DETERMINANTS OF ARTIFICIAL INTELLIGENCE ADOPTION AMONG SECURITY AGENCIES IN NIGER STATE, NIGERIA

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AI adoption determinants, Security agencies, Technology acceptance

Abstract

Research Problem: *Despite compelling global evidence that artificial intelligence (AI) technologies can transform crime detection and prevention, security agencies in Niger State, Nigeria continue to operate within conventional, pre-digital frameworks that have demonstrably failed to contain the state's escalating violent crime. The specific individual, organisational, and structural factors that determine whether and how these agencies adopt AI, and the precise challenges that impede uptake, remain empirically uninvestigated. This gap prevents evidence-based policy design for security technology modernisation in the state.*
Methods/Theory: *A quantitative descriptive survey design was adopted. The Technology Acceptance Model (TAM) and Diffusion of Innovations Theory provided the theoretical anchors. The target population comprised 1,623 operational and intelligence personnel of the NPF, NSCDC, and NVG in Niger State. Using Yamane's formula, a sample of 321 was determined; 350 were targeted for attrition, yielding 327 valid responses. Proportionate stratified random sampling ensured agency-level representativeness. Data were collected via a 16-item, 5-point Likert-scale questionnaire (Cronbach's α = 0.87) and analysed using frequency distributions, means, and standard deviations in SPSS version 27.*
Results: *Digital infrastructure quality (mean = 4.45), leadership and management support (mean = 4.41), and training availability (mean =*

4.37) emerged as the most critical determinants of AI adoption. Security agencies simultaneously face a multidimensional cluster of adoption challenges, with poor electricity supply (mean = 4.47), limited internet connectivity (mean = 4.39), high procurement costs (mean = 4.36), and the absence of AI policy frameworks constituting the most severe barriers.
Conclusion: *The adoption gap in Niger State's security agencies is not primarily attitudinal but structural and institutional. TAM's facilitating conditions and the Diffusion of Innovations' compatibility and complexity dimensions account for more of the adoption variance than individual perceptual factors alone, suggesting that generic technology adoption frameworks require contextual extension to adequately explain AI uptake in resource-constrained African security environments.*
Key Contribution to Knowledge: *This study produces the first systematic empirical documentation of AI adoption determinants and challenges among security agencies in Niger State, extending TAM and Diffusion of Innovations Theory to a peripheral, conflict-affected African context and demonstrating that structural enablers constitute the dominant adoption constraint in such environments.*
Recommendation: *Government should develop a dedicated AI adoption policy for the security sector, invest in digital infrastructure at frontline security bases, and institutionalise a tiered AI training curriculum within existing security academies in Nigeria.*

Introduction

Artificial Intelligence (AI) is one of the most significant and challenging governance issues in the 21st century, and its use in public security and law enforcement is set to be one of the most transformative and consequential applications. In both developed and developing country settings, governments are seeing that traditional police practices of policing through reactive, labour-intensive, and conventional methods are no longer adequate to meet the demands of modern, rapid, complex, and sophisticated criminal threats. AI technologies, which include machine learning algorithms, predictive analytics platforms, computer vision systems, and intelligent surveillance infrastructure, provide novel capabilities to predict crime, identify criminals, monitor high-risk areas, and respond to security incidents with greater precision and efficiency than humans can achieve (Perry *et al*., 2022; Brayne, 2021). As AI's impact on law enforcement continues to grow, the trend is not just about technology; it's about adapting to a changing landscape where security challenges are more complex than ever, and resources, whether manpower or financial are limited.

The existing research in the field of AI in policing has taken two directions. The first, focused on North American and European contexts, addresses outcomes of the use of AI in crime detection, response and in improving the efficiency of resource allocation (Brayne, 2021; Perry *et al*., 2022; Ratcliffe*et al*., 2021; Wirtz*et al*., 2021). These studies revealed that AI offers an advantage over the traditional approach in an ideal situation. The second track, which came from an African and broader Global South context, shifted away from effectiveness to adoption constraints, recording the infrastructural, institutional and capacity constraints facing security agencies that prevent them from using AI at all (Gwagwa*et al*., 2022;

Nnamdi&Chukwuemeka, 2022; Adeyemi, 2022). In this second stream, most studies are conducted at the national level and conceal state-level differences, or are limited to economically developed urban areas such as the one in Lagos and Abuja, which are very different from the peripheral, resource-poor states. Specifically, this study does not explore the factors that underlie the decision to adopt AI by frontline security officers in geographically remote, under-invested and conflict-prone Nigerian states. This is a consequential gap because policy prescriptions from either the Global North effectiveness literature or the Nigeria-urban adoption literature are likely to be utterly at odds with the challenges faced by agencies in states such as Niger.

