

AI Adoption and Usage in the Kenyan Economy: Infrastructure, Institutions, and Sectoral Intensity

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Abstract—Kenya’s payments system is dense. Its measured AI use is not. This paper places the Digital Economy Blueprint, the National Digital Master Plan 2022–2032, the Data Protection Act 2019, and the Artificial Intelligence Strategy 2025–2030 (released 27 March 2025) against published infrastructure, energy-access, readiness, and usage series. I define an AI adoption-intensity index over infrastructure, data, talent, governance, and observed use, with stated weights, $\varepsilon = 10^{-3}$, and numeric anchors for Low/Medium/High. A documentary coding of the eight strategy sectors is then converted into two rankings. Finance is first, and MSMEs and the creative sector last, under both an enabler-heavy and a use-heavy weight vector (Kendall $\tau = 0.71$). Agriculture, health, and public services sit in the middle: named as priorities, thinner on production use. National series point the same way. Oxford Insights (2024) scores Kenya 43.56 overall, with the government pillar well above the technology pillar. A Microsoft-telemetry User Share of 7.83 percent of the working-age population is a national ceiling, not a sectoral census. The remaining constraints are last-mile connection quality (urban electricity access near 100 percent, rural about 70 percent), farm and clinic records, price, language coverage beyond English and Swahili, and operational resilience on a payment rail that already carries a large share of GDP.

Index Terms—Artificial intelligence, Kenya, digital economy, technology adoption, mobile money, data protection, public-sector digitalization.

I. INTRODUCTION

Kenya’s digital history is a payments history. After M-PESA launched in 2007, store-of-value and person-to-person transfer moved onto the phone. More than 80 percent of adults now use some form of mobile money, and the International Trade Administration repeats an industry estimate that close to two-thirds of GDP transits the payment system [1]. The household evidence is older than the present AI debate. Access to M-PESA raised consumption and lifted an estimated 194,000 households (about 2 percent of Kenyan households) out of extreme poverty, with larger effects in female-headed households [2, 3]. That record still shapes how ministers and investors talk about “Silicon Savannah” [1].

AI does not travel the same way. Mobile money asked users for a short menu action and an agent down the road. Current systems consume data, compute, and specialized labor, and they write mistakes into credit files, clinic queues, farm advice, and administrative rankings [4, 5]. On 27 March 2025 the Ministry of Information, Communications and the Digital Economy released the Kenya Artificial Intelligence Strategy 2025–2030 [6–8]. OECD.AI records three pillars (infrastructure, data, research and innovation) and four enablers (governance,

talent, investment, and ethics, equity and inclusion) [8]. The priority list is long: agriculture, healthcare, education, public service delivery, security, financial services, micro-, small and medium-sized enterprises (MSMEs), the creative sector, and sustainability [8, 9].

Vendor numbers do not settle where those priorities stand. The same commercial guide puts the 2024 Kenyan AI market at about \$240 million, with a published compound growth rate of 28.22 percent through 2030, and startup funding near \$800 million in 2023 [1]. Those are receipts and capital inflows. They do not say how often a county clinic, a tea factory, or a hardware kiosk actually runs a model. Government readiness scores are a second, different object. Oxford Insights’ 2024 Government AI Readiness Index gives Kenya 43.56 overall, with the government pillar (56.20) well above the technology-sector pillar (30.98) [10]. A Microsoft-telemetry estimate of AI User Share puts Kenya at 7.83 percent of the working-age population, and 21.65 percent among the internet-connected [11]. Both series are national. Neither is sectoral.

This paper builds a sectoral object that can take those series, and later survey microdata, without changing its definition. I place AI on Kenya’s existing digital public infrastructure (payments, fiber, the Digital Superhighway, and the \$390 million Kenya Digital Economy Acceleration Project) [1, 12]. I define an AI adoption-intensity index (AIAI) with stated weights, a stated stabilizer $\varepsilon = 10^{-3}$, and numeric anchors for Low/Medium/High. I then compute the index on a documentary coding of the eight strategy sectors and report rank stability under two weight vectors.

Section II situates the index against adoption theory, readiness rankings, and language and energy constraints. Section III states the design, the rubric, and the algebra. Section IV reports national indicators and the computed AIAI. Section V turns to law, inclusion, and operational resilience. Section VI closes.

