



# Internet Technology Application Driving Urban Digital Transformation in Africa: Research and Policy Recommendations

1<sup>st</sup> Poloko Felix Motoane \*

Botswana International University of Science and Technology

Palapye, Botswana

polokofm@outlook.com

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**Abstract**—Africa’s rapid urbanization imposes significant pressure on infrastructure and public service delivery. While mobile internet technology offers a potential pathway for leapfrog development, a standardized and quantitative approach to evaluate its association with urban digital transformation remains limited. This paper proposes a replicable quantitative assessment framework, the Technology–Application–Performance (TAP) model, which defines key performance indicators (KPIs) across three layers: technological infrastructure (e.g., 4G coverage, data affordability), service applications (e.g., mobile payment penetration, e-governance availability), and socio-economic performance (e.g., financial inclusion, administrative efficiency). To demonstrate the framework’s utility, we conduct a comparative analysis of five major African cities—Cairo, Lagos, Nairobi, Kigali, and Johannesburg—using multi-source secondary data for 2022–2024. Results show a statistically significant positive relationship between the Mobile Technology Adoption Index (MTAI) and the Urban Service Efficiency Index (USEI) ( $R^2 = 0.768$ ,  $p = 0.021$ ). Kigali, for example, exhibits notable gains in administrative efficiency following the rollout of its Irembo e-governance platform. The TAP framework provides a practical, data-driven tool for benchmarking city performance, diagnosing transformation bottlenecks, and informing engineering-oriented resource allocation and policy design.

**Keywords**—Urban Digital Transformation, Quantitative Assessment, Mobile Internet, Smart City, Technology–Application–Performance (TAP) Model, Key Performance Indicators (KPI)

## 1. INTRODUCTION

The African continent is undergoing the world’s most rapid urbanization, with its urban population projected to increase by nearly 900 million by 2050 [1]. This demographic shift imposes immense strain on urban infrastructure, including transportation, energy, and public service systems, presenting formidable engineering and governance challenges. Concurrently, the proliferation of mobile internet technology across Africa offers a unique opportunity to bypass traditional developmental stages and engineer data-driven, efficient urban ecosystems, often

termed “smart cities.” As of 2023, mobile technologies and services generated 8.1% of GDP in Sub-Saharan Africa, a contribution of \$170 billion, indicating its profound economic impact [2].

However, the deployment of these technologies often lacks a corresponding framework for quantitative evaluation. Many urban digital transformation projects are assessed using qualitative descriptions such as “improved efficiency” or “enhanced citizen satisfaction,” which are insufficient for rigorous engineering analysis and investment accountability. This absence of a standardized, data-centric evaluation methodology creates a significant technical gap. Without it, city planners and engineers cannot effectively measure the return on investment (ROI) of digital infrastructure projects, identify underperforming service areas, or benchmark their city’s progress against peers. Existing studies on African digitalization tend to be either high-level macroeconomic analyses [3] or specific, non-generalizable case studies [4], failing to provide a replicable engineering tool for city-level assessment.

To address this problem, this paper aims to develop and validate a quantitative framework for assessing the impact of mobile internet technology on urban digital transformation in Africa. The primary research objective is to quantify and benchmark the relationship between mobile technology adoption and measurable improvements in urban service delivery and socio-economic performance. Rather than relying on qualitative descriptions (e.g., “improved efficiency”), this study proposes a standardized, data-centric methodology to support engineering analysis and investment accountability. Specifically, we introduce the Technology–Application–Performance (TAP) model, which decomposes digital transformation into three measurable layers—Technology enablers, service Applications, and Performance outcomes—and operationalizes each layer with practical KPIs that can be populated using publicly available or locally collected data. The core innovation of this research lies in two aspects: first, the creation of a structured, quantitative assessment model tailored to the specific context of African cities, which emphasizes mobile-centric technologies. Second, the introduction of two novel composite indices, the Mobile Technology Adoption Index (MTAI) and the Urban Service Efficiency Index (USEI),

\*Poloko Felix Motoane, Botswana International University of Science and Technology, Palapye, Botswana, polokofm@outlook.com

which allow for standardized comparison and benchmarking across different urban environments.

## 2. RELATED WORK

This section reviews existing engineering and theoretical frameworks for evaluating digital transformation and information and communication technology (ICT) impact, identifying the specific research gap that our proposed Technology-Application-Performance (TAP) model addresses.

### 2.1. Smart City and Digital Transformation Evaluation Frameworks

A substantial body of literature exists on evaluating smart cities. Many comprehensive index systems have been developed, such as the IMD Smart City Index [5] and the ISO 37122 series of standards for smart cities [6]. These frameworks are typically designed for cities in developed countries and rely on the availability of extensive, fine-grained data from sources like IoT sensor networks and mature government databases. While valuable, their direct application to the African context is problematic due to different technological bases and data availability constraints [7]. Some research has attempted to adapt these models for Africa, but they often remain qualitative or focus on a narrow set of governance indicators, lacking a holistic, engineering-oriented performance measurement [8].

### 2.2. Technology Acceptance and Impact Models

In the domain of information systems, several models have been developed to explain and predict the adoption of new technologies. The Technology Acceptance Model (TAM) and its successors, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), provide robust frameworks for understanding individual user behavior [9] [10]. However, their primary focus is on the micro-level of individual acceptance. They are not designed to measure the macro-level engineering and socio-economic impact of technology on an entire urban system. Our work extends beyond individual acceptance to measure collective, system-level performance.

### 2.3. Quantitative Analysis of ICT in Africa

Quantitative research on ICT in Africa has provided critical insights, but often focuses on specific verticals or determinants rather than a holistic urban system. A significant portion of this research has focused on the economic impact of mobile money, particularly M-Pesa in Kenya. These studies have rigorously quantified its positive

effects on poverty reduction and economic resilience using household-level data [4] [11]. Other studies have used regression analysis to identify the determinants of the digital divide across the continent, linking factors like income, education, and infrastructure to internet penetration rates [12] [13]. While these studies provide excellent examples of quantitative rigor, they are typically focused on a single technology or a single issue. There is a lack of research that integrates multiple technology indicators and application domains into a unified model to assess the overall digital performance of a city.