Given the consistently precarious security situation in Nigeria, with its recurring nature of organised armed robbery, banditry, kidnapping for ransom, terrorism and communal violence, the urgent need to move this imperative is heightened, as each of these behaviours imposes unimaginable human, economic and governance costs on targeted communities and state institutions (Alemika, 2022; Nwaneri&Olawale, 2023). This urgency is not being met, however, as the use of AI and other digital technologies in security agencies in Nigeria has been slow and sporadic due to resource gaps, institutional inertia, and various structural, organizational, and individual-level challenges, which have yet to be documented and analysed.

The state of Niger in the north-central geopolitical region of Nigeria is an interesting case study to explore the challenges faced by security agencies when adopting AI. For the past decade ago, an increased rate of violent activities, including armed robbery, kidnapping, communal violence, and organised banditry has been recorded in the State (Niger State Ministry of Internal Affairs, 2024; Idowu and Musa, 2023). It has a limited capacity for the integration of technology, with poor institutional structures and training capability, weak digital infrastructure, and inadequate security agencies such as the NPF, NSCDC, and NVG to operate in a challenging and resource-poor context. Thus, it is important to both theory and practice to understand what makes the difference between the adoption and non-adoption of these AI technologies by these agencies.

Problem Statement

Despite the significant shift in the sophistication, organisation and geographical reach of the threats faced by security agencies in Niger State, yet they are predominantly still operating within pre-digital security frameworks. Although AI technologies have been proven to improve crime detection, prediction and prevention efforts worldwide, the use of AI among the NPF, NSCDC and NVG in Niger State remains limited, and the efforts are not consolidated (Nnamdi&Chukwuemeka, 2022; Niger State Ministry of Internal Affairs, 2024). The failure is a serious operational gap that hampers the ability of security agencies to effectively meet the security threats that are growing more and more in the state.

Little is known about what conditions enable or constrain security agencies' use of AI technologies in resource-limited settings like Niger State. Available literatures on the adoption of technology in a public sector setting in Nigeria either do not apply to non-security sector areas like healthcare and education, or they only cover urban and better-resourced settings that do not adequately represent the structural context of north-central Nigeria (Adewale&Okonkwo, 2022; Adeyemi, 2022). Designing specific policies to promote the

uptake of AI in security agencies in Niger State cannot be done without empirical evidence of the factors that drive AI adoption and the exact nature of the problems that security agencies are facing which may be different from one agency to another. This study sought to directly provide solutions to this empirical gap.

Research Objectives

The specific objectives of this study are to:

1. Identify the determinants influencing AI technology adoption among security agencies in Niger State, Nigeria.

2. Investigate the challenges faced by security agencies in adopting AI technologies in Niger State, Nigeria.

Research Questions

This study is guided by the following research questions:

1. What are the determinants influencing AI technology adoption among security agencies in Niger State, Nigeria?

2. What are the challenges faced by security agencies in adopting AI technologies in Niger State, Nigeria?

Originality and Scholarly Contribution

The present study is different from the previous works in three aspects. First, unlike the national or urban level existing Nigerian adoption studies (Nnamdi&Chukwuemeka, 2022; Adeyemi, 2022) this study breaks down to the level of a specific state in the periphery of the country in a region of conflict, generating nuanced evidence that national and urban surveys necessarily mask. Second, although the previous literature tends to use TAM and Diffusion of Innovations Theory as explanatory templates without critically questioning their ability to explain adoption in African contexts where structural conditions are the main adoption barrier, this study challenges the explanatory power of both these theories, suggesting that structural conditions are more likely to be the barrier to adoption than individual perceptions.