II. RELATED WORK

A. Adoption as a layered problem

Rogers treats a new technique as spreading under relative advantage, compatibility, complexity, trialability, and observability [13]. Davis and Venkatesh move the same problem to the person (usefulness, ease of use, social influence, facilitating conditions) [14, 15]. Tornatzky and Fleischer add organizational slack and external pressure [16]. Comin and Hobijn show that the lag between invention and intensive use is itself an economic object [17].

AI sits on all three layers and adds two practical complications. Many of the valuable uses ride existing digital public

infrastructure: identity, payments, and administrative registries [5]. And model error is a legal event when the model scores credit, triages patients, or ranks beneficiaries [4, 18]. The OECD principles on inclusive growth, transparency, robustness, and accountability therefore belong inside the constraint set, not in a footnote [19]. Kenya’s 2025–2030 strategy cites the same list [8].

B. Readiness indices and usage shares

Oxford Insights scores governments, not sectors. The 2024 index covers 188 countries on government, technology-sector, and data-and-infrastructure pillars. Kenya’s 43.56 overall score, and the 25-point gap between the government pillar and the technology pillar, is the quantitative version of a familiar qualitative claim: Nairobi writes strategy faster than firms ship models [10]. Malatji’s 2026 reading of the same family of scores places Kenya in the middle of the leading sub-Saharan group (about 44.8 in that compilation), behind Mauritius, South Africa, and Rwanda, and notes that AI scores do not move one-for-one with GDP per capita [20]. AIAI is built for a different question. It asks which Kenyan sectors already use models and which only appear in the strategy.

Misra et al. convert anonymized Microsoft telemetry into a population-normalized AI User Share for 147 economies [11]. For Kenya they report 7.83 percent of the working-age population and 21.65 percent of the internet-connected. I treat that pair as a national ceiling on U , not as a sectoral observation. The metric also inherits Microsoft’s user base. A finance clerk on Outlook is more visible than a farmer on a feature phone.

Language is a separate limiter. Misra et al. (a related usage paper) estimate that low-resource-language countries have an AI user share about 20 percent below their socioeconomic baseline [21]. Joshi et al. documented how few languages sit in the training distribution [22]. A 2025 survey of African LLM coverage finds that four languages (Amharic, Swahili, Afrikaans, Malagasy) absorb most of the documented work, while more than 98 percent of African languages remain unsupported [23]. Kenya’s official pair is English and Swahili. County service, agricultural advice, and clinic intake still run in Kikuyu, Dholuo, Kalenjin, Somali, and other languages. I keep language out of the five-coordinate index and return to it as an adjustment on D and G .

C. Kenya’s digital sequence

Jack and Suri showed that M-PESA cut the cost of risk sharing; Suri and Jack extended the result to long-run poverty and occupational change [2, 3]. That sequence (cheap transfer, thicker insurance, then occupational shift) is the right baseline for AI because the first paying Kenyan uses sit on the same rail: fraud detection, credit scoring, merchant analytics, and customer-service automation [1, 24]. The 2024 FinAccess survey puts formal financial access at 84.8 percent, up from 83.7 percent in 2021 [25].

Policy stacked on that rail. The Digital Economy Blueprint (2019) set five pillars [26]. The National Digital Master Plan 2022–2032 treated ICT as an enabler of health, education, the creative economy, and agriculture [27]. The Data Protection Act

2019 created the Office of the Data Protection Commissioner and a cross-border transfer rule that demands “appropriate safeguards” and comparable protection in the receiving jurisdiction, without yet saying what proof looks like inside a training pipeline [1, 28]. The Computer Misuse and Cybercrimes Act 2018 remains the main criminal statute for attacks on systems [29]. Until March 2025 there was no dedicated AI statute [1, 9].

The 27 March 2025 strategy is the first comprehensive national AI roadmap [6, 7]. Bowmans, whose lawyers sat on the technical working group, record the alignment with Vision 2030, the ICT Master Plan, the Bottom-up Economic Transformation Agenda, and the African Union Continental AI Strategy [9, 30]. EY records the stated growth channel: productivity, revenue, and public-service delivery [31]. Public-sector project work now cites the Blueprint, the Master Plan, and the AI Strategy as one stack [32].

Andersson Lipcsey groups AI diffusion into global value chains, research collaboration, and firm-to-firm knowledge transfer, and finds a still-wide gap between high-income and lower-middle-income countries [33]. In that vocabulary the May 2024 Microsoft–G42 campus and API access are disembodied diffusion: weights travel without a local factory [1]. Embodied channels, if they appear, look more like the CHIPS/ITSI semiconductor partnership and on-the-ground data-center build. AIAI does not estimate those channels. It leaves room for them in I and T .

