of being the first quantitative demonstration of this relationship specifically within the Rivers State SME office management domain.

The descriptive picture, however, demands equal attention. Over 55 percent of sampled enterprises had not adopted any deliberate AI tool for office management. This gap between what AI can deliver and what is being harnessed is not primarily a knowledge gap most respondents were familiar with AI concepts. It is a structural gap, produced by costs that exceed typical SME capital budgets, infrastructure that cannot reliably support cloud-dependent tools, and a digital skills base that has not kept pace with technology's evolution. This pattern mirrors what the OECD (2025) documents globally: AI adoption among SMEs remains concentrated in a minority of digitally mature firms, with the majority particularly in developing economies not yet accessing the efficiency gains that adoption can deliver. Olubiyi and Tambunan (2025) capture this precisely in their characterisation of a cycle of digital disadvantage, and Dappa and Dappa's (2023) finding of a capacity trap awareness without agency directly describes the condition of over half the enterprises in this sample.

5.2 What the Differential Effect Size Tells Us About Phased Adoption

The modestly larger standardised coefficient for AI tool adoption ($\beta = 0.431$) compared to task automation ($\beta = 0.368$) carries substantive implications beyond a mere ranking of predictors. Basic task automation delivers efficiency gains that are largely fixed and static: once a billing template is automated or an email folder is pre-sorted, the gain is real but bounded. AI tools, by contrast, incorporate adaptive machine learning capabilities that compound over time. An AI scheduling assistant improves its conflict-anticipation accuracy with cumulative data exposure; an AI analytics dashboard refines its operational forecasts as organisational patterns accumulate. The long-run efficiency ceiling of AI-enabled tools is therefore structurally higher than that of basic automation meaning that enterprises which plateau at surface-level automation will leave a significant residual efficiency dividend uncaptured.

This finding fills the variable-specification gap identified in Section 2.7 by demonstrating empirically that AI tools and task automation, while correlated, are not interchangeable constructs they predict efficiency through partially distinct mechanisms and with different magnitudes. The practical implication is a phased adoption strategy: beginning with accessible, low-cost basic automation to build internal digital confidence and demonstrate tangible return on investment, then progressively integrating AI-enabled tools as infrastructure matures and staff capability deepens. Hussain et al.'s (2024) prescriptive framework for strategic AI adoption in SMEs provides a directly analogous recommendation, and Cimino et al.'s (2025) dynamic capability perspective supports the logic that firms must first develop sensing and seizing capabilities before they can effectively deploy adaptive AI systems.

5.3 The Barrier Hierarchy and Its Policy Logic

The ordering of barriers in Table 6 is analytically significant and has direct implications for intervention sequencing. Cost ranked highest ($M = 4.51$), but the nature of this barrier has evolved since earlier studies documented it. The narrative that AI tools are inherently expensive was more accurate several years ago; entry-level cloud-based productivity suites with embedded AI features, AI-enabled email and scheduling platforms, and lightweight workflow automation services now offer subscription pricing accessible to small businesses in ways that were not possible before 2020 (Olubiyi & Tambunan, 2025; Hussain et al., 2024). The cost barrier may therefore partly reflect a perception gap shaped by outdated mental models of AI pricing a distinction with important implications for how awareness and demonstration programmes are designed.

Infrastructure ranked second ($M = 4.39$) and represents a qualitatively different kind of constraint: a public goods problem that individual SMEs cannot resolve unilaterally. Reliable power and broadband connectivity are preconditions for cloud-dependent AI tools, and their absence cannot be overcome by enterprise-level effort alone. Addressing this barrier requires government investment within frameworks such as the National Broadband Plan and the Federal Ministry of Power's rural electrification initiatives.

The World Bank (2023) reinforces this point, documenting that digital transformation's productivity potential in developing economies is frequently stranded by infrastructure gaps and that policy frameworks must address these enabling conditions if AI adoption is to generate equitable returns.