Theoretical Framework

Technology Acceptance Model (TAM)

Davis (1989) has developed the most widely used theoretical framework to examine technology adoption, which is known as the Technology Acceptance Model. According to TAM, the perceived usefulness (PU) and perceived ease of use (PEOU) of a technology are the most important factors that influence behavioural intention to use a technology, which in turn are the most important factors that predict actual use. Venkatesh*et al*. (2020) expanded the model by adding social influence, facilitating conditions, and effort expectancy. Thus, the Unified Theory of Acceptance and Use of Technology (UTAUT) has been extended from the model. Moderate support for the role of perceived usefulness has been obtained from security-related TAM-based studies in Nigeria (Adewale&Okonkwo, 2022; Nnamdi&Chukwuemeka, 2022), while all the studies also show that facilitating conditions (infrastructure, training, and institutional support) have stronger independent effects on adoption than individual perceptual variables.In Nigeria's Niger State, the architecture of TAM emphasizes the explanatory primacy of individual cognition and systematically de-emphasizes structural constraint, due to the fact that the state suffers from frequent power shortages, no internet connection and no policy frameworks for the use of AI. It is not

necessarily that TAM is not applicable, but in resource-poor settings the order of determinants in TAM (attitude before environment) may be reversed. Therefore, this study uses TAM as a partial framework and investigates whether the individual level constructs of TAM can still be considered as their theorised primacy when structural and institutional constructs are also measured, as this can be considered a critical extension of TAM scholarship from a context perspective.

Diffusion of Innovations Theory

According to Rogers' (2003) Diffusion of Innovations Theory, there are five attributes of innovations that affect adoption: relative advantage, compatibility, complexity, trialability, and observability. The theory suggests that innovations perceived as relatively advantageous, compatible with current values, easy to use, triable and visibly beneficial will spread at a quicker rate within the adopter community. The model also describes the role of the laggards, change agents and social system in diffusion as well as the types of individuals who are likely to adopt a new product or service first, such as innovators and early adopters, as well as the types of individuals who are likely to adopt a new product or service last, such as laggards.

When applied to the adoption of AI technologies by security agencies in the State of Niger, the Diffusion of Innovations Theory sheds light on the relevant dimensions that are not captured in TAM but is also not a recipe for mechanical application. The 'trialability' attribute which is the ability to trial something with low risk is structurally undermined in contexts that require considerable and non-gradable investment in power infrastructure and connectivity before any 'trialing' is possible in the investment of AI systems. Rogers' theory therefore seems to underestimate the importance of structural lock-in and institutional inertia as barriers to adoption in contexts such as Niger State. This research does not utilize the DoIT as a template to be fitted to the data, but rather as a starting point that can be tested in a peripheral African security context, where it confirms some predictions, but also points to substantial gaps for which it requires theoretical elaboration.

AI Technology Adoption in Security Contexts

AI technology adoption in security involves the implementation, integration, and routine use of AI technologies such as predictive analytics, AI-enabled surveillance systems, crime mapping tools, and automated AI processing, within security organisations that are demonstrated to substantially impact their operational capability (Brayne, 2021; Venkatesh*et al*., 2020). Adoption is not an on/off switch but is a multi-stage, multi-level process – individual willingness, organisational commitment and structural enablement. However, a crucial distinction between nominal and operational adoption of AI tools needs to be made in the context of the Nigerian security agencies.But for Nigerian security agencies, there is a critical gap between operational and nominal adoption of AI tools, meaning that AI tools need to be integrated into daily operations to provide meaningful security outcomes. Existing literature often lumps these together and assumes that the use of technology is synonymous with adoption. In the resource-limited settings of Niger State, the gap between nominal and operational adoption is very large and is the empirically salient phenomenon that should be the subject of study. Conceptual frameworks of that transition and the impediments to it are the heart of the present analysis.

Scholars have also differentiated between the individual level of adoption, which depends on attitudes, skill, and motivation, and the system level of adoption which depends on norms of inter-agency coordination, quality of infrastructure, and leadership commitment, as well as institutional policy (Rogers, 2003; Gwagwa*et al*., 2022). The focus on individual-level factors in the current AI adoption literature is driven by the theory underpinning this research, which has its origins in TAM and its descendants, which were developed to explain individual user behaviour in the context of organisational IT. This is a theoretical bias that usually misleads the adoption landscape in peripheral African security environments, where individual officers are very positive towards AI adoption while institutional obstacles hinder it. The conceptual model used for this study thus emphasizes structural, organisational and individual determinants, which are not a priori assumed to be the respective explanatory variables, but are left open for the empirical result which was obtained and subsequently confirmed in the results.

