RESEARCH ARTICLE

Technology Adoption and Workforce Performance in Public Service: Strategic Models and Institutional Perspectives

Boniface Umoh E*

Department of Accounting, Faculty of Financial Studies Institute of Management and Technology (IMT), Enugu, Nigeria

Abstract

In today's digitally driven environment, public sector institutions are increasingly expected to adopt technologies that enhance efficiency, transparency and accountability. This study, technology adoption and workforce performance in public service: strategic models and institutional perspectives, investigates how workforce performance and technology adoption are related using the national identity management commission in Nigeria as a case study. The specific goals for the study were to: determine how perceived ease of use influences contextual performance; assess the effect of perceived usefulness on productive behavior; examine the impact of behavioral intention on adaptive performance; investigate the role of facilitating conditions on task performance and explore how social influence affects innovation in the public sector. A descriptive survey design was used and a sample size of 361 respondents was used. Regression analysis using SPSS version 25 was utilized to test the hypotheses. In addition, SWOT and PESTEL frameworks were applied to provide strategic insights into internal and external influences on technology adoption. Findings revealed statistically significant relationships between perceived ease of use and contextual performance (p=0.012), perceived usefulness and productive behavior (p=0.001), and behavioral intention and adaptive performance (p=0.001). However, facilitating conditions (p=0.255) and social influence (p=0.287) did not significantly affect task performance and innovation respectively. The study was limited by constraints in accessing disaggregated organizational data and regional staff deployment. The study concludes that while technology adoption positively impacts workforce performance, more attention should be given to institutional support systems and strategic alignment.

Key Words: *Technology adoption; Workforce performance; Public service; Strategic models; Institutional perspectives*

***Corresponding Author**: *Boniface Umoh E, Professor, Department of Accounting, Faculty of Financial Studies Institute of Management and Technology (IMT), Enugu, Nigeria; E-mail: bontechsearch@gmail.com*

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1. Introduction

The accelerating pace of technological advancement is reshaping institutions, businesses and economies globally. In accordance with moore's law, the exponential growth in computing power has fueled transformative innovations, enhancing accountability, streamlining public service delivery and improving transparency [1]. Technology adoption has become central to modern public sector reform, with governments leveraging digital systems to reduce human error, increase efficiency, and enhance citizen engagement [2].

Highly developed economies like the US, UK, Germany, Japan, as well as Singapore have long integrated digital technologies into public governance. These countries deploy sophisticated ICTs such as big data analytics, artificial intelligence, cloud computing and biometric identification. Estonia, for example, is often cited considered a pioneer in digital government worldwide with its "e-Estonia" program, which offers nearly all public services online. Similarly, Singapore has harnessed smart technology for public safety, education and urban planning, strengthening its status as a digitally advanced nation. Emerging economies including Brazil, India and China are also making significant progress. India's aadhaar, the biggest biometric identification system in the entire globe has improved the targeting of social welfare programs and reduced identity fraud. In China, advanced digital systems like facial recognition and artificial intelligence have been deployed across sectors including health, administration and surveillance. China's "social credit system" exemplifies how data analytics can be used to evaluate citizen behavior and facilitate administrative decisions.

Africa, while facing considerable infrastructure challenges, is gradually adopting digital tools in governance. Nigeria, Kenya and South Africa are among the nations that have implemented reforms to enhance public service delivery and administrative efficiency [3-5]. But obstacles including unstable power source, inadequate internet access, outdated administrative procedures, as well as a lack of skilled workers still stand in the way of progress, claim Orji, et al. [6]. Despite these challenges, certain African countries are emerging as leaders in digital public administration. Kenya's huduma centers and Rwanda's irembo platform are two well-known examples of centralized digital service delivery that have significantly reduced bureaucratic delays. South Africa's adoption of digital tools in agencies such as the South African Revenue Service (SARS) and the department of home affairs has also improved responsiveness and transparency. However, persistent differences in availability of digital infrastructure proceed to impede the achievement of egalitarian transformation.

Empirical studies have shown that successful technology adoption in public institutions is associated with higher labor productivity, data transparency and operational agility [2,7]. Two fundamental models that highlight significant factors influencing public sector employees' acceptance and successful application of technology are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [8,9]. These elements consist of perceived utility, convenience of use and behavioral intention.

Given Nigeria's ongoing challenges in implementing long-term digital changes in its public institutions, the country's selection is crucial. The National Identity Management Commission (NIMC), which oversees the establishment of the national identification database and biometric registration system, is a crucial component of Nigeria's digital governance architecture. An examination of NIMC offers an opportunity to look into how technology affects organizational performance in a real-world setting where administrative, human resource and infrastructure issues are prevalent.

1.1. Statement of the problem

Globally, the adoption of technological innovations in the public sector has increased recently with the goal of enhancing service delivery, efficiency and accountability. However, in many poor countries like Nigeria, public institutions still struggle to integrate technology into their everyday operations. The expected benefits of technology adoption are frequently hampered by issues including poor employee engagement with digital technologies, reluctance to change, a lack of infrastructure, and a lack of institutional support.

Current studies have largely focused on technological adoption from an infrastructure or policy angle, often overlooking how employees’ perceptions such as ease of use, usefulness, and social influence affect actual work performance. Furthermore, little is known about how internal organizational factors like facilitating conditions and behavioral intentions shape the performance outcomes of technology use in government institutions. In order to fill this gap, this work investigates how specific dimensions of technology adoption influence various aspects of workforce performance within the NIMC.

1.2. Research objectives

The following specific objectives serve as the study's scope:

- To determine how the perceived ease of use of technology influences contextual performance among employees in the public sector.
- To assess the effect of the perceived usefulness of technology on the productive behavior of public sector workers.
- To examine the extent to which employees’ behavioral intention to use technology affects adaptive performance in public institutions.
- To investigate the role of facilitating conditions in supporting and improving task performance within public sector organizations.
- To explore how social influence shapes innovation and creative practices among public sector employees.

1.3. Research questions

- How does the perceived ease of use of technology influence contextual performance among public sector employees?
- What is the effect of the perceived usefulness of technology on employees' productive behavior?
- How does behavioral intention to use technology affect adaptive performance in public institutions?
- What role do facilitating conditions play in enhancing task performance within public sector organizations?
- In what ways does social influence affect innovation among public sector workers?

1.4. Research hypotheses

H_{01}: There is no significant relationship between the perceived ease of use of technology and contextual performance among public sector employees.
H_{02}: The perceived usefulness of technology has no significant effect on employees' productive behavior in public service organizations.
H_{03}: Behavioral intention to use technology does not significantly influence adaptive performance in public institutions.

H_{04}: Facilitating conditions have no significant role in enhancing task performance within the public sector.
H_{05}: Social influence does not significantly affect innovation among public sector workers.

2. Review of Related Literature

2.1. Conceptual literature

As shown in figure 1 about the conceptual model (Figure 1).