### 2.4. Research Gap

The review of existing literature reveals a clear gap: the absence of a standardized, quantitative, and replicable framework for assessing the system-level impact of mobile internet technology on urban digital transformation in the specific context of Africa. The proposed TAP model is designed to fill this gap by providing an engineering-focused tool that is context-specific, holistic, quantitative, and actionable.

## 3. METHODOLOGY AND SYSTEM DESIGN

To quantitatively assess the impact of mobile internet technology on urban digital transformation, this study proposes the Technology-Application-Performance (TAP) model. This framework provides a structured methodology for data collection, analysis, and benchmarking. The system is designed to be replicable across different urban contexts, relying on publicly available data or data that can be reasonably collected at the municipal level.

### 3.1. The Technology-Application-Performance (TAP) Model Architecture

The TAP model is a hierarchical framework composed of three distinct but causally linked layers, as illustrated in Figure 1.

The Technology Layer (T) is the foundational layer that quantifies the core technological enablers. It measures the quality and accessibility of the digital infrastructure that underpins all subsequent applications and impacts. The Application Layer (A) is the intermediate layer that measures the adoption and penetration of key digital services within the urban environment. It acts as a bridge, translating technological potential into tangible solutions that address specific urban needs. The Performance Layer (P) is the top layer that measures the socio-economic outcomes and engineering value derived from the deployment and use of digital applications.

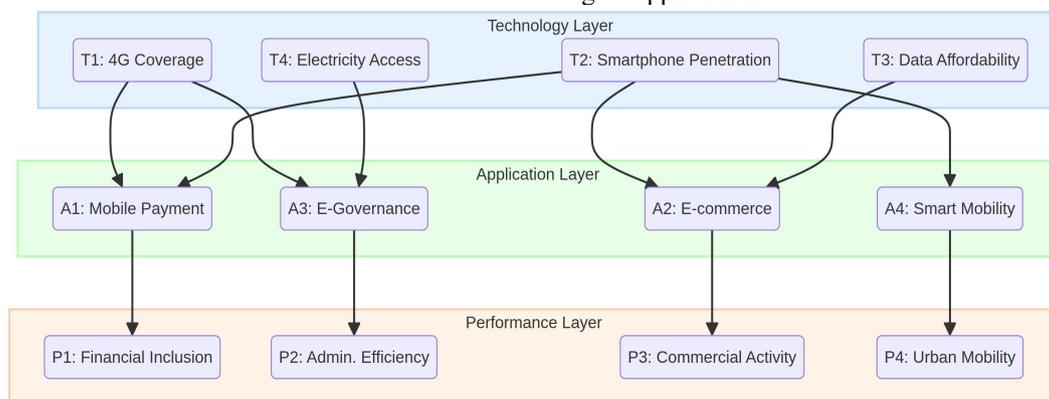


Figure 1. The Technology-Application-Performance (TAP) Model Architecture

### 3.2. Key Performance Indicator (KPI) Definition

For each layer, a set of specific, measurable, achievable, relevant, and time-bound (SMART) KPIs has been defined. These KPIs were selected based on a review of literature from organizations like the ITU, World Bank, and GSMA, and adapted for the African context. The complete list of KPIs is presented in Table 1.

TABLE I. KEY PERFORMANCE INDICATORS OF THE TAP MODEL

Layer	ID	KPI Name	Description	Data Source
Technology	T1	4G Network Coverage (%)	Population covered by a 4G signal.	GSMA Intelligence
	T2	Smartphone Penetration (%)	Percentage of mobile subscribers with smartphones.	GSMA, Statista
	T3	Data Affordability Index	Cost of 1GB data as % of monthly GNI per capita.	Cable.co.uk, World Bank
	T4	Electricity Access (%)	Population with access to electricity.	World Bank
Application	A1	Mobile Payment Penetration (%)	Adults using mobile payments.	World Bank Global Findex
	A2	E-commerce Adoption (%)	Population purchasing goods/services online.	Statistic
	A3	E-Governance Availability (Count)	Number of transactional public services online.	Gov. portals, UN Survey
	A4	Ride-Hailing Penetration (%)	Urban population using ride-hailing services.	Market research reports
Performance	P1	Financial Inclusion Rate (%)	Adults with a financial/mobile money account.	World Bank Global Findex
	P2	Admin. Efficiency Gain (%)	Time reduction in processing key public services.	Field measurement
	P3	Digital Retail Market Size (%)	E-commerce revenue as % of total retail.	National statistics
	P4	Urban Mobility Improvement (%)	Reduction in average commute time.	TomTom, local authorities

TABLE II. CASE CITY SELECTION AND CHARACTERISTICS

Region	Country/City	Population (Million)	Internet Penetration (%)
North Africa	Egypt/Cairo	21.3	81.9
West Africa	Nigeria/Lagos	15.4	48.0
East Africa	Kenya/Nairobi	4.9	45.9
East Africa	Rwanda/Kigali	1.2	37.0
Southern Africa	South Africa/Johannesburg	5.8	78.9

### 3.4. System Modeling and Quantitative Formulation

To enable comparative analysis, the raw KPI data must be normalized and aggregated into composite indices. All KPI values are normalized to a scale of 0 to 1 using the Min-Max normalization formula. For KPIs where a higher value is better (e.g., 4G Coverage):

$$\text{Normalized}_{\text{value}} = (X - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}}) \quad (1)$$

For KPIs where a lower value is better (e.g., Data Affordability):

$$\text{Normalized}_{\text{value}} = (X_{\text{max}} - X) / (X_{\text{max}} - X_{\text{min}}) \quad (2)$$

We define two primary composite indices:

Mobile Technology Adoption Index (MTAI):

$$\text{MTAI} = (1/4) * \sum(T_{i_n} \text{ormalized}), \text{for } i=1 \text{ to } 4 \quad (3)$$

Urban Service Efficiency Index (USEI):

$$\text{USEI} = (1/4) * \sum(P_{j_n} \text{ormalized}), \text{for } j=1 \text{ to } 4 \quad (4)$$

### 3.5. Validation Method: Regression Analysis

To validate the core hypothesis of the TAP model, we employ a simple linear regression analysis:

$$\text{USEI} = \beta_0 + \beta_1 * \text{MTAI} + \epsilon \quad (5)$$

A statistically significant and positive  $\beta_1$  coefficient, along with a high coefficient of determination (R-squared), would provide strong evidence supporting the validity of the TAP framework.

## 4. EXPERIMENTS AND RESULTS

This section presents the results of applying the TAP framework to the five selected African cities.

### 3.3. Data Collection and Case City Selection

Data for the KPIs were collected from a range of public sources for the period 2022-2024. For the experimental validation, we selected five major African cities that represent a diversity of regional and economic contexts. The selection criteria and characteristics of these cities are summarized in Table 2.

### 4.1. Data Collection Results

Table 3 reports the raw (pre-normalization) values of the 12 KPIs defined in Table 1 for the five case-study cities over the 2022–2024 observation window. The indicators span the three TAP layers: Technology (T1–T4), Application (A1–A4), and Performance (P1–P4). To ensure cross-city comparability, all variables are expressed using consistent units and directional interpretations (i.e., higher values indicate better performance, except for the Data Affordability Index, where lower values imply greater affordability and are treated as “lower-is-better” in subsequent normalization). The dataset was compiled from publicly available sources (GSMA Intelligence, World Bank/Global Findex and development indicators, UN E-Government Survey, Statista, and national statistical agencies). Where city-level measures were not directly available in a harmonized form, we adopted the closest comparable official proxies and documented the operational definitions, units, and extraction procedures in the Supplementary Material (Data Extraction Sheet). This raw KPI matrix constitutes the empirical input for the min–max normalization (Eqs. 1–2) and the construction of the composite indices (Eqs. 3–4), forming the basis for the benchmarking and regression analyses reported in Section 4.

### 4.2. Index Calculation and City Ranking

The raw KPI values reported in Table 3 were normalized to a 0–1 scale using the min–max procedures defined in Eqs. (1) and (2). The normalized indicators were subsequently aggregated with equal weights to compute the Mobile Technology Adoption Index (MTAI) and the Urban Service Efficiency Index (USEI) for each city, as specified in Eqs. (3) and (4). The resulting composite scores are presented in Table 4.

Table 4 shows clear cross-city variation in both technology adoption and performance outcomes. Cairo (0.87) and Johannesburg (0.78) record the highest MTAI values, reflecting comparatively strong digital infrastructure foundations. In contrast, Kigali achieves the highest USEI score (0.81) despite a moderate MTAI (0.54), suggesting a relatively efficient conversion of technological inputs into performance gains. This outcome is primarily associated

with its strong administrative efficiency improvements (P2) and measurable urban mobility gains (P4). Nairobi demonstrates a balanced profile, with relatively aligned MTAI (0.65) and USEI (0.67) scores. Lagos ranks lowest on both indices (MTAI = 0.35; USEI = 0.29), indicating structural constraints in both infrastructure provision and downstream service performance.

TABLE III. RAW KPI DATA FOR FIVE AFRICAN CITIES (2022-2024)

KPI ID	Indicator	Cairo	Lagos	Nairobi	Kigali	Johannesburg
T1	4G Network Coverage (%)	92	75	85	96	94
T2	Smartphone Penetration (%)	70	55	60	30	75
T3	Data Affordability Index (%)	0.8	1.5	1.2	2.5	2.1
T4	Electricity Access (%)	100	59	78	61	88
A1	Mobile Payment Penetration (%)	45	50	88	65	60
A2	E-commerce Adoption Rate (%)	35	25	30	15	40
A3	Digital Gov. Services (Count)	75	30	55	102	65
A4	Ride-Hailing Penetration (%)	40	35	38	20	45
P1	Financial Inclusion Rate (%)	55	51	91	68	70
P2	Admin. Efficiency Gain (%)	30	15	25	45	28
P3	Digital Retail Market Size (%)	8.5	11.5	9.0	10.5	7.0
P4	Commute Time Reduction (%)	5	2	8	12	6

<sup>a</sup> Data Sources: Compiled from publicly available datasets and official reports, including GSMA Intelligence, World Bank (Global Findex and development indicators), UN E-Government Survey, Statista, and national statistical agencies (2022–2024).

Overall, the divergence between MTAI and USEI across cities highlights that a strong technological base does not automatically translate into superior performance outcomes, reinforcing the analytical relevance of the TAP framework in distinguishing infrastructure capacity from conversion efficiency.

administrative efficiency (P2) and significant gains in urban mobility (P4). Lagos scores the lowest on both indices, reflecting significant challenges in both infrastructure and service delivery.

TABLE IV. NORMALIZED COMPOSITE INDEX SCORES

City	MTAI	USEI
Cairo	0.87	0.58
Lagos	0.35	0.29
Nairobi	0.65	0.67
Kigali	0.54	0.81
Johannesburg	0.78	0.54

### 4.3. Regression Analysis Results

To validate the relationship between technology adoption and urban performance, a linear regression was performed with MTAI as the independent variable and USEI as the dependent variable. The regression equation is:

$$USEI = 0.118 + 0.755 * MTAI \quad (6)$$

The coefficient of determination (R-squared) was 0.768, indicating that approximately 76.8% of the variance in the USEI can be explained by the MTAI. The p-value for the MTAI coefficient was 0.021 ( $p < 0.05$ ), confirming that the relationship is statistically significant. Figure 2 provides a visual representation of this relationship.