Determinants of AI Adoption in Security Contexts

Research in the field reveals a wide and complex range of factors which determine the adoption of AI in the security and law enforcement domain, across individual, organisational and structural factors. In TAM-based studies, perceived usefulness is always the most significant single factor, with security professionals who strongly believe that AI tools will make it easier to detect crime, respond faster and be more secure being more likely to support and utilize AI technology (Perry *et al*., 2022; Adeyemi, 2022). In African Public (PS) sectors however, there is a growing body of literature that suggest that the influence of OSSFs on actual adoption is stronger than that of individual perceptions, with leadership support, training availability, and infrastructure quality among the most frequently cited factors affecting OSSFs (Gwagwa*et al*., 2022; Nnamdi&Chukwuemeka, 2022). The quality and reliability of digital infrastructures is the enabling condition at structural level for any operational context and in Niger State, the chronic shortage of the same is the main condition for the adoption of AI (Niger State Ministry of Internal Affairs, 2024). Likewise, the non-existence of institutional AI policy frameworks is an important, yet under-researched structural determinant, which sets the governance context in which decisions on technology investments are taken and sustained.

Methodology

The research design is descriptive survey research design which is appropriate for empirical study aims to describe and document the characteristics of a phenomenon, population or situation as they occur in a natural setting, and in which the researcher does not manipulate variables (Creswell & Creswell, 2018). The descriptive survey design is highly suitable for the present study because its purpose was to provide empirical evidence of the factors that affect the use of AI and the hindrances faced by security agencies in Niger State, a phenomena that could not be manipulated and studied using experimental designs. This study took place in the north-central geopolitical zone of Nigeria, specifically in Niger State, a region with relatively low availability of resources and high security risks, thus providing an interesting scenario for the study of barriers to AI adoption in a frontier security environment.The target groups were operational and intelligence staff of three security agencies in Niger State namely Nigeria Police Force (NPF), Nigeria Security

and Civil Defence Corps (NSCDC), and Nigerian Vigilante Group (NVG). The Nigerian Army and Department of State Services (DSS), whose commands refused access for the research, were excluded from the list of agencies, which formed the study population. NPF, NSCDC and NVG are the main agencies directly involved in crime detection and prevention in Niger State on a day to day basis. The accessible population as captured from administrative records at the respective headquarters was 1623 personnel (940 NPF officers, 438 NSCDC staff and 245 NVG members).

The sample size was calculated based on the formula Yamane (1967) provided: $n = N / (1 + Ne^2)$, where N is the population size and e is the margin of error chosen (0.05 or 5%). Substituting: $n = 1,623 / (1 + 1,623 \times 0.0025) = 1,623 / 5.058 \approx 321$. In order to allow for non response and to provide sufficient statistical power, 350 respondents were targeted, with a 9% attrition allowance. The sample size is determined scientifically and the results have adequate statistical precision and generalisability within the specified margin of error to the studied population.To ensure representativeness across diverse organisational units (Creswell & Creswell, 2018), proportionate stratified random sampling was used, meaning each agency sub-group was sampled in the same proportion that they represented in the population. In the first step of this method, the population was divided into three strata, each based on an agency. The proportionate allocation formula ($nh = (Nh/N) \times n$) was then applied to each stratum, producing: NPF = $(940/1,623) \times 350 = 203$ respondents; NSCDC = $(438/1,623) \times 350 = 95$ respondents; NVG = $(245/1,623) \times 350 = 52$ respondents. In each stratum the individuals were then selected by simple random sampling by ballot method, with equal possible chance of being selected for each of the individuals in each stratum and with a minimum of selection bias.