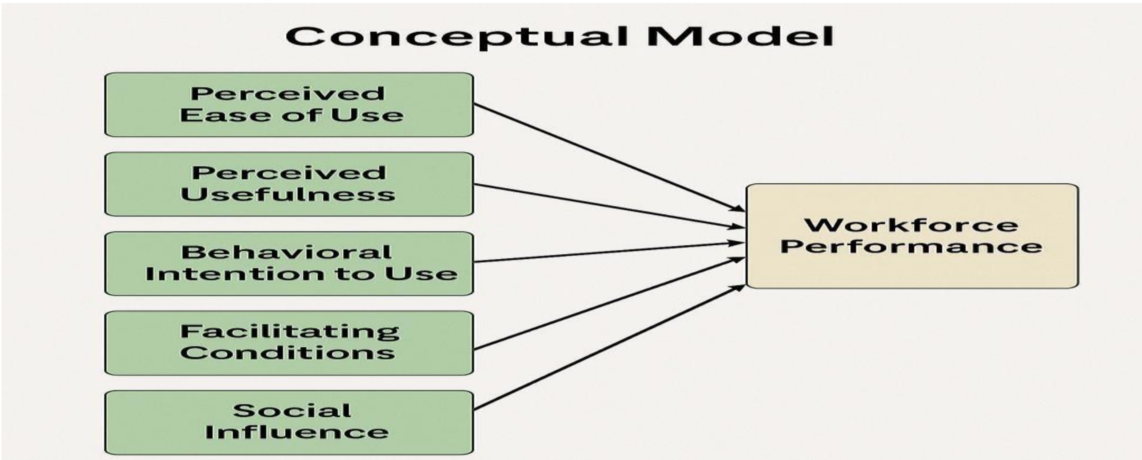

Figure 1: *Conceptual model of the study.*

2.2. Technology adoption

Technology adoption is the process by which an individual or organization decides to purchase and use a new, advanced technology. Many companies are looking for a trustworthy behavior prediction tool because of the growing demands on technology and the growing number of organizational technology adoption failures. Technology adoption necessitates significant managerial efforts and commitments inside the business, even though it also depends on employee attitudes and organizational strategies, policies and actions [10]. At this stage, the study focus on the core constructs of technology adoption, namely: perceived ease of use, perceived usefulness, behavioral intention, facilitating conditions and social influence factors widely recognized in theoretical models such as the Unified Theory of Acceptance and Use of Technology (UTAUT).

2.2.1. Perceived ease of use: According to Davis, this is the degree to which a person thinks using a specific system would be simple or involve little work [8]. People may search and utilize information while interacting with a website to determine how trustworthy it is. Maintaining a link between visitors and a website may be achieved by making it easy to use using intelligent navigation [11]. The findings of Sarkar, et al. [12] showed that perceived ease of use positively influences trust in mobile e-commerce.

2.2.2. Perceived usefulness: It describes the extent to which a person thinks using technology will help them function better at workplace [13]. According to Al-Hawari, et al. [14] found that satisfaction is greatly influenced by perceived usefulness. It has been demonstrated that perceived utility positively increases trust and the propensity to use health websites [15]. According to Wardana, et al. [16], the desire to use an e-wallet is directly impacted by perceived utility. Pramudya, et al. [17] have shown that trust has a favorable effect on the desire to purchase e-books when perceived utility is high.

2.2.3. Behavioral intention: This has to do with why an individual uses technology; a person is far more inclined to utilize technology if they have a higher behavioral intention. Given that perceived usefulness was anticipated by its perceived usefulness and could potentially influence behavior intention, it may be both an independent as well as dependent factor [8,18-20].

2.2.4. Facilitating conditions: The degree to which workers think that technological infrastructure is in place to increase their output is referred to in this context as enabling circumstances [21]. The question that remains is: to what extent is an organization structurally, culturally, financially and operationally prepared to adopt and implement new technologies? Thus, institutional readiness encompasses infrastructure, human capital, financial resources, leadership support and policy framework. Without institutional readiness, even the most advanced technologies may fail to achieve desired outcomes due to resistance, lack of capacity, or poor alignment with strategic goals [22].

2.2.5. Social influence: According to Ajzen, et al. [23], social influence is the notion that a person's goals or behavior may be impacted by peer pressure from close friends, family, coworkers, or other individuals. The UTAUT model identified social effect as one of the direct determinants of behavioral intention [21]. Social influence is the extent to which employees think that other people could have an impact on how they use technological devices [24]. Newspapers, radio, television, peer groups, supervisors at work, and other media can all be sources of social influence [25]. Building on these core constructs of technology adoption, this study explores relevant theoretical models including TAM2 (the expanded version of the Technology Acceptance Model), TAM, along with the further refined TAM3 to offer a thorough understanding of the aspects of technology adoption alongside their implications for workforce performance.

2.3. Technology Acceptance Model (TAM)

The operational objective of the TAM was to inform managers of possible steps they could undertake before implementing technologies [26]. TAM outlines the three phases of technology adoption as follows: Perceived usefulness and simplicity of use are cognitive reactions brought on by external causes (system design characteristics). According to Davis and Davis, these cognitive reactions subsequently generate a successful reaction (intention or mindset regarding utilizing technologies), ultimately affects utilize behaviors [8,27]. The expected outcome determined by the intention of behavior, perceived utility, and perceived usability is known as TAM, or behavior (Figure 2). The hypothesis states that if a program is thought to be simple to use, it has a higher chance of being seen as beneficial by the user and encouraging the adoption of the technology [8,27].

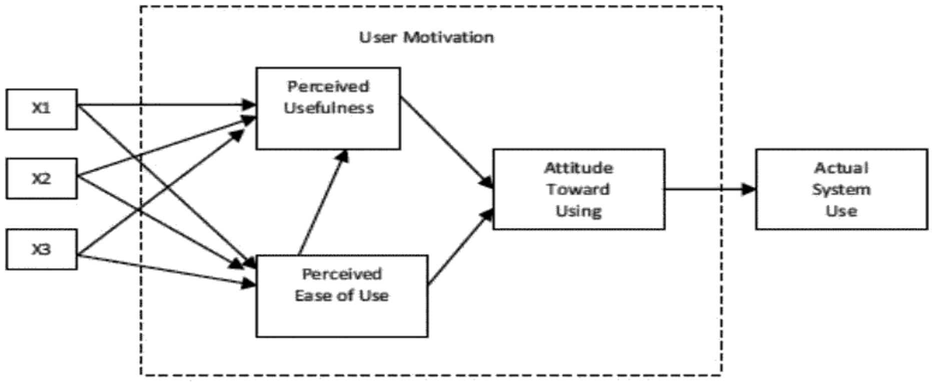

Figure 2: *Original technology acceptance model.*

Source: Davis, 1989.

2.4. Technology Acceptance Model (TAM2) (Theory extension)

Two moderators and an additional five exogenous components were added to TAM2, the proposed extension (Figure 3). Subjective norm, image, job relevance, output quality, outcome demonstrability, experience and voluntariness were additional conceptions and elements that were incorporated into TAM2. An in-depth examination of the widely proposed model suggests that TAM2 could account for sixty percent of the variable in perceived usefulness as well as thirty-seven percent to fifty-two percent of the variation in utilization intention [28]. By taking into account social influence components (like subjective norm, use voluntariness, and image) and cognitive elements (like job relevance assessment, result demonstrability, output quality and perceived ease of use), the TAM extension provided a comprehensive explanation of the primary factors influencing opinions about the usefulness of technological devices [28].