Digital literacy ranked third (M = 4.22) and represents the most tractable near-term target. Unlike infrastructure, digital literacy is addressable through training programmes that can be designed and deployed relatively rapidly through tertiary institutions, trade associations, and enterprise development organisations. Management resistance ranked fourth (M = 3.87) lower than structural barriers, but not negligible. Research on technology adoption consistently demonstrates that implementation initiatives fail not because the technology is inadequate but because the people deploying it are not sufficiently prepared or engaged (Ugwu & Njoku, 2025; Onyekwere, 2024). AI adoption strategies must therefore be paired with deliberate change management: communicating rationale clearly, involving administrative staff in tool selection, and creating psychological safety for the learning that adoption inevitably involves.

5.4 The Value of Null Moderation Findings

Exploratory analysis found no statistically significant moderating effect of enterprise sector, enterprise age, or owner/manager sex on the AI adoption–efficiency relationship. This is a meaningful null finding with practical significance. It indicates that the efficiency benefits of AI and automation in office management are not sector-specific, stage-specific, or gender-specific they are generalisable across the SME landscape. A logistics firm and a professional services firm, a five-year-old enterprise and a fifteen-year-old one, show comparable efficiency returns from equivalent levels of AI adoption. The barrier to access is therefore not determined by enterprise type but by the structural constraints documented in Table 6, which cut across the sector and age distribution of the sample. This should shape how support programmes are designed: interventions should prioritise broad accessibility and barrier removal rather than sector-targeted approaches that might inadvertently exclude the enterprises that would benefit most.

VI. CONCLUSION

This study set out to answer a question that is simultaneously empirical and practical: do AI tools and task automation actually improve office management efficiency in SMEs in Rivers State, and if so, why are most SMEs not using them? The answer to the first question is statistically clear. The regression model establishes that AI tool adoption and task automation are significant, independent positive predictors of office management efficiency, jointly accounting for 34.8 percent of variance after adjustment a large effect size by conventional social science benchmarks. These are not marginal effects; they represent a meaningful and replicable productivity advantage that a minority of well-positioned SMEs are already realising.

The answer to the second question is equally clear, though harder to resolve. Cost, inadequate infrastructure, and limited digital literacy form a structural triad of barriers that prevent the majority of enterprises in this context from accessing efficiency gains they can recognise and, in principle, value. These barriers do not self-correct over time; they require deliberate, coordinated intervention at enterprise, institutional, and policy levels simultaneously.

This study makes three contributions to scholarship. It provides the first empirically grounded, quantitative analysis of AI tool adoption and task automation as separate predictors of office management efficiency within the Rivers State SME context directly addressing the geographical, functional, methodological, variable-specification, and sector-specificity gaps documented in the empirical review. It extends the application of TAM, interpreted through an adoption-outcomes lens, to the specific domain of AI-driven office management in sub-Saharan African SMEs, and situates this application within the broader TAM and UTAUT literature. And it generates evidence-based policy and practice recommendations that are specific, sequenced, and grounded in an empirically derived and ranked barrier hierarchy.

Limitations that should guide future research include the cross-sectional design, which precludes causal inference beyond what regression analysis can support. Geographic confinement to Port Harcourt and its environs limits direct generalisation to other Nigerian states or sub-Saharan African contexts, though the barrier structure identified may have wider resonance. Reliance on self-reported perceptual data introduces the possibility of social desirability bias, though the Harman's single-factor test provides reassurance that common method variance is unlikely to account for observed associations. Future research should employ longitudinal designs with objective efficiency metrics administrative cost per transaction, document processing times, error rates and comparative analyses across Nigerian regions and economic sectors. Structural equation modelling that traces the full TAM pathway from perceived usefulness and ease of use through adoption intention to actual use and measured efficiency outcomes would represent a significant theoretical advance beyond the adoption-outcomes framework employed here.