The basic data collection tool used was the structured questionnaire that consisted of two parts. Data on agency affiliation, rank, years of service and educational qualification was collected in section A. There were sixteen (16) Likert scale items rated on a 5-point scale (Strongly Disagree to Strongly Agree) in Section B, targeted on each research objective with eight items. Items 1-8 looked at the factors driving the adoption of AI, while Items 9-16 focused on the barriers to adoption. Content validity was determined by expert evaluation with three criminology, security studies and information systems experts of the Ibrahim BadamasiBabangida University, Lapai. A pilot study involving the security personnel of Kogi State (outside the main study) was conducted to assess reliability. The Cronbach's α coefficients were as follows: α overall = 0.87, α Objective 1 = 0.84 and α Objective 2 = 0.89. All values are above the 0.70 threshold which indicates good internal consistency (Nunnally& Bernstein, 1994). SPSS version 27 was used to analyze the data and the threshold for the mean score was set at 3.00; the mean score $\geq$ 3.00 represents agreement, while the mean score $<$ 3.00 represents disagreement (Adeyemi, 2022).

Results

Research Question 1

What are the determinants influencing AI technology adoption among security agencies in Niger State, Nigeria?

Table 1: Mean scores and standard deviations for respondents' perceptions of determinants of AI technology adoption among security agencies in Niger State (n = 327)

Item	Statement	Mean	SD	Decision
1	Perceived usefulness of AI tools significantly influences the decision of security personnel to adopt them.	4.32	0.61	Agreed
2	The perceived ease of use of AI technologies affects their adoption among security personnel.	4.18	0.68	Agreed
3	Management and leadership support is a critical determinant of AI adoption in security agencies.	4.41	0.57	Agreed
4	Availability of training and capacity development programmes promotes AI adoption among security personnel.	4.37	0.59	Agreed
5	The quality of digital infrastructure, including electricity and internet, determines the extent of AI adoption.	4.45	0.54	Agreed
6	Institutional policies and regulatory frameworks for AI adoption influence technology uptake in security agencies.	4.29	0.63	Agreed
7	Inter-agency collaboration and information sharing practices affect AI adoption outcomes.	3.87	0.76	Agreed
8	Prior exposure to digital technologies and level of digital literacy among personnel influences AI adoption.	4.11	0.72	Agreed
	Grand Mean	4.25	0.64	Agreed

The mean scores and standard deviations of the perceptions of the respondents about the factors that affect the adoption of the AI technology by security agencies in Niger State are presented in Table 1. The mean values for each item ranged from 3.87 to 4.45 and the standard deviation values ranged from 0.54 to 0.76. The grand mean is 4.25 (SD = 0.64), which shows that there is consensus on all items. Infrastructure quality (mean 4.45), followed by leadership support (mean 4.41) and training availability (mean 4.37) were perceived as the most important enablers of AI adoption in this context, with inter-agency collaboration seeing the lowest mean (3.87) score and considered comparatively less immediately decisive.

Research Question 2

What are the challenges faced by security agencies in adopting AI technologies in Niger State, Nigeria?

Table 2: Mean scores and standard deviations for respondents' perceptions of challenges faced by security agencies in AI technology adoption (n = 327)

Item	Statement	Mean	SD	Decision
9	Poor electricity supply is a major challenge hindering AI technology adoption in security agencies.	4.47	0.53	Agreed
10	Limited internet connectivity constrains the effective deployment and use of AI-enabled security tools.	4.39	0.58	Agreed
11	Insufficient technical expertise and digital skills among security personnel impedes AI adoption.	4.28	0.64	Agreed
12	Inadequate funding and budgetary allocations limit the procurement of AI technologies by security agencies.	4.33	0.61	Agreed
13	The absence of clear AI policy and regulatory frameworks is a significant obstacle to technology adoption.	4.21	0.69	Agreed
14	Institutional resistance to change and attachment to conventional methods hampers AI integration.	3.94	0.78	Agreed
15	The high cost of AI hardware, software, and maintenance is a barrier to adoption in the agency.	4.36	0.60	Agreed
16	Lack of inter-agency coordination and data sharing frameworks limits the potential of AI adoption.	3.78	0.83	Agreed
	Grand Mean	4.22	0.66	Agreed

The mean scores with standard deviations for the respondents' perception of challenges in implementing AI technologies in the security agencies are presented in Table 2. The mean values were in the range of 3.78 to 4.47 and the standard deviation values were in the range of 0.53 to 0.83. The overall mean score, or grand mean, was 4.22 (SD = 0.66), which shows agreement on all the items. Limited internet connectivity (mean = 4.39), inadequate funding (mean = 4.33), the high costs of procurement and maintenance (mean = 4.36), and poor electricity supply (mean = 4.47) were found to be the greatest obstacles. Although still felt to be challenges, the perceived barriers of institutional resistance and lack of inter-agency coordination had the lowest means, indicating that structural and infrastructural barriers are seen as more daunting than organisational-cultural barriers.