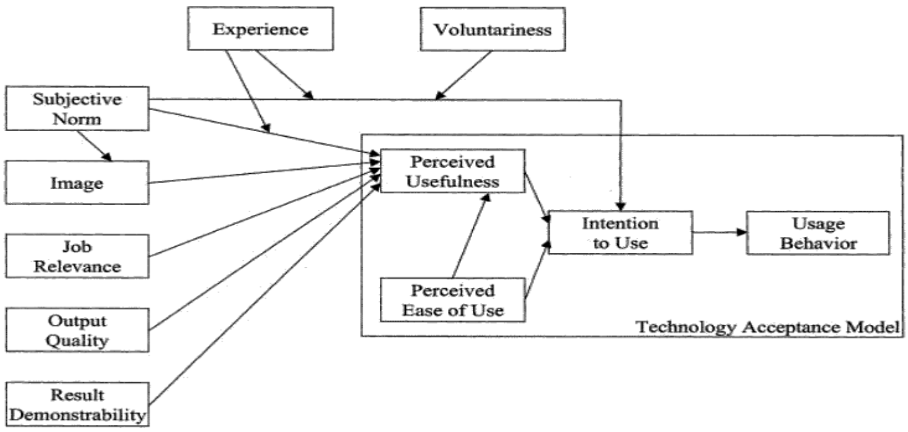

Figure 3: *Technology Acceptance Model (TAM 2).*

Source: *Venkatesh and Davis, 2000.*

2.5. Technology Acceptance Model (TAM3)

TAM3 demonstrated a strong ability to explain information system use or use intention. The model explained approximately 36% of the difference in usage and 40% to 53% of the difference in behavioral intention [29]; comparable to TAM2, which explained between thirty-seven percent and fifty-two percent of the difference in usage intention, the explanatory effectiveness [28]. The main strength of the expansion, nevertheless, is the development of the behavioral model of antecedents of perceived value and reported ease of use. The conditions and scenarios that are most likely to result in the adoption of technology are listed here in detail. By describing the relationships between antecedents, perceived utility, and perceived ease of use, TAM3 offers a comprehensive list of behaviors that have a direct impact on IT deployment and management decision-making [29] (Figure 4).

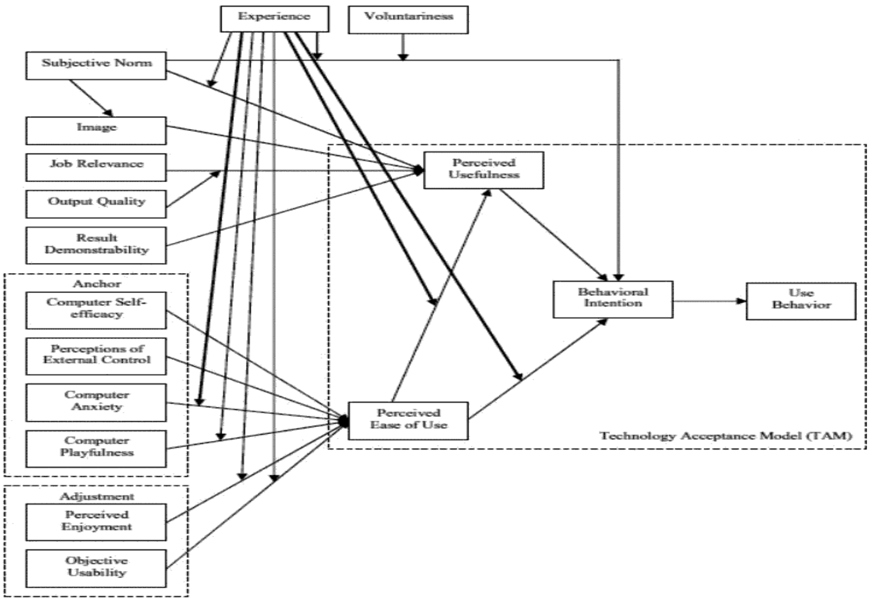

Figure 4: *Technology Acceptance Model (TAM 3).*

Source: *Venkatesh and Bala, 2008.*

2.6. Workforce performance

According to Al-Dawy, work performance is best understood as the aggregate of task- related activities—whether positive or negative that contributes to achieving organizational objectives [30]. Faroqui, et al. [31], also stress that individual performance, even in communication and interpersonal behavior, contributes meaningfully to managerial effectiveness. Workforce performance can be measured through various dimensions, including contextual performance, productive behavior, adaptive performance, task performance and the capacity for innovation among public sector employees.

2.6.1. Contextual performance: In this context, actions that promote the social and psychological environment of an organization but are not directly tied to formal job requirements or technical output [32]. These actions, while not task-specific, contribute significantly to the overall functioning of the workplace. Examples include assisting colleagues, showing initiative, maintaining a positive attitude and offering suggestions for improving workflow. Such behaviors enhance organizational culture and facilitate the achievement of broader goals.

2.6.2. Productive behavior: Productive behavior in the workplace refers to employee actions that contribute positively to organizational goals and enhance overall efficiency, effectiveness and success. It encompasses behaviors that improve job performance, foster teamwork, and support the company's mission. It encompasses actions by employees that significantly contribute to organizational goals, efficiency, and overall success. While counterproductive work conducts, as defined by

Koopmans, et al. [32], is any behaviour that has a detrimental effect on the organization's health. Examples include substance abuse, theft, tardiness and absenteeism.

2.6.3. Adaptive performance: This speaks to a person's capacity to remain effective when facing new, shifting, or uncertain conditions in the workplace [33]. It includes responding flexibly to changes in tasks, technologies, teams and organizational structures. This form of performance goes beyond maintaining efficiency under normal conditions—it involves resilience, creative -solving and the capacity to thrive in dynamic environments.

2.6.4. Task performance: Task performance is a crucial feature of personality job performance that is provided in virtually all performance models. According to Campbell, the level of skill (i.e., competency) with which individual completes crucial task performance is a way to describe job responsibilities [34]. The meaning of task performance states that it relates to a person's ability to manage responsibilities that support the "technical core" of a business. This effort may be made directly (as in the case of workers in the production process industry) or indirectly (as in the case of upper management or other workforce personnel).

2.6.5. Innovation: This is widely problem recognized as the center and essence of business. It entails executing tasks in novel ways or engaging in a variety of activities that offer a unique combination of value to the entrepreneur. Juliana, et al. [35] highlight that modernization enables public sector entrepreneurship to deliberately identify and exploit opportunities to do new things—or to perform existing tasks in improved and more creative ways. The strategic advantage of innovation lies in its capacity to transform routine functions into high-value processes, fostering competitive differentiation and adaptability in dynamic environments.