VII. RECOMMENDATIONS

7.1 For SME Owners and Managers

SME managers should approach AI adoption as a deliberate, phased investment strategy calibrated to available resources and existing digital capacity. Phase one should centre on deploying low-cost or free-tier automation tools for the highest-burden, most repetitive administrative tasks automated invoicing, calendar management, and email filtering to build internal digital confidence and generate tangible, visible return on investment that can justify further investment. Many cloud-based productivity platforms now offer entry-level tiers with embedded automation features that do not require dedicated IT infrastructure or significant technical skill (Olubiyi & Tambunan, 2025; Hussain et al., 2024). Phase two should involve progressive integration of AI-enabled tools document management platforms with semantic search, intelligent scheduling assistants, and operational reporting dashboards as staff capability and infrastructure reliability mature.

Before committing to any tool, enterprises should conduct a brief digital readiness audit covering three dimensions: infrastructure readiness (stable internet access, reliable power, adequate device provision); human readiness (staff digital literacy and psychological readiness for workflow change); and process readiness (clarity about which office tasks are most time-intensive and most structurally amenable to automation). Involving administrative staff in tool selection rather than imposing decisions from above is not merely good practice; it is empirically associated with higher adoption rates and faster competency development (Ugwu & Njoku, 2025).

7.2 For Government and Regulatory Agencies

The Rivers State Government and relevant federal agencies NITDA, SMEDAN, and the Ministry of Communications should design dedicated SME AI adoption support programmes comprising three complementary components. First, a technology access fund providing co-financing arrangements for AI tool subscriptions and digital hardware for qualifying SMEs. Second, a digital infrastructure improvement programme prioritising reliable power and broadband connectivity in SME-dense commercial districts, aligned with the National Broadband Plan and the Rural Electrification Agency's mandate. Third, a regulatory clarity initiative providing accessible, practical guidance on data governance, digital transaction standards, and liability frameworks for small businesses deploying AI tools.

A time-limited technology investment tax relief mechanism covering qualifying AI tool subscriptions and staff digital training costs would directly address the cost barrier ranked highest by respondents, without requiring substantial direct public expenditure. Such an instrument is consistent with the type of policy-level enabling environment that the World Bank (2023) and OECD (2025) identify as necessary for AI's productivity potential to be distributed equitably across enterprise sizes in developing economies.

7.3 For Tertiary Institutions and Training Organisations

Universities, polytechnics, and vocational training institutions in Rivers State should systematically integrate practical AI literacy into business administration, secretarial studies, and entrepreneurship curricula. This means not merely conceptual familiarity with AI but hands-on competency in tool selection, basic deployment, prompt engineering for generative AI applications, and digital workflow design. Short-course AI literacy programmes for current SME administrative staff and managers offered through continuing education departments in partnership with trade associations such as the Manufacturers Association of Nigeria (Rivers State Chapter) and the Port Harcourt Chamber of Commerce represent the most tractable near-term intervention given the digital literacy gap identified as the third most severe adoption barrier. The National Board for Technical Education (NABTEB) and the Rivers State Skills Development Authority are well-positioned to coordinate and accredit such programmes at scale.

7.4 For Technology Providers

AI tool providers seeking to serve the Rivers State SME market should invest in localised support infrastructure: network of local-agent technical support personnel, and offline-capable or low-bandwidth versions of tools designed for environments with unreliable connectivity. The evidence that over half of sampled enterprises have not adopted any AI tool points not to a lack of demand most managers recognised AI's potential but to a product-market fit gap: tools currently available are not sufficiently designed for the deployment realities of this context. Providers who close this gap through localised support, flexible subscription models, and bandwidth-efficient design stand to access a commercially significant and largely untapped market. Future research should investigate whether localised onboarding in widely spoken vernacular languages including Nigerian Pidgin reduces adoption friction a question the broader technology diffusion literature suggests is empirically worth pursuing.

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