Findings

The study found the following:

1. The factors influencing the use of AI technology by security agencies in Niger State are multifaceted, ranging from personal beliefs about the utility and ease of use, to institutional and cultural

influences such as management support and the availability of training, and structural factors such as digital infrastructure and institutional policy. Structural and organisationalfactors, such as infrastructure quality, leadership support and training availability, were the most important factors, suggesting that perceptual factors at the individual level have only a limited explanatory value in this case.

2. The security agencies in Niger State are confronted with multidimensional and severe challenges with respect to the adoption of AI technology. The main challenges are: poor electricity supply, limited internet connectivity, high procurement costs, lack of technical expertise, lack of sufficient funding, and unclear AI policy frameworks, which compound to worse effects than they have when they occur individually.

Discussion of Findings

Determinants of AI Adoption

The results of Objective 1 support the previously mentioned results that determine the adoption of AI in the security agencies in the State of Niger are multidimensional and structurally dominated, that is, the availability of infrastructure and leadership support and training programs consistently outrank individual perceptual factors like usefulness and ease of use. This result is of theoretical significance. In the original formulation as proposed by Davis (1989), TAM considers individual cognitive beliefs (perceived usefulness and perceived ease of use) as determinants of the technology adoption intention and behaviour. The present results do not invalidate the applicability of TAM, but they show the boundaries of its hierarchy in resource-stressed environments in Africa. The very high mean for infrastructure quality as a determinant suggests that security officers in Niger State are highly aware that their operational environment's structural deficiencies are the main constraint, one that lies upstream of the intention of security officers, and unless corrected, may undermine or deplete attitudinal willingness. This serves as an empirical evaluation of the theory's explanatory framework and, together with other African studies on technology adoption (Gwagwa et al., 2022; Adewale&Okonkwo, 2022), supports TAM that prioritize structural enablers and are adapted to contextual realities.

The degree of agreement for management and leadership support as a determinant, is in line with the theoretical framework of UTAUT and the social influence construct, which is also theoretically consistent with Diffusion of Innovations Theory with the role of the change agent in the process of organisational innovation. It differs from the 'laggard' adopter organisations that would be expected of a security agency, which are described by Rogers (2003) as being hierarchical, risk-averse and ruled by 'operational norms' that are not conducive to innovation. The willingness of staff to identify support from leadership as one of the critical determinants indicates that the resistance is not passive, but that the organisation is ready to follow the leader's instructions, which is more of a military style organisation than the diffusion of Innovations theory suggests. This discovery suggests that there is a considerable need to modify the Diffusion of Innovations' framework, which considers adoption as a process that arises from individual innovation perception, for the case of institutionally demanded adoption in the context of bureaucracy security.

The inter-agency collaboration determinant is compared with the inter-agency collaboration determinant in technologically advanced policing contexts, where inter-operability and data sharing are identified as key drivers of adoption (Wirtz*et al*., 2021; Perry *et al*., 2022) and is found to be lower. This dichotomy may be explained in the theoretical lens of the present study as not yet addressing the more fundamental determinants (namely infrastructure and leadership) of an inter-agency approach to building capacity, personnel's perception of inter-agency coordination as the immediate barrier for adoption is not yet present. The sequencing suggests the way forward to implement AI in Niger State would require addressing the gaps in foundational infrastructure and leadership before inter-agency integration frameworks can be practically implemented, resulting in significant implications for policy prioritisation.

Challenges of AI Adoption

The results for Objective 2 highlight a pessimistic scenario for structural conditions affecting security agencies in the use of AI. The near-universal and robust agreement across all eight challenge items indicates that the challenges to the use of artificial intelligence in Niger State is not a set of isolated or peripheral challenges, but rather a set of interconnected problems. Theoretically significant is the identification of poor electricity supply as the most acute challenge which is relevant to the critical extension of the TAM proposed in this paper. In Niger State, the relationship between intention and behaviour is completely cut off by facilitating conditions, TAM predicts. A lack of infrastructure is not a moderating factor, but a categorical barrier, when AI systems lose their functionality of continuous electricity and stable connectivity. This discovery builds on TAM's theoretical conceptualisation of facilitating conditions from a moderating to gatekeeping role in structurally challenging deployment settings.