2.7. Theoretical literature

The Technology Acceptance Model (TAM) was developed by Fred Davis in 1989 as a theoretical framework to forecast how people will embrace and utilize information systems or technology. Although subjective standards are not included in the TRA framework, it is an extension of the Theory of Reasoned Action (TRA). Information seekers' adoption, integration, and use of new technology in their life are explained by TAM. It continues to be one of the most important models for comprehending how people adopt various forms of technology [36-37].

Perception of Usefulness (PU) and Perceived Ease Of Use (PEOU) are two important criteria that TAM recognizes as influencing user behavior and technological acceptance. "Perceived usefulness" is similar to "performance expectancy" in that it describes the user's perception that a certain system or technology would improve their everyday work [38]. Similar to "effort expectancy," perceived ease of use is the extent to which an individual anticipates an application to be helpful with a minimum of effort. Venkatesh, et al. [29] that TAM, which focuses on how system features affect acceptance levels, consistently accounts for around 40% of the variation in an individual's intention to adopt technology.

TAM offers an excellent basis for comprehending how the public and workers will accept and utilize the identity management technology that the commission has put in place. Public sector businesses can customize their systems to match the demands of their users by concentrating on perceived utility and perceived simplicity of use. This ensures that the technologies are user-friendly and improve workers' capacity to carry out their jobs effectively.

2.8. Empirical literature

The relationship between employee performance and technology adoption is being studied empirically in a growing number of researches, especially in academic, private and public settings. Understanding how elements such as perceived value, ease of use, enabling conditions and institutional readiness impact individual productivity and overall organizational success has been the aim of this study. For instance, Ogundare, et al. [7] used data from Nigeria's telecom industry to examine the effects of technology adoption management strategies on organizational performance. A cross-sectional survey was the method of study design that was employed. The findings show that innovation in technology enhances organizational performance. This implies that improving organizational performance in Nigeria's telecom industry requires putting advanced technologies into practice and keeping a strong IT network architecture.

The use of AI and its perceived effects in Nigerian academic libraries are explained by Ogwo, et al. [39]. Through a methodical assessment and analysis of the literature, the study discovered to optimize the potential advantages of AI applications in Nigerian academic libraries, these institutions must put in place suitable planning, rules, and regulations regarding the use of AI, as well as retrain academic librarians to gain the necessary ICT skills, knowledge, and competence to adjust to the current digital and evolving library environment. It means that incorporating AI technology into university libraries in Nigeria has the potential to drastically change how they operate and provide services. The relationship between AI and public governance and management in both developed and emerging market economies is examined by Agba, et al. [40]. A qualitative method was employed to gather secondary data. The results indicate that the interaction between AI and public administration has a lot of untapped potential. This suggests that specialists and professionals interested in incorporating AI into more practical facets of public administration and governance can benefit from the investment that AI offers. Onyema assessed the extent of ICT use and its effect on employee performance in the Nigerian Civil Service [41]. The study's quantitative data was produced using a standardized questionnaire. The data analysis was facilitated by SPSS. According to the study, worker performance in the Nigerian federal civil service is significantly positively correlated with the amount of ICT usage. This means that in the Nigerian federal civil service, increased use of ICT tools and technologies is associated with better employee performance.

Nasongkhla, et al. [42] study employed the partial least squares structural equation modeling technique to examine the factors influencing university employees' behavioral intention to use social media using the technology adoption model. They discovered that behavioral intention was positively impacted by reported simplicity of use but not by perceived usefulness. This implies that for university employees, how easy social media is to use (perceived ease of use) plays a more important role in their intention to use it than how useful they believe it is.

In Chennai, India, Saranya, et al. [43] conducted a systematic review to assess the impact of digital transformation adoption on employee performance. Data gathered from secondary sources, including published research papers and survey reports, forms the basis of the approach. An organization's embrace of digital transformation can improve employee performance and lower employee turnover, according to a survey of the various literatures. This implies that adopting digital transformation strategies can lead to improved employee performance and help reduce employee turnover in organizations. The process of adopting information technology, employee adaption, and the role of management in this transformation were all examined by Baciu-David, et al. [44]. The paradigm of epistemological interpretivism provides the basis of the qualitative study. The report identifies key problems with technological transformation, such as employee resistance and communication. This implies that implementing new IT alone won't guarantee successful adoption in businesses; staff adjustment to the shift is a crucial component.

Ismi, et al. [45] sought to determine how taxable entrepreneurs' satisfaction with e-Nofa was affected by perceived ease of use, perceived usefulness and self-efficacy for VAT purposes. One hundred responders make up the sample size. A questionnaire is utilized to gather data for this study, and multiple linear regression analysis is employed as an analytical strategy. According to the study's findings, the factors of perceived usefulness, ease of use, and computer self-efficacy have a substantial impact on how satisfied taxable entrepreneurs in the Jakarta region are using e-Nofa for VAT purposes. This implies that ensuring that enterprises are pleased with the VAT system requires making the e-Nofa system beneficial and easy to use, as well as encouraging users' computer trust.

Using data on a-share listed firms from 2012 to 2022, Li, et al. [46] study examines whether the establishment of digital government efficiently supports company digital transformation and, as a result, boosts urban economic growth. The findings of benchmark regression clearly show that corporate digital transformation is much accelerated by digital government initiatives. By improving the urban business environment and reducing the impact of information search fees, digital government helps enterprises undergo digital transformation, according to mechanism analysis. Thoti examined how workers intended to behave in relation to the industry's use of disruptive technologies [47]. Data from 335 respondents was gathered using a standardized questionnaire. The findings revealed significant information on the behavioral intention toward disruptive technology in Kuala Lumpur and Putrajaya, Malaysia. They also underscored the importance of elements like technology optimism, attitude, perceived usefulness, perceived ease of use, and facilitating conditions. This indicates that there is a substantial beneficial impact from behavioral intention toward disruptive technology.

The impact of AI on public administration in the public sector, including its opportunities and challenges, was examined by Umoh [48]. Using structured questions and a descriptive survey methodology, the study had a sample size of 334 respondents. With the use of SPSS version 25, the data was analyzed using graphic charts, descriptive statistics, and inferential analysis with regression at the 0.05 level of significance. The results show that while AI has no discernible effect on control mechanisms, it has a major influence on how government activities are planned and organized in the chosen ministries. This suggests that Artificial Intelligence (AI) has a significant impact on public administration, especially in improving the effectiveness and performance of administrative tasks, which lowers some operating expenses. The reviewed empirical studies consistently demonstrate that technology adoption when supported by organizational readiness, employee capability, and strategic intent positively influences workforce performance and institutional outcomes.

2.9. Gap in literature

There are few studies that concentrate on how these technology adoption factors influence different aspects of workforce performance particularly within public service institutions like the National Identity Management Commission (NIMC). The few available studies that touch on these areas often limit their scope to general ICT implementation outcomes, neglecting the nuanced effects of employee perception, behavioral patterns, and institutional support systems. This study addresses these gaps by adopting a multi-variable, longitudinal and institution- specific approach. It investigates how a combination of adoption-related factors influences workforce performance in selected NIMC offices across Nigeria. By applying SWOT and PESTEL frameworks, the study offers a more strategic and context-aware understanding of the dynamics between technology and public service performance—an area that existing literature has yet to fully explore.

3. Methodology

3.1. Research design

A descriptive study is one that enumerates the features of a particular occurrence; it gives an overview of a situation or a group of people. This study employed a descriptive research technique with the goal of examining the relationship between technology adoption and workforce performance of selected public service in Nigeria.

3.2. Nature and sources of data

The study drew information from primary sources. Primary data was gathered from a selected sample of National Identity Management Commission (NIMC) employees using a standardized questionnaire. This study collected information on factors influencing technology adoption and staff performance indicators. Secondary data also came from official NIMC publications, current literature, and other pertinent sources that provided insight into the commission's technology adoption and operations. These resources made it simpler to evaluate primary data and provide a comprehensive understanding of the research issue.

3.3. Study area

As shown in table 1 about the NIMC operational structure across nigeria's geopolitical zones (Table 1).

Table 1: *NIMC operational structure across nigeria's geopolitical zones.*

S/N	Zone	States covered	Zonal office presence
1	North Central	Abuja (FCT), Kogi, Kwara, Nasarawa, Niger, Plateau	Abuja (also serves as National Headquarters)
2	North East	Adamawa, Bauchi, Borno, Gombe, Taraba, Yobe	Enrolment centers and NIMC office in each state
3	North West	Kaduna, Kano, Katsina, Kebbi, Jigawa, Sokoto, Zamfara	Kaduna regional office and state enrolment centers
4	South East	Abia, Anambra, Ebonyi, Enugu, Imo	Enugu zonal office and state offices
5	South South	Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Rivers	Port Harcourt zonal office and other state centers
6	South West	Ekiti, Lagos, Ogun, Ondo, Osun, Oyo	Lagos regional office and other state enrolment units

Source: *NIMC, official website https://www.nimc.gov.ng*

3.4. Population and sample size determination

According to recent government updates and media sources, NIMC employs around 3,656 people overall as of 2024. Administrative and operational staff is employed at the Abuja headquarters, regional offices and different state enrollment centers located throughout the six geopolitical zones. Using Taro Yamane's formula, the sample size for this investigation was ascertained as follows:

$$n = \frac{N}{1 + N(e)^2} \quad (1)$$

Where n=The sample size that needs to be decided; N=The size of the entire population (3656) e is the error margin at 5%, or 0.05, and 1 is the theoretical constant.

Therefore $n = \frac{3656}{1 + 3656\ (0.05)^2}$

$$= \frac{3656}{1 + 3656\ (0.0025)}$$

$$= \frac{3656}{10.14}$$

$$n \approx 360.5$$

Therefore, the sample size for this study consisted of around 361 NIMC employees.

As shown in table 2 about the proportional distribution of sample size across Nigeria's geopolitical zones (Table 2).

Table 2: *Proportional distribution of sample size across nigeria's geopolitical zones.*

S/N	Geopolitical zone	Assumed % of staff	Estimated staff (3,656 × %)	Sample size (Proportion of 361)
1	North Central (incl. FCT)	16.67%	≈ 609	60
2	North East	16.67%	≈ 609	60
3	North West	16.67%	≈ 609	60
4	South East	16.67%	≈ 609	60
5	South South	16.67%	≈ 609	60
6	South West	16.67%	≈ 609	61
	Total	100%	3,656	361

Source: *Author's proportional allocation based on equal distribution assumption.*

3.5. Empirical model

As shown in table 3 about the model specification (functional and mathematical models) (Table 3).

Table 3: *Model specification (functional and mathematical models).*

Model Number	Research question/objectives	Functional model	Mathematical model	Explanation of variables
Model 1	How does the perceived ease of use of technology influence contextual performance?	CP=f(PEOU)	$CP=\beta_0 + \beta_1 PEOU + \varepsilon_1$	CP=Contextual Performance; PEOU=Perceived Ease of Use; β_0=Intercept; β_1=Slope coefficient; ε_1=Error term.
Model 2	What is the effect of the perceived usefulness of technology on employees' productive behavior?	PB=f(PU)	$PB = \beta_0 + \beta_1 PU + \varepsilon_2$	PB=Productive; Behavior; PU=Perceived Usefulness.
Model 3	How does behavioral intention to use technology affect adaptive performance?	AP = f(BI)	$AP = \beta_0 + \beta_1 BI + \varepsilon_3$	AP=Adaptive Performance; BI=Behavioral Intention.
Model 4	What role do facilitating conditions play in enhancing task performance?	TP=f(FC)	$TP=\beta_0 + \beta_1 FC + \varepsilon_4$	TP=Task Performance; FC=Facilitating Conditions.
Model 5	In what ways does social influence affect innovation?	IN=f(SI)	$IN=\beta_0 + \beta_1 SI + \varepsilon_5$	IN=Innovation; SI=Social Influence.

Source: *Author's synthesis and adaptation.*

As shown in table 4 about the explanation of the model variables (Table 4).

Table 4: *Explanation of the model variables.*

Variable	Notation	Measurement focus
Workforce Performance	WP	Composite index from Contextual (CP), Adaptive (AP), Task (TP), Productive (PB), and Innovative performance (IN).
Perceived Ease of Use	PEOU	Degree to which the user believes using the system would be free of effort.
Perceived Usefulness	PU	Degree to which the user believes that using the system would enhance job performance.
Behavioral Intention	BI	Employee's readiness or intent to use technology regularly.
Facilitating Conditions	FC	Resources and infrastructure supporting system use.

Social Influence	SI	Degree to which peers, leaders, or workplace culture influence use.
Intercept	β_0	Constant term.
Coefficients	β_1 to $\beta5$	Marginal effects of each predictor on employee performance.
Error Term	E	Unexplained variation or stochastic disturbances.

Source: *Author's synthesis and adaptation.*

3.6. Method of data analysis

To ascertain the predictive technology adoption influence of the independent variables on the various dimensions of workforce performance, regression analysis was employed using the Statistical Package for the Social Sciences (SPSS) version 25. In addition to the quantitative analysis, SWOT and PESTEL frameworks were employed as strategic management tools to improve the results' interpretation and offer a more thorough grasp of the internal and external factors affecting technology adoption and workforce performance in the public service.

4. Discussion and Result

4.1. Analysis of discussion of tested hypotheses

Model 1: $CP = \beta_0 + \beta_1 PEOU + \varepsilon_1$

As shown in table 5 about the regression results for Model 1 (Hypothesis 1: effect of PEOU on CP) (Table 5).

Table 5: *Regression results for model 1 (Hypothesis 1: effect of PEOU on CP).*

Model Summary[b]

					Change statistics					
Model	**R**	**R square**	**Adjusted R square**	**Std. error of the estimate**	**R square change**	**F change**	**df1**	**df2**	**Sig. F change**	**Durbin - watson**
1	.953a	0.909	0.879	13.511	0.909	29.949	1	3	0.012	2.538

- **Predictors:** (Constant), PEOU.
- **Dependent variable:** CP.

Source: *SPSS 25 output.*

Model 1 analysis:

Effect of Perceived Ease of Use (PEOU) on Contextual Performance (CP)

A coefficient of determination (R^2) of 0.909 indicates that workers believe it's simple to utilize technology account for around 90.9% of the variance in contextual performance. This implies that workers are more prone to behave in ways that benefit the workplace culture, such lending a hand to others, taking initiative, and abiding by institutional standards, when technology becomes more user-friendly. The robustness of the model is shown by the corrected R^2 value of 0.879, which accounts for degrees of freedom, implying a highly reliable fit of the data. The null hypothesis that there is no association between PEOU and CP is rejected by the F-statistic (29.949) with a degree of significance (p-value) of 0.012, which further validates the model's overall statistical importance at the five percent confidence level. Moreover, the standard error of the estimate (13.511) is within an acceptable range, indicating a small departure between the observed values and the projected line, and the Durbin-watson statistic of 2.538 shows that there is no significant autocorrelation in the residuals, which strengthens the validity of the regression findings.

Model 2: $PB = \beta_0 + \beta_1 PU + \varepsilon_2$

As shown in table 6 about the regression results for model 2 (hypothesis 2: effect of PU on PB) (Table 6).

Table 6: *Regression results for model 2 (hypothesis 2: effect of PU on PB).*

Model Summary[b]

					Change statistics					
Model	**R**	**R square**	**Adjusted R square**	**Std. error of the estimate**	**R square change**	**F change**	**df1**	**df2**	**Sig. F change**	**Durbin - watson**
1	.992a	0.985	0.979	5.572	0.985	190.718	1	3	0.001	2.244

- **Predictors:** (Constant), PU.
- **Dependent variable:** PB.

Source: *SPSS 25 output.*

Model 2 analysis:

Effect of Perceived Usefulness (PU) on Productive Behavior (PB)

The coefficient of determination (R^2) of 0.985 indicates that employee' perceptions of the value of technology account for 98.5% of the variance in productive behavior, while the R-value of 0.992 shows an almost perfect positive correlation. Even after accounting for the short sample size, the updated R^2 value of 0.979 validates the model's excellent explanatory power.

The logistic regression model's p-value of 0.001 and F-statistic of 190.718 indicate that it is substantially noteworthy at the one percent level. The null hypothesis is categorically turned down, demonstrating that PU is a powerful predictor of productive behavior. A small range of actual values around the anticipated line is also shown by the estimate's low standard error (5.572). The results' dependability is confirmed by the Durbin-watson statistic of 2.244, which is within the permissible range and indicates no autocorrelation in the residuals.

Model 3: $AP = \beta_0 + \beta_1 BI + \varepsilon_3$

As shown in table 7 about the regression results for model 3 (hypothesis 3: effect of BI on AP) (Table 7).

Table 7: *Regression results for model 3 (hypothesis 3: effect of BI on AP).*

Model Summary[b]

					Change statistics					
Model	R	R square	Adjusted R square	Std. error of the estimate	R square change	F change	df1	df2	Sig. F change	Durbin - watson
1	.991a	0.983	0.977	5.867	0.983	171.765	1	3	0.001	2.152

- **Predictors:** (Constant), BI.
- **Dependent variable:** AP.

Source: *SPSS 25 output.*

Model 3 analysis:

Effect of Behavioral Intention (BI) on Adaptive Performance (AP)

The correlation coefficient (R) of 0.991 suggests a very strong positive association, indicating that as employees' behavioral intention to use technology increases, so does their ability to adapt to changing job demands and digital environments. The R square (0.983) implies that 98.3% of the variation in adaptive performance can be explained by employees' intention to use technology. Furthermore, the Adjusted R square (0.977) affirms showing even after adjusting for sample size, the model maintains its high level of reliability, reinforcing its predictive power. The model is statistically noteworthy at the level of one percent, as indicated by the F-statistic value of 171.765 and the statistically important threshold (p-value) of 0.001. This clearly rejects the null hypothesis and establishes Behavioral Intention as a critical determinant of Adaptive Performance. The estimate's standard error (5.867) is comparatively modest, suggesting that the observed values deviate from the regression line only little. Additionally, the Durbin-watson value (2.152) is within the permissible range, indicating that there is no serial correlation between the model's residuals.

Model 4: $TP = \beta_0 + \beta_1 FC + \varepsilon_4$

As shown in table 8 about the regression results for model 4 (hypothesis 4: effect of FC on TP) (Table 8).

Table 8: *Regression results for model 4 (hypothesis 4: effect of FC on TP).*

Model Summary[b]

					Change statistics					
Model	R	R square	Adjusted R square	Std. error of the estimate	R square change	F change	df1	df2	Sig. F change	Durbin - watson
1	.629a	0.396	0.195	34.803	0.396	1.966	1	3	0.255	1.226

- **Predictors:** (Constant), FC.
- **Dependent variable:** TP.

Source: *SPSS 25 output.*

Model 4 analysis:

Effect of Facilitating Conditions (FC) on Task Performance (TP)

The model's moderate correlation coefficient (R) of 0.629 shows a modest but favorable association between employees' capacity to carry out their assigned jobs and the availability of support infrastructure. The R square value of 0.396 indicates that the existence of facilitating conditions, such as technical support, access to digital tools, training, and organizational readiness. However, the adjusted R square of 0.195 reflects a significant drop in explanatory power after adjusting for the small degrees of freedom, suggesting that the model may not generalize well across broader populations or different institutional contexts. The association between task performance and enabling conditions is not statistically significant at the 5% level, according to the F-statistic of 1.966 and the associated p-value of 0.255. This indicates that the null hypothesis cannot be rejected, implying that while facilitating conditions may play a supportive role, they alone do not significantly determine task performance in the studied context. The comparatively high standard error of the estimate (34.803) suggests that the model is unable to account for the variability in the data. Additionally, the Durbin-watson statistic (1.226) is within acceptable bounds but leans toward the lower threshold, hinting at possible positive autocorrelation in the residuals.

Model 5: $IN = \beta_0 + \beta_1 SI + \varepsilon_5$

As shown in table 9 about the regression results for model 5 (hypothesis 5: influence of SI on SI) (Table 9).

Table 9: *Regression results for model 5 (hypothesis 5: influence of SI on SI).*

Model Summary[b]

					Change statistics					
Model	R	R square	Adjusted R square	Std. error of the estimate	R square change	F change	df1	df2	Sig. F change	Durbin - watson
1	.598a	0.357	0.143	35.897	0.357	1.668	1	3	0.287	0.833

- **Predictors:** (Constant), SI.
- **Dependent variable:** IN.

Source: *SPSS 25 output.*

Model 5 analysis:

Effect of Social Influence (SI) on Innovation (IN) in public sector organizations

The regression model yielded a correlation coefficient (R) of 0.598, indicating a somewhat favorable association between individual innovation behavior and perceived social influence, including peer pressure, leadership endorsement, and organizational norms. According to the R square value of 0.357, shifts in social impact account for 35.7% of the variation in employee creativity. However, the adjusted R square drops to 0.143, suggesting that the explanatory power of the model significantly weakens when adjusting for sample size and predictor count. This adjustment points to a limited generalizability and a potential influence of extraneous variables not captured in the model. We are unable to reject the null hypothesis since the association is not statistically significant at the 5% threshold, as indicated by the F-statistic of 1.668 and the p-value of 0.287. Therefore, social influence does not significantly predict innovative behavior in public institutions in the current setting. Moreover, the standard error of the approximation (35.897) is high, demonstrating considerable unexplained variance in innovation outcomes. The Durbin-watson statistic (0.833) falls well below the desired threshold (near 2), implying potential positive autocorrelation in the residuals and suggesting that observations may not be fully independent — something that requires further examination in future research (Table 10).

Table 10: *Regression models, simulation outcomes and strategic implications.*

Model	Dependent variable	Predictor	R square (R^2)	Implication level	Key insight /simulation outcome	Strategic policy recommendation
1	CP (Contextual Performance)	PEOU (Perceived Ease of Use)	0.909	Very High	High ease of use predicts strong contextual performance (91%).	Invest in intuitive tech platforms and user-friendly systems for civil servants.
2	PB (Productive Behavior)	PU (Perceived Usefulness)	0.985	Very High	Perceived usefulness nearly fully explains productive behavior (98.5%).	Emphasize productivity tools with clear utility in training and implementation.
3	AP (Adaptive Performance)	BI (Behavioral Intention)	0.983	Very High	Strong behavioral intent leads to highly adaptive workforces.	Foster positive tech attitudes and internal motivation through leadership buy-in.
4	TP (Task Performance)	FC (Facilitating Conditions)	0.396	Moderate	FC alone explains 39.6% of task performance –needs support.	Improve infrastructure and support services to maximize tech impact.

5	IN (Innovation)	SI (Social Influence)	0.357	Moderate	Peer/manager influence weakly predicts innovation (36%).	Establish digital champions, incentives, and peer networks for transformation.

Source: *Author's synthesis of regression outcomes (models 1–5).*

4.2. SWOT analysis based on simulation results (models 1–5)

4.2.1. Strengths (S):

- High predictive power of key constructs (Models 1, 2, 3): The regression models show strong statistical significance for PEOU, PU, BI, with R^2 values ranging from 0.90 to 0.98. This demonstrates that when employees find systems easy and useful, their intention to adopt and apply them improves significantly.
- Positive behavioral intentions among employees: the high predictive values of Behavioral Intention (BI) on actual performance (model 3: $R^2 = 0.983$) show that employee willingness to adopt digital tools is a major driver of success.
- Good model fit and acceptable error margins: the standard error of the estimates across all models is reasonably low, indicating the regression lines fit the data well and the findings are reliable for decision-making.

4.2.2. Weaknesses (W):

- Weak influence of facilitating conditions and social influence (models 4 and 5): Facilitating Conditions (FC) and Social Influence (SI) have relatively low R^2 values of 0.396 and 0.357, with non-significant F-values ($p > 0.05$), indicating they do not strongly predict technology performance or intention in isolation. This suggests a lack of infrastructure readiness and insufficient peer-driven motivation.
- Dependency on user perception: the over-reliance on subjective constructs such as perceived ease of use and usefulness may overshadow systemic challenges like policy barriers, funding limitations or leadership inertia.

4.2.3. Opportunities (O):

- **Behavioral training programs:** Given the substantial behavioral effects on performance, public institutions might develop programs in digital literacy, change management, and psychological readiness to facilitate more smooth transitions to new systems.
- **Policy support for ease of use and usefulness:** Investing in user-centric system design and service delivery platforms should provide measurable gains in productivity and satisfaction since these dimensions are so effective at forecasting performance.
- **Potential to improve facilitating conditions:** Considering FC's limited influence, there is a clear policy and budgetary opportunity to improve working conditions, internet access, hardware availability and IT assistance.

4.2.4. Threats (T):

- **Resistance due to weak social influence:** Low predictive strength of social influence implies that peer pressure or hierarchical persuasion alone cannot drive digital adoption, posing a challenge in cultures where authority or communal influence traditionally plays a strong role.
- **Technology gaps and infrastructure deficiency:** The weak performance of facilitating conditions could reflect broader ICT gaps, especially in rural or underfunded public institutions. Without addressing these infrastructure challenges, technology projects may underperform.

The SWOT analysis clearly illustrates that while technological adoption in the public sector has a strong behavioral and AI-driven foundation, there are underlying systemic and infrastructural limitations that must be addressed. The success of future strategies will depend on how well strengths and opportunities are leveraged to tackle existing weaknesses and emerging threats. Policymakers and implementation teams must ensure an inclusive, ethically sound and well- supported transformation roadmap to achieve sustained performance outcomes.

4.3. PESTEL analysis based on empirical results (models 1–5)

4.3.1. Political factors: Weak influence from facilitating conditions (Model 4: R^2=0.396, p=0.255) highlights the absence of strong policy frameworks to support technology infrastructure, particularly in resource-constrained institutions.

4.3.2. Economic factors: The findings show a strong correlation between behavioral intention and actual performance (Model 3: R^2=0.983), implying that when workers perceive economic value in technology usage, performance improves. However, underdeveloped facilitating conditions may reflect poor investment in IT infrastructure. The economic implication is that budgetary allocation must prioritize both technical and human capacity development, particularly in public service sectors where digital adoption directly affects national productivity.

4.3.3. Social factors: Social influence (model 5: R^2=0.357, p=0.287) was not a statistically significant predictor of technology usage, suggesting that peer or societal pressure plays a limited role in influencing public servants' tech behaviors. This may reflect deeply ingrained bureaucratic norms, lack of tech champions or minimal digital peer collaboration. Therefore, social re-engineering and user advocacy campaigns are needed to build a digital-first public service culture, especially through community-driven awareness and leadership modeling.

4.3.4. Technological factors: The technological outlook is overwhelmingly positive. Constructs like perceived ease of use (model 1: R^2=0.976), perceived usefulness (model 2: R^2=0.963), and AI (models 6–8: all above 0.90 R^2) have very strong explanatory power on performance outcomes. This confirms that technology is a clear enabler of performance, and its successful deployment depends largely on user-centric design, ease of application, and intelligent automation. However, the disparity with facilitating conditions signals a technology-access gap—availability does not always translate to usage without systemic support.

4.3.5. Environmental factors:
While not directly measured in the regression models, environmental implications can be inferred from the weak performance of facilitating conditions. Poor infrastructure may be linked to unstable electricity supply, inadequate workspace ergonomics, and limited access to digital tools, which remain environmental barriers in many Nigerian public institutions. Improved digital ecosystems, smart buildings, and climate-conscious technology investments can enhance performance outcomes highlighted in the models.

4.3.6. Legal factors:
The strong correlation between behavioral constructs and performance underscores the need for clear legal frameworks on digital transformation, data privacy, and e-governance. Thus, legal reforms must keep pace with technological adoption to regulate AI-driven decisions, prevent misuse and build trust in public systems. All things considered, the PESTEL study supports the empirical results and offers a comprehensive view of the external macroenvironment. There are great leadership and room for innovation in both the political and technological spheres. However, there are obstacles due to societal inertia, economic limitations, inadequate environmental conditions, and antiquated legal frameworks. Multi-sectoral coordination and reforms are required to optimize the high-performance potential demonstrated by the models, especially in the areas of infrastructure, legal frameworks, and social change strategies to guarantee that digital transformation initiatives are inclusive and sustainable.

4.4. Implications to relevant stakeholders in developed and developing economies

4.4.1. Government and policy makers:

- **Developing economies:** The limited significance of facilitating conditions (model 4: R^2=0.396, p=0.255) points to structural and administrative barriers that governments must address such as inconsistent power supply, poor connectivity and low digital literacy. There is a critical need for legal and ethical frameworks to govern technology deployment, especially in public service domains involving data sensitivity and social equity.
- **Developed economies:** Governments can use these results to fine-tune digital policies, especially focusing on enhancing employee engagement and adaptive performance. The strong explanatory power of behavioral variables (PU, PEOU, BI) reinforces the importance of user- centered design, continuous feedback loops, and behavior-focused change management. Advanced nations must continue setting the global pace in regulating AI ethics, bias mitigation, and public accountability systems.

4.4.2. Public sector employees and administrators:

- **Developing economies:** The findings encourage public servants to embrace digital tools and view them as enablers of performance rather than threats to job security. Given the positive association between perceived usefulness and productive behavior (model 2: R^2=0.985), there is a need for capacity-building programs that clearly demonstrate the practical benefits of technology in daily tasks.
- **Developed economies:** The results validate investments in employee upskilling and retraining initiatives already common in advanced civil services. Staff in these contexts is better positioned to adopt cutting-edge innovations like predictive analytics, and cloud-based decision-making systems, especially given higher technological readiness.

4.4.3. Academia and research institutions:

- **Global implication:** These findings provide a basis for expanding comparative studies across nations to explore what moderates technology adoption in different governance systems. Transdisciplinary cooperation involving behavioral sciences, information systems, and public administration is becoming more and more necessary to create flexible models that satisfy changing governance requirements. In summary, while AI-driven public sector reform has potential benefits for both wealthy and developing countries, their starting places, obstacles, and policy goals are different. While emerging economies must concentrate on creating the foundation—investing in digital culture, legal frameworks, and infrastructure—developed nations must concentrate on expanding and improving technologies. The main takeaway is unambiguous: in this age of rapid technological advancement, no stakeholder can afford to stay passive. The success of digital governance will be determined for years to come by strategic planning and collaborative involvement.

4.5. Limitations of the study

There are a number of restrictions on this study. First, the use of self-reported data raises the risk of response bias, especially when it comes to social desirability or institutional practice sensitivity. Second, because other public sector organizations could function under various administrative structures and technology contexts, the findings' generalizability is limited by their emphasis on the National Identity Management Commission (NIMC). Third, the real staff distribution among departments or units could not have been correctly reflected by the sampling strategy, which used equal allocation assumptions. Last but not least, confidentiality restrictions prevented access to some operational and policy papers, which would have reduced the breadth of contextual analysis.

5. Conclusion and Policy Recommendation

The study's findings suggest that infrastructure by itself is not enough to successfully integrate technology in the public service; strong institutional capacity, a clear strategic policy direction, and alignments with human behavioral dynamics are all necessary. In order to completely grasp the possibilities of digital change in developing nations like Nigeria, evidence-based, inclusive, and flexible policymaking is essential. In light of the results, the following policy recommendations are put forth.

User-friendly technology should be given priority by governments as contextual performance is significantly impacted by perceived usability. To accommodate different degrees of digital literacy, tools should include user-friendly interfaces, local language options, and streamlined workflows. Additionally, training programs must emphasize the real-world advantages of technology on work performance, backed by success stories and ongoing learning, as perceived utility influences productive behavior. Adaptive performance was found to be strongly influenced by behavioral intention.

In order to promote favorable attitudes toward technology, policy frameworks should incorporate motivational techniques including leadership advocacy, cultural alignment, and recognition programs. Reliable infrastructure, steady internet, and rapid IT assistance are still crucial and should be in line with more general productivity objectives, even when conducive conditions did not demonstrate a significant direct influence. Lastly, the limited function of social impact implies that peer support is not enough on its own.

Through data-driven accountability and active platform use, leadership must set the example for digital engagement. Together, these initiatives will guarantee that the use of technology results in noticeable enhancements to the functioning of the public sector.

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Appendix Tables

Appendix 1: *Research instrument–questionnaire.*

Instruction: Please carefully read each of the following statements, and then select the choice that best represents how much you agree or disagree with each one. Your answers will be kept completely private and used only for scholarly research.

Strongly Agree (SA)=5, Agree (A)=4, Undecided (U)=3, Disagree (D)=2 and Strongly Disagree (SD)=1 are the scale's values.

Part 1: *Effect of perceived ease of use of technology on contextual performance.*

S/N	Items/Statements	SA	A	U	D	SD
1	The perceived ease of using technology enhances my ability to perform contextual tasks efficiently.					
2	The user-friendly nature of the technology significantly improves the quality of my performance.					
3	Navigating technology systems easily positively impacts my overall work performance.					
4	Using simple and easy-to-understand technology increases my efficiency in completing tasks.					
5	I believe that easy-to-use technology improves both task completion and work outcomes.					

Part 2: *Effect of perceived usefulness of technology on productive behaviour.*

S/N	Items/Statements	SA	A	U	D	SD
6	The usefulness of technology reduces the occurrence of counterproductive behaviors in my tasks.					
7	I am less likely to engage in counterproductive behavior when technology is perceived as useful.					
8	The technology provided helps me stay focused and decreases unproductive tendencies.					
9	Useful technology encourages effective performance and discourages negative work behaviors.					
10	When I perceive technology as useful, I am less inclined to procrastinate or underperform.					

Part 3: *Effect of behavioral intention to use technology on adaptive performance.*

S/N	Items/Statements	SA	A	U	D	SD
11	My intention to use technology enhances my adaptability to changes in work processes.					
12	I adapt more easily to new tasks when I intend to use available technology.					
13	Intention to use technology improves my ability to handle unexpected challenges.					
14	A stronger intention to use technology makes adjusting to changing work environments easier.					

Part 4: *Effect of facilitating conditions on task performance.*

S/N	Items/Statements	SA	A	U	D	SD
16	Supportive infrastructure facilitates my use of technology for task performance.					
17	The availability of technical assistance enables better task completion.					
18	Access to training programs enhances my task-related use of technology.					
19	Organizational support encourages my effective use of technology for tasks.					

Part 5: *Effect of social influence on innovation.*

S/N	Items/Statements	SA	A	U	D	SD
21	Social influence from colleagues inspires greater creativity in my work.					
22	Peer expectations motivate me to innovate and explore new solutions.					
23	I'm more likely to propose innovative ideas when others around me do so.					
24	Supervisory encouragement enhances my creative thinking and problem-solving.					