Agricultural D should be scored the way Vedamurthy et al. score public farm data in India: latency against the decision cycle, a shared geocode, machine-readable APIs, and a consent rule [34]. Kenya’s named agricultural data-sharing platform is a start. It is not yet those four tests. On the rail itself, Adewusi et al. specify a hybrid USSD-plus-JWT authentication path for e-government when the packet is intermittent [35]. That design is the concrete version of the failover discussion later in the paper.

III. METHODOLOGY

A. Design

The unit of analysis is the Kenyan economy at two resolutions: national enabling conditions, and the eight sectors named as AI priorities in the 2025–2030 strategy [8, 9]. I do not field a new firm or household survey. Sources are statutes, ministry strategies, the World Bank project record, the ITA Digital Economy note of 18 September 2024, the Oxford Insights 2024 index, the Misra et al. usage series, IEA and World Bank energy-access figures, KNBS FinAccess, and the Communications Authority’s mid-2025 connectivity note [1, 10–12, 25, 36, 37].

Coding is single-author. Appendix A states the numeric anchors and the tightness rule. A second coder is not reported here. Ties are broken downward.

B. Anchors, stabilizer, and missingness

Ordinal labels map to the closed set $\{L, L/M, M, M/H, H\} = \{0.20, 0.35, 0.50, 0.65, 0.80\}$. Those five points are conventions. Section IV jitters each cell

by ± 0.05 (2,000 draws) so the ranking is not an artifact of the particular numbers.

Let $\mathcal{S}$ be the sector set and

$$\mathbf{x}_s = (I_s, D_s, T_s, G_s, U_s)^\top \in \mathbb{R}_+^5$$

the scores on infrastructure access, usable data, talent, governance fit, and observed use. I is access and reliability at the point of use, not the national generation mix. D is whether records exist in machine-readable form with identifiers and a consent rule. U is documented production use, not a named opportunity in a strategy annex.

Definition 1 (AI adoption intensity). Fix $\mathbf{w} = (w_I, w_D, w_T, w_G, w_U)$ with $w_k > 0$ and $\sum_k w_k = 1$. For each coordinate k ,

$$\hat{x}_{s,k} = \frac{x_{s,k} - \min_{j \in \mathcal{S}} x_{j,k}}{\max_{j \in \mathcal{S}} x_{j,k} - \min_{j \in \mathcal{S}} x_{j,k} + \varepsilon}, \quad \varepsilon = 10^{-3}. \quad (1)$$

The sector index is

$$\text{AIAI}_s(\mathbf{w}) = \sum_{k \in \{I, D, T, G, U\}} w_k \hat{x}_{s,k}. \quad (2)$$

A national headline is

$$\overline{\text{AIAI}}(\mathbf{w}) = \sum_{s \in \mathcal{S}} \lambda_s \text{AIAI}_s(\mathbf{w}), \quad \lambda_s \geq 0, \quad \sum_s \lambda_s = 1. \quad (3)$$

If a coordinate is missing for some s , that coordinate is dropped for all sectors and the remaining weights are renormalized to one. No cell is imputed. The residual in the later reduced form is written η_{is} , so it is not confused with the stabilizer ε .

Two weight vectors are used throughout:

$$\begin{aligned} \mathbf{w}^E &= (0.25, 0.25, 0.20, 0.20, 0.10), \\ \mathbf{w}^U &= (0.15, 0.15, 0.15, 0.15, 0.40). \end{aligned} \quad (4)$$

$\mathbf{w}^E$ asks where a system could be stood up. $\mathbf{w}^U$ asks where a system already runs. Rank agreement is Kendall's τ .

λ_s is reported two ways: equal weights 1/8, and a crude value-added scheme that puts the IEA 2023 agricultural share (22 percent of GDP) on agriculture and splits the residual equally across the other seven sectors [36]. The eight strategy sectors do not partition GDP, so neither λ is a national accounts identity. They are sensitivities. An employment-weighted λ would put still more mass on agriculture and informal MSMEs. I do not have a clean eight-way employment file, so I do not invent one. The tail ranks (finance first; MSME and creative last) survive the two λ I can defend.

When more than one noisy proxy exists for a coordinate, the natural next estimators are a principal-component weight, an expert AHP weight, or an ordered-probit / IRT map from $L/M/H$ into a latent score. Those estimators need more than one series per cell. Kenya does not yet publish that panel at sector resolution. I stay with stated weights and a Monte Carlo around them.