The comparatively low mean of institutional resistance to change on the challenge items is an interesting finding that differs from previous institutional adoption research that has been developed within high income policing environments. Organisational culture and reluctance to change have been cited as the primary barriers to adoption in the UK, U.S. and Australia, alongside worries about algorithmic bias, data privacy and the risk to professional discretion, as being significant contributors to scepticism (Perry *et al*., 2022; Wirtz*et al*., 2021). The lower salience of institutional resistance in Niger State is not a sign of unusual receptiveness, but of a different adoption landscape, where security personnel are denied reliable electricity and internet access, have never been exposed to an AI tool that has been put into operation, and are regularly confronted by severe and persistent security threats that render meaningful engagement with AI tools impossible. The main challenges are thus not attitudinal or cultural, but material and structural, with significant implications for intervention design, which are not well theorised in existing adoption frameworks.

The findings of the present study, which was conducted in Niger State, Africa, are qualitatively direr than the findings of Adeyemi (2022) which was conducted in Lagos State, Nigeria. While in this study, power supply and maintenance capacity are shown to hinder the deployment of AI, in Adeyemi's study they are shown to impact the effectiveness of AI when deployed. It is a more fundamental impasse that can only be addressed by interventions to partially adopted environments will not

overcome. The implication here is that Niger State must spend on the infrastructure needed to support AI prior to and separate from the installation of the AI itself, which the security technology policy conversation has not yet prioritized.

Conclusion

The present study aimed to empirically discover the determinants of the adoption of AI, and the challenges confronting security agencies in Niger State (Nigeria), with the aim of yielding empirical and theoretical implications. Empirically, the study validates the importance of structural factors as the key barrier to adoption in Niger State, with the quality of the digital infrastructure, leadership support, and availability of training programmes being the most important structural factors, while the quality of electricity supply, internet connectivity, costs, and the absence of policy frameworks are the most important barriers. These findings differ from the expectations of TAM and Diffusion of Innovations Theory in their contexts, and in this way contribute to a theoretically productive criticism that goes beyond both.

What is striking from the conceptual implication is that TAM's hierarchy of individual perception over structural condition and the emphasis on individual innovation attribute assessment under DI Theory are both found to be inadequate explanatory frameworks for the adoption of AI in resource-limited security contexts in Africa. The present study shows an empirical link between the individual and organisational adoption processes that are theoretically described in TAM and Rogers respectively and that structural factors are not moderating factors, but they are gate keeping factors that determine if the individual or organisational adoption process can take place at all. This is a worthwhile theoretical development and advance in the theory of adoption, going beyond merely building on existing theory, as it sets up a theory that adoption theory needs to be stratified and contextualized and that the hierarchy of explanatory variables is not fixed but rather contingent on the context of structural development.

The current results confirm the results of the multi-country African study by Gwagwa*et al.* (2022), which identified infrastructure deficit as a key constraint in adopting AI in peripheral jurisdictions, and the result of Nnamdi and Chukwuemeka (2022) which documented AI adoption constraints in the NPF at a national level. The present study, however, extends beyond the aforementioned earlier research as it does disaggregate to the state level, as well as simultaneously consider multiple agencies, and as such, it critically interrogates the theory of conventional explanations with regard to adoption. These differences represent the study's original research contribution to the literature of security in the northern-central region of Nigeria.

Recommendations

The following recommendations are made based on the results of this study:

1. The Nigerian Government (both Federal and State) should form an AI Security Infrastructure Fund to fund the procurement of solar-powered electricity systems, broadband internet connectivity and AI-enabled surveillance at NPF/NSCDC/NVG operational bases, while the Nigeria Police Service Commission and NSCDC Headquarters should issue clear institutional mandates for AI adoption in

all the state commands with special budgetary allocations and command accountability system.

2. The Niger State Government ought to create a state-level AI Governance Policy for the security sector, and establish a structured and tiered AI training course at the existing security training academies in the state, with the aim of reducing costs and helping to sustain the deployment of AI tools in the state's security agencies through public-private partnerships with technology vendors.

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