Johannesburg and Cairo exhibit the highest MTAI scores, indicating a strong technology foundation. Conversely, Kigali, despite a moderate MTAI, achieved the highest USEI score, largely driven by its exceptional performance in

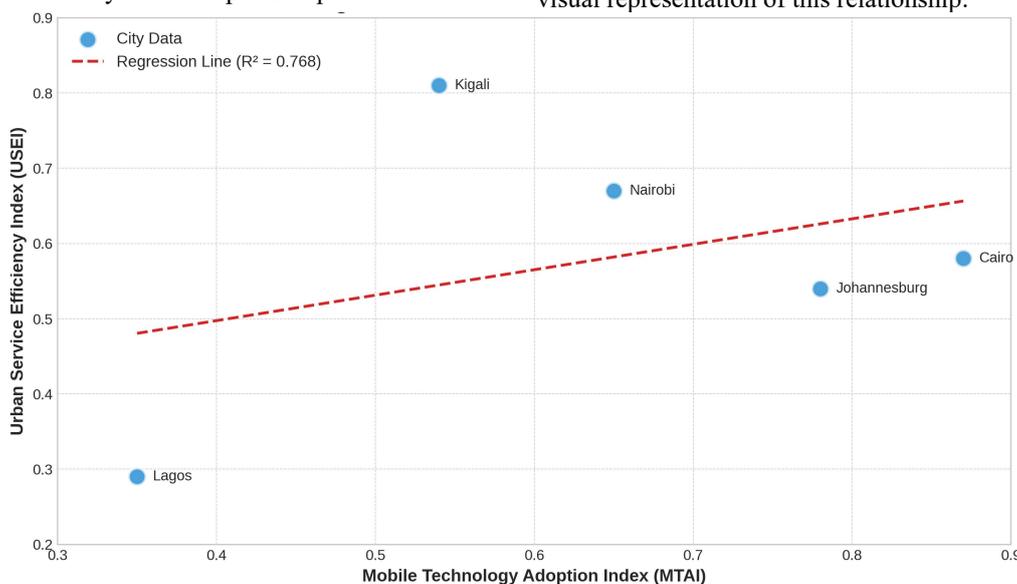


Figure 2. Correlation between MTAI and USE

#### 4.4. Robustness Checks

Given the small number of case cities (n = 5), we conducted robustness checks to assess whether the observed relationship between MTAI and USEI is overly driven by any single city or by distributional assumptions. First, we computed the Spearman rank correlation between MTAI and USEI, which remained positive and consistent with the Pearson-based regression results. Second, we performed a leave-one-out analysis by iteratively excluding one city and refitting the regression model. Across these specifications, the estimated association between MTAI and USEI remained positive, indicating that the main finding is not solely driven by a single influential observation. These checks support the stability of the TAP framework’s core empirical relationship in this pilot-scale validation.

#### 4.5. Case Highlight: Quantifying Efficiency Gains in Kigali

A standout result from the performance analysis is the impact of the Irembo e-governance platform in Kigali. Our data for KPI P2 (Administrative Efficiency Gain) shows a 45% average reduction in the time required to process a basket of key public services. For instance, the application for a birth certificate, which previously required an average of 10 working days and multiple physical visits, can now be completed online within 2 days, representing an 80% time reduction for that specific service. The 45% figure is the weighted average gain across the five most frequently used services, providing a concrete, quantitative measure of the engineering value delivered by the system.

TABLE V. COMPARISON OF KEY INTERNET DEVELOPMENT INDICATORS BY AFRICAN REGION

Region	Avg Internet Penetration (%)	Mobile Broadband Users (Million)	Avg Data Cost (Index)
North Africa	84.9	185	2.8
Southern Africa	74.9	98	3.5
West Africa	53.2	245	1.9
East Africa	28.9	78	1.1
Central Africa	19.1	12	4.2

Affordability patterns further complicate the picture. While East Africa reports the lowest average data cost index (1.1), Central Africa shows the highest (4.2), indicating that cost barriers remain unevenly distributed across regions. These disparities highlight that infrastructure availability, user scale, and affordability evolve along partially independent dimensions, reinforcing the need for a multi-layered evaluation framework such as TAP that distinguishes technological capacity from downstream application and performance outcomes.

This development is strongly linked to economic factors, as illustrated in Figure 3, which shows a positive correlation between a country’s GDP per capita and its internet penetration rate. However, notable outliers such as Rwanda and Kenya, which have relatively low GDP per capita but active internet applications, indicate that government policy orientation and specific technology path choices also play key roles.

#### 5.2. The Mobile-First Paradigm

Africa’s internet development exhibits distinct “mobile-first” characteristics. Due to historically severe lag in fixed telephone lines and broadband network construction, the African continent has directly skipped the PC internet era and entered the mobile internet era with smartphones as the

### 5. ANALYSIS AND DISCUSSION

The experimental results provide quantitative evidence supporting the TAP framework’s utility in assessing urban digital transformation. This section interprets the engineering significance of these findings, analyzes the performance variations between cities, and discusses the framework’s limitations.

#### 5.1. Contextualizing Africa’s Digital Landscape

The transformation trajectory of African cities is embedded within a highly uneven digital landscape characterized by pronounced regional disparities and a predominantly mobile-first development pattern. Table 5 summarizes key regional indicators, revealing substantial variation in infrastructure penetration, user scale, and affordability conditions.

North Africa exhibits the highest average internet penetration rate (84.9%), followed by Southern Africa (74.9%), indicating comparatively mature digital infrastructure environments. In contrast, East Africa (28.9%) and Central Africa (19.1%) remain significantly below the continental leaders, reflecting structural constraints in network deployment and access. However, the scale of mobile broadband users does not strictly align with penetration rates. West Africa, for instance, records the largest user base (245 million) despite only moderate penetration levels (53.2%), suggesting high population concentration and strong mobile reliance.

main access terminal. According to GSMA data, approximately 74% of network traffic in Africa in 2024 comes from mobile devices, far higher than the global average [2]. As shown in Figure 4, Nigeria, Egypt, and South Africa are the three countries with the largest mobile broadband user scale. This trend profoundly affects the form of African urban digital applications, where mobile applications rather than web pages become mainstream, and mobile payments rather than credit cards become the first choice.

Mobile payments represent one of the most prominent and measurable application domains within Africa’s digital ecosystem. Mobile money services—most notably Kenya’s M-Pesa—have significantly expanded access to formal financial services, contributing to financial inclusion in previously underbanked populations. As illustrated in Figure 5, Nigeria, South Africa, Kenya, and Morocco account for some of the largest digital payment user bases on the continent, reflecting both demographic scale and mobile-centric adoption patterns.

Table 6 compares the major mobile payment platforms operating in Africa. The data indicate substantial variation in launch timing, geographic coverage, and user scale. MTN Mobile Money and Orange Money, operating across multiple countries, report the largest aggregated user bases (58 million

and 45 million, respectively), demonstrating the scalability of cross-border telecom-led financial ecosystems. In contrast, M-Pesa, although primarily concentrated in Kenya, maintains a strong user base (32 million) and represents an early-mover model of mobile financial infrastructure. The temporal distribution of platform launches (2007–2018) also highlights the progressive institutionalization of mobile money as a foundational digital service layer across the continent.

These patterns underscore the central role of mobile payments as a bridge between technological infrastructure (T layer) and socio-economic performance outcomes (P layer), particularly in relation to financial inclusion and digital retail expansion.

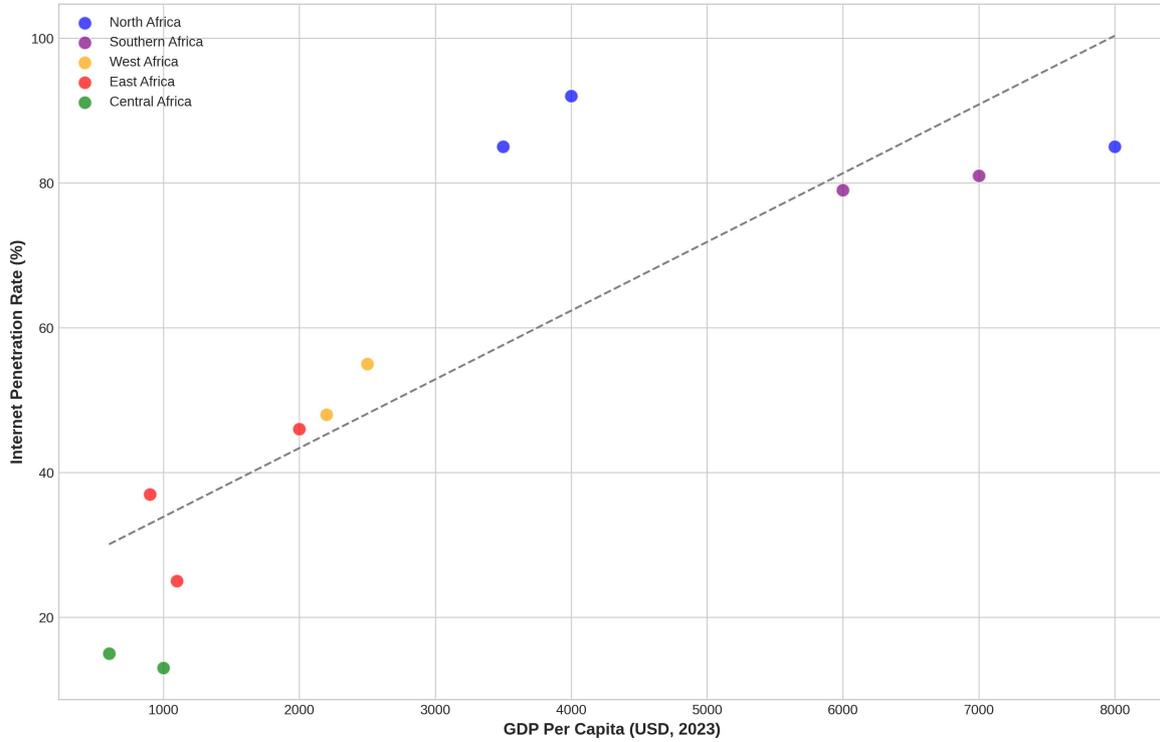


Figure 3. Relationship between Internet Penetration and GDP Per Capita in Africa

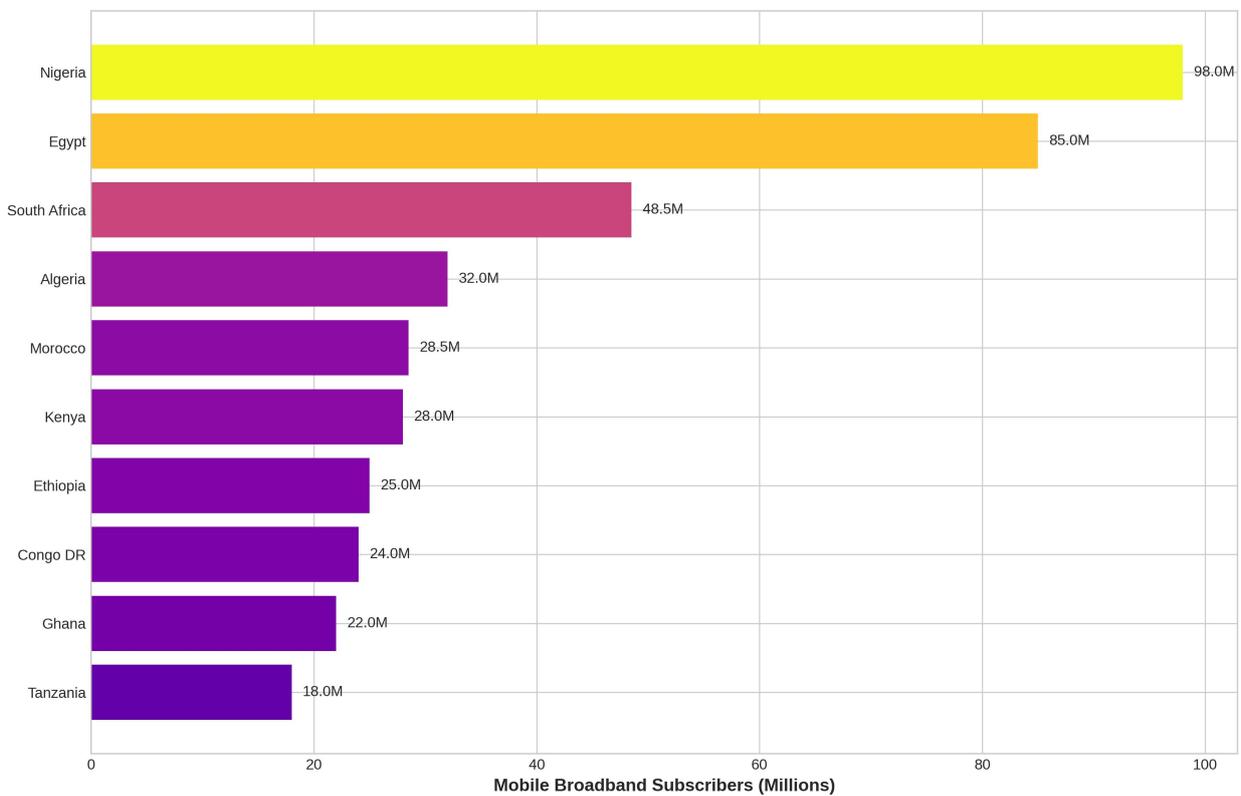


Figure 4. Top 10 African Countries by Mobile Broadband Subscribers

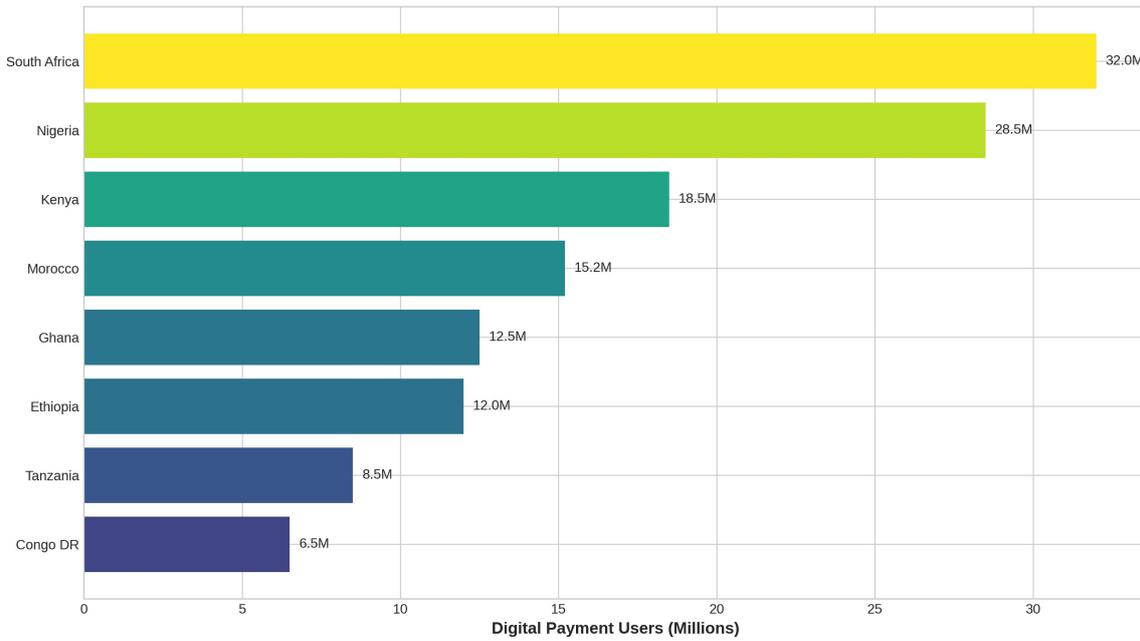


Figure 5. Top African Countries by Digital Payment Users

TABLE VI. COMPARISON OF MAJOR MOBILE PAYMENT PLATFORMS IN AFRICA

Platform Name	Primary Country	Launch Year	Active Users (Million, ~2023)
M-Pesa	Kenya	2007	32.0
OPay	Nigeria	2018	18.0
MTN Mobile Money	Multiple	2009	58.0
Orange Money	Multiple	2008	45.0
Airtel Money	Multiple	2010	28.0

Figure 6. Urban areas, due to high population density, concentrated economic activities, and relatively complete infrastructure, become the main scenarios and driving forces for internet applications. Conversely, the proliferation of internet technology is also profoundly changing Africa’s urbanization process. Digital platforms enable urban services (such as education, healthcare, finance) to radiate to surrounding areas at lower costs. However, this interactive relationship is not always benign. Rapid urbanization may lead to the expansion of slums, and these areas often lack basic digital infrastructure, forming new “digital slums.”

5.3. Urbanization-Digitalization Nexus

There is an obvious positive correlation between urbanization rate and internet penetration rate, as shown in

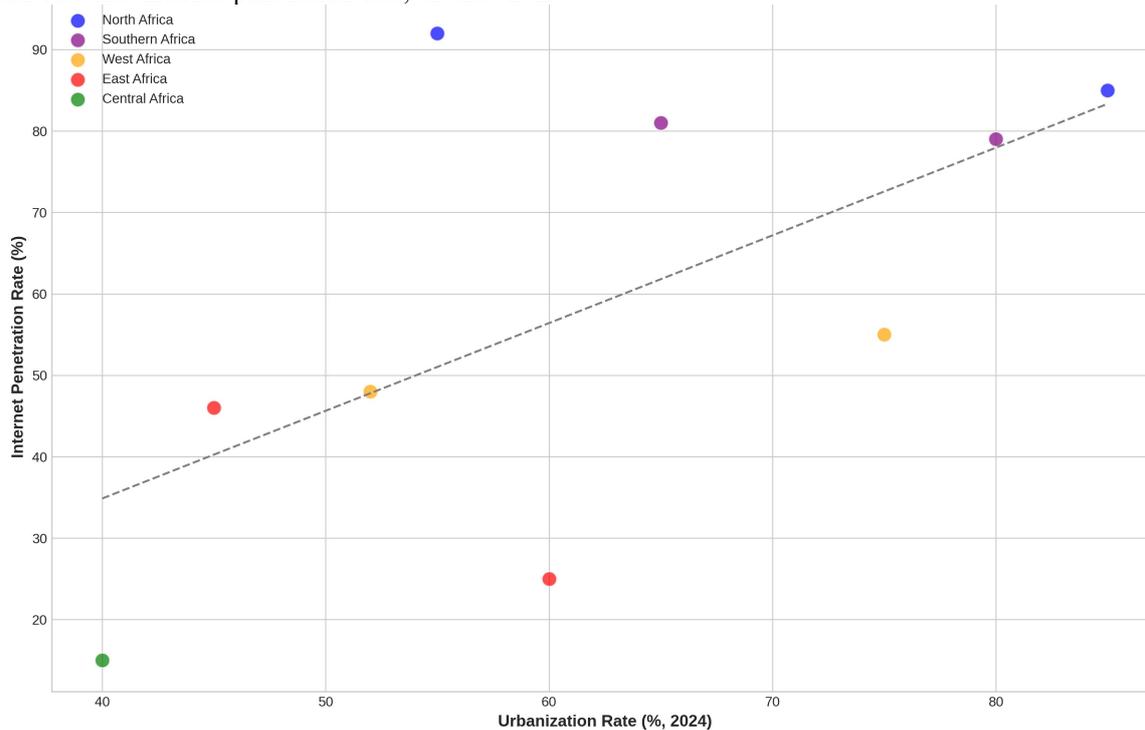


Figure 6. Relationship Between Urbanization and Internet Penetration in Africa

5.4. Comparative Analysis of Transformation Pathways

The radar chart in Figure 7 provides a multi-dimensional comparison of the case study cities, revealing their relative strengths and weaknesses across key transformation indicators. Kigali’s strength in Policy Support and E-Governance is evident, while Johannesburg leads in Infrastructure.

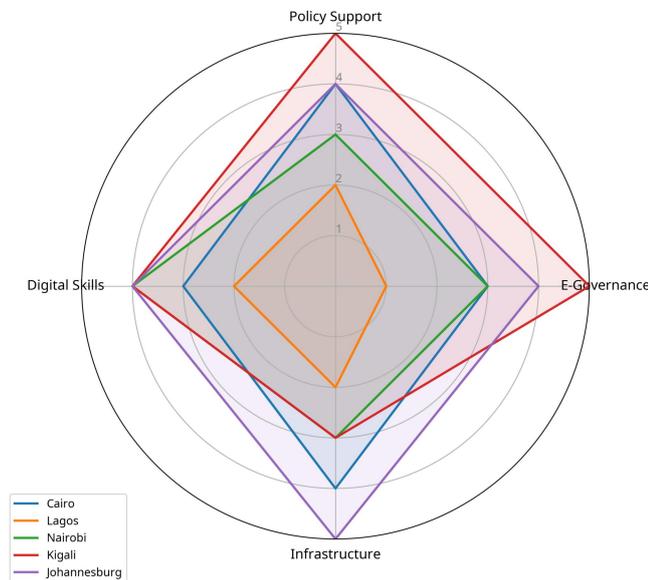


Figure 7. Key Digital Transformation Indicators Comparison Across Case Study Cities

The city-specific results reveal that the path from technology adoption to performance is not uniform. The relationship is mediated by local policy, economic structure, and implementation strategy. Kigali’s position as a positive outlier (moderate MTAI, highest USEI) demonstrates that a superior technology base is not the sole determinant of success. Rwanda’s strong, government-led, top-down strategy has created a highly efficient pipeline for converting technological capability into performance gains. Johannesburg and Cairo exhibit high MTAI scores but only achieve moderate USEI scores, suggesting a conversion bottleneck. Lagos’s low scores on both indices highlight the foundational challenge of building a digital city on weak infrastructure.

Factors such as the cost of mobile data also play crucial roles. As shown in Figure 8, there is an inverse relationship between mobile data cost and digital payment adoption, suggesting that affordability is a key enabler for the uptake of digital services.

The final composite digital transformation scores, as shown in Figure 9, provide a summary of the overall performance. Johannesburg leads with the highest composite score, followed closely by Nairobi, while Lagos trails significantly. However, the true value of the TAP framework lies not in this single score, but in its ability to deconstruct this performance into actionable components at each layer.

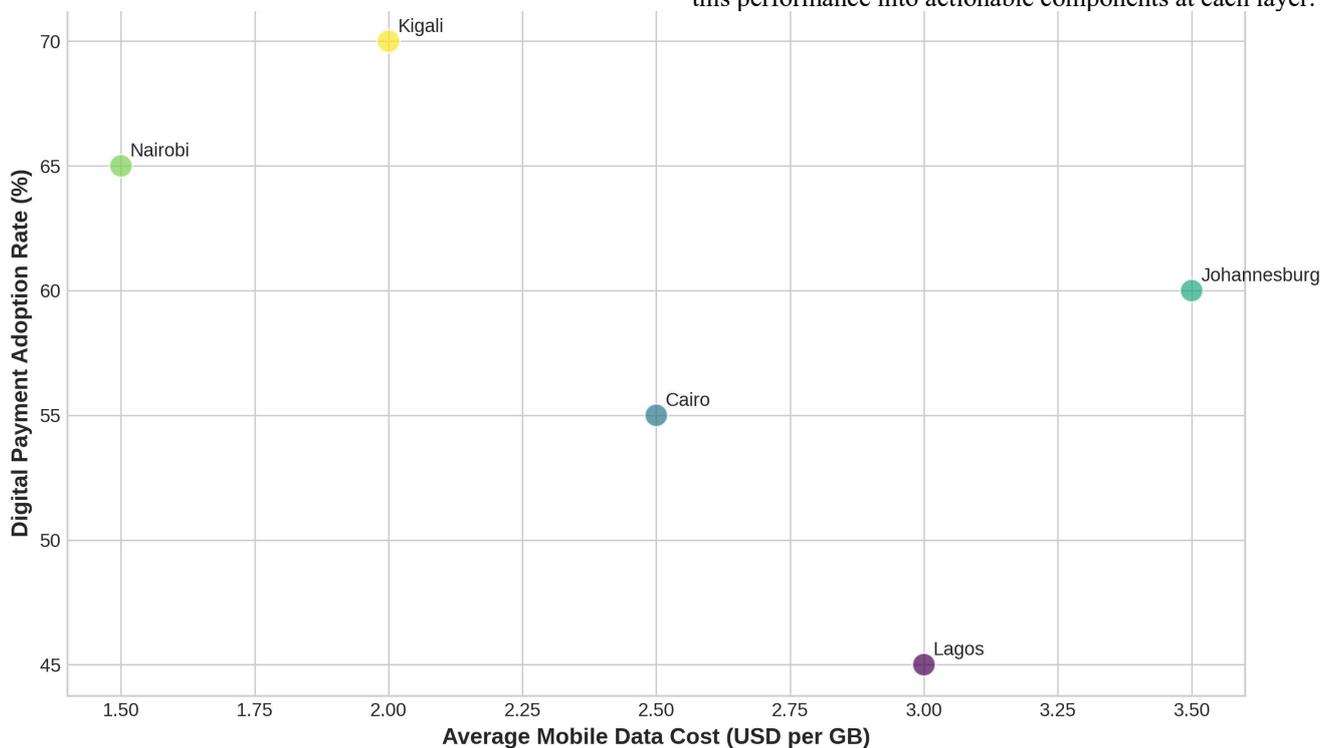


Figure 8. Relationship between Mobile Data Cost and Digital Payment Adoption

5.5. Limitations and Future Work

In addition, the pilot validation uses a small sample of cities due to the limited availability of standardized and comparable municipal-level datasets across Africa. Future work will expand the sample size and incorporate

longitudinal observations to improve statistical power and enable more robust causal inference strategies.

This study has several limitations that provide avenues for future research. First, the selection of KPIs was

constrained by the availability of comparable public data. Second, the model assigns equal weights to all KPIs for simplicity; future iterations could employ expert-driven weighting methods such as the Analytic Hierarchy Process (AHP). Third, the linear regression model is a simplification

of a complex process; future research could explore non-linear models. Finally, the study is a cross-sectional analysis; a longitudinal study tracking the evolution of these cities' KPIs over a longer period would provide deeper insights.

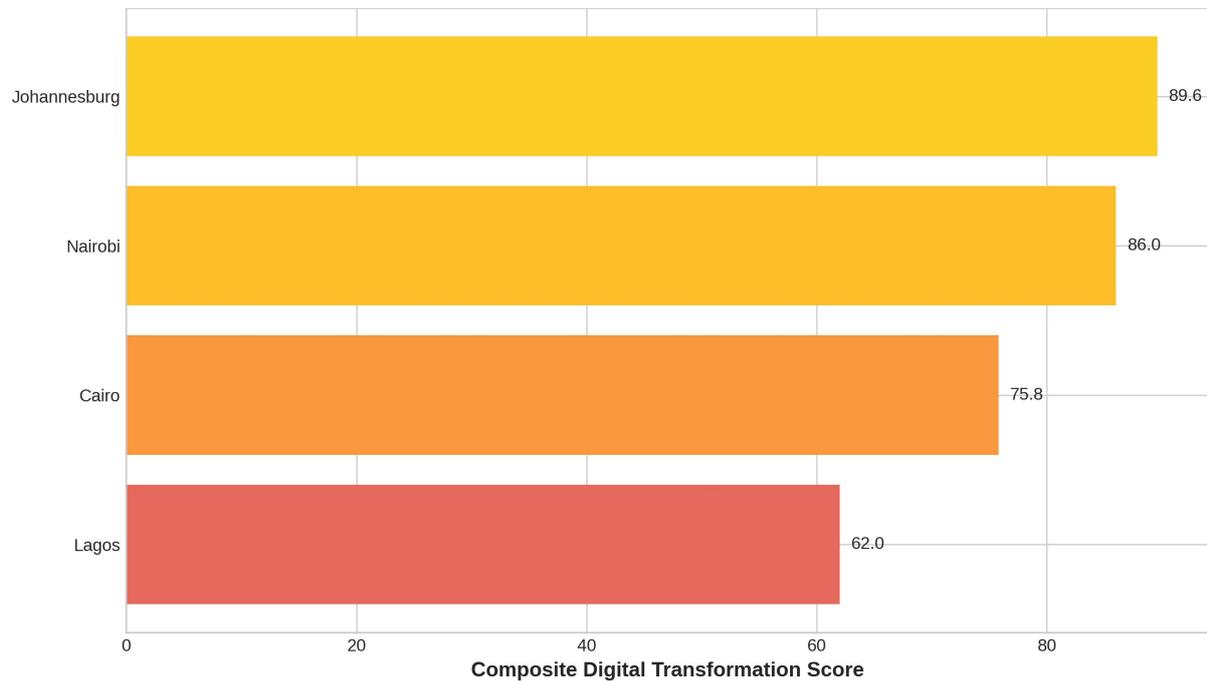


Figure 9. Overall Digital Transformation Performance Across Case Study Cities

## 6. CONCLUSION

This paper addressed the critical need for a quantitative, engineering-oriented approach to evaluating urban digital transformation in Africa. We successfully developed and validated the Technology-Application-Performance (TAP) model, a hierarchical framework that provides a structured and replicable methodology for this purpose. The core technical contribution of this work is the formulation of a standardized assessment tool that translates the complex, multifaceted process of digital transformation into a set of measurable Key Performance Indicators (KPIs) and actionable composite indices, the Mobile Technology Adoption Index (MTAI) and the Urban Service Efficiency Index (USEI).

Our experimental application of the TAP model to five major African cities yielded significant quantitative results. We found a strong positive association ( $R\text{-squared} = 0.768$ ) between the level of mobile technology adoption and the efficiency of urban services, empirically confirming the engineering value of digital infrastructure investments. The analysis highlighted diverse transformation pathways, from Kigali's policy-driven efficiency to Johannesburg's infrastructure-rich potential, providing a diagnostic tool for cities to identify their specific strengths and weaknesses. The case of Kigali, which achieved a 45% gain in administrative efficiency through its e-governance platform, provides a concrete example of the substantial return on investment possible through well-executed digital projects.

The primary value of the TAP framework lies in its practical application for engineers, city planners, and policymakers. It provides a data-driven basis for strategic decision-making, enabling cities to move beyond qualitative

assessments to a quantitative, evidence-based management of their digital transformation journey. By benchmarking their performance, cities can more effectively allocate resources, justify technology investments, and design targeted interventions to maximize the socio-economic and engineering impact of mobile internet technology. This research provides a foundational step toward a more rigorous, data-centric, and ultimately more successful approach to building the smart cities of Africa's future.

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Poloko Felix Motoane conceived and designed the study, developed the Technology–Application–Performance (TAP) framework and the KPI system, and led the modeling and quantitative formulation (including normalization, composite index construction, and regression validation), while also compiling and curating the multi-source secondary dataset for the five case-study cities (2022–2024), conducting the comparative analysis and robustness checks, interpreting the results and policy implications, and writing, revising, and finalizing the manuscript.

**COMPETING INTERESTS**

The authors declare no competing interests.

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