Remark 1. A later firm survey replaces only the U column. Validation checks on that insert are: $U_s \in [0, 1]$; no sector jumps more than two ranks after a 5-point change in any one coordinate; and monotonicity of AIAI_s in each coordinate under both $\mathbf{w}$.

C. Constraint tightness

Tightness is not a sixth AIAI coordinate. It records whether the sources name a present blocker of production use. High: two or more independent sources name the same blocker and the blocker is current (for example, the 2023 denial-of-service incidents on payment apps). Medium: the blocker is named once, or is partial. Low: no blocker is documented. Appendix A reprints the cell-level anchors.

D. A later estimator

Payments intensity M_{is} and cyber exposure enter I and G rather than as a second theory. A latent usage propensity for organization i in sector s is

$$u_{is}^* = \alpha_s + \beta_I I_{is} + \beta_D D_{is} + \beta_T T_{is} + \beta_G G_{is} + \gamma M_{is} + \mathbf{z}_{is}^\top \delta + \eta_{is}, \quad (5)$$

with $U_{is} = \mathbf{1}\{u_{is}^* > 0\}$ and $\mathbf{z}_{is}$ holding size, county, and export status. Equation (5) is the TOE-consistent target for a later estimator [15, 16]. It is not estimated here.

E. The stack

Figure 1 is the picture. Generation mix and undersea cables sit in the bottom layer; they are not the same thing as a clinic's transformer or a county's last mile. Data and the 2019 Act sit above. Talent and investment convert those stocks into models. Use cases are the top layer the strategy names. A hospital can buy a diagnostic model before the county finishes a records standard. That timing mismatch is a source of risk, not a sequence error.

IV. RESULTS

A. National enabling conditions

Table I collects the public series that fill the bottom three layers of Fig. 1.

Connectivity and generation look abundant at the national mean. The ITA note records six undersea cables, internet penetration of 85.2 percent (Internet World Stats), and a Digital Superhighway plan for 100,000 km of fiber and 25,000 public Wi-Fi hotspots [1]. The IEA's 2024 energy review puts generation near 90 percent renewable and electricity access at 79 percent in 2023 (urban near 100 percent, rural about 70 percent) [36]. The World Bank's 2024 access rate is 77.0 percent [38]. Those two facts need to be kept apart. A geothermal plant in Olkaria is an argument for a hyperscale campus. It is not an argument that a dispensary in Turkana can keep a GPU-free inference box on through the afternoon. SAIDI and SAIFI are not published here at county resolution, so reliability enters only as this urban–rural split.

Payments intensity is already high. Adult mobile-money use above 80 percent, formal financial access at 84.8 percent in FinAccess 2024, and the two-thirds-of-GDP claim put Kenya in a different complement set from most lower-middle-income peers [1, 24, 25]. Equation (5) then has a large M_{is} for urban and peri-urban firms. The same rail is a concentration risk. The 2023 “Anonymous Sudan” incidents took down eCitizen and mobile-money applications [1].

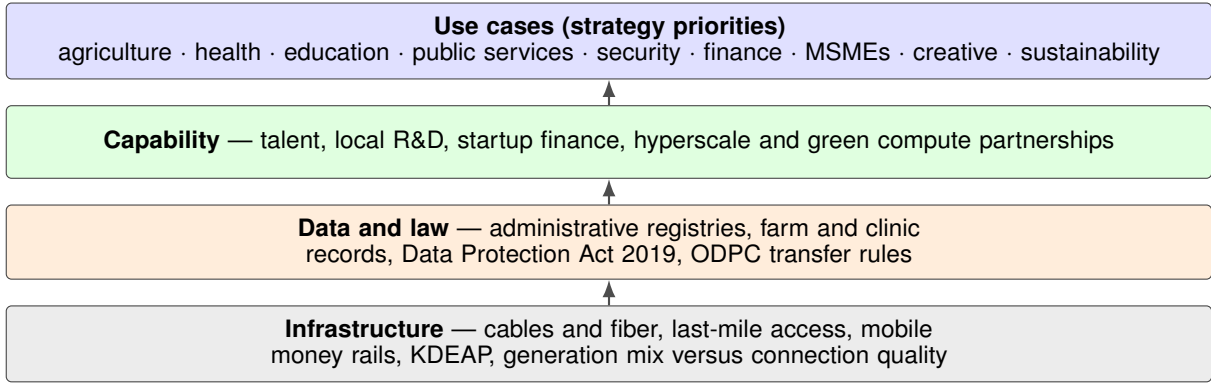


Fig. 1. Four-layer stack used to interpret AI adoption in Kenya. Lower layers are complementary inputs. National generation mix is not a substitute for household or clinic connection quality.

The AI overlay is still thin. A \$240 million 2024 vendor market, even at the published 28.22 percent growth rate, sits beside a digital-economy share that BMI expected to reach 9.24 percent of GDP by 2025 and beside ICT-sector growth of 10.8 percent a year over the prior decade [1]. Misra et al.’s 7.83 percent working-age User Share is consistent with that picture [11]. KNBS reports that agriculture still accounts for more than 20 percent of GDP and that the economy created most new jobs in the informal sector [36, 39]. Informal firms are exactly the units least visible in Microsoft telemetry.

Institutions moved in 2023–2025. The 30 percent domestic equity rule for technology firms was repealed in August 2023. VAT on exported services was removed. Kenya became the first African ITSI partner under the CHIPS Act. MICDE and the U.S. Department of Commerce signed an April 2024 joint statement on data flows, AI, and skills. KDEAP began operations in 2024 (\$390 million, plus an intended \$100 million in private broadband capital) [1, 12]. The 27 March 2025 strategy sits on that step [6].

B. Documentary codes and computed AIAI

Table II records the ordinal codes. Table III converts them with the anchors in Section III and reports $AIAI_s(\mathbf{w}^E)$ and $AIAI_s(\mathbf{w}^U)$.

Finance is the only sector scored High on both U and D . That is a claim about production (fraud, credit decisioning, chatbots, merchant analytics) on a rail that already has paying customers and a data exhaust [1]. It is not a claim that model risk is solved. Agriculture and health are High on strategy demand and Medium on documented use. Advisory systems, telemedicine, and drone logistics appear as opportunities; farm identifiers, clinic records, and last-mile power do not [1, 8, 36]. Public service delivery is Medium on use and Medium/High on infrastructure because eCitizen already runs at national scale and because the 2023 outages showed that scale arrived before failover [1]. Education is Medium on several enablers and Low/Medium on use: intelligent tutoring is a strategy sentence, not a classroom census [8]. MSMEs and the creative sector sit at the bottom on data and talent. Security is scored Medium on most coordinates and Low/Medium on governance because

the public record is thin and dual-use systems should not be marked up from vendor copy.

Finance is first, and MSME and creative last, under both weights. Kendall $\tau = 0.71$. The disagreement is in the middle. Education ranks third on enablers (some connectivity and an education-management information system) and sixth once use is loaded. Agriculture moves the other way, from sixth to fifth, because the strategy already records advisory pilots even while farm data remain thin. That pattern is what the two vectors were built to show.

Equal-weight national means are 0.410 ($\mathbf{w}^E$) and 0.421 ($\mathbf{w}^U$). Tilting λ toward agriculture’s 22 percent GDP share lowers both means by about 0.01–0.02. The headline is stable. It is also still a coded object. Replacing U with a firm-survey probability would change the level more than the rank order of the tails.

C. A three-sector proxy check

Table IV puts published series next to the documentary codes for finance, health, and public services. The national User Share (7.83 percent of working age; 21.65 percent of the internet-connected) is a ceiling on U , not a sector observation [11]. The Communications Authority’s mid-2025 note puts mobile penetration at 143 percent and the smartphone share of that stock at 80.8 percent [37]. Those two numbers raise I for any use that needs a screen. They do not raise I for a USSD menu on a feature phone.

I do not have sectoral tender counts, ODPC case tallies, or Safaricom model-deployment disclosures that can be cited as a series. In their absence the proxy check is local to these three sectors. Replace U in finance with the internet-connected User Share (0.2165) and U in health and public services with the working-age User Share (0.0783), keep the documentary I, D, T, G , and renormalize inside the trio. Finance remains first, public second, and health third under both weight vectors ($AIAI^E$ of 0.996, 0.307, and 0.000; $AIAI^U$ of 0.995, 0.199, and 0.000). The High label on finance is not doing the work by itself. Health hits the floor because it is the minimum on four of the five coordinates inside this small set.

TABLE I
PUBLISHED NATIONAL INDICATORS USED AS ENABLING CONDITIONS

Indicator	Published value	Layer
Internet penetration	85.2% (Internet World Stats, via ITA)	Access
Undersea cables	Six landing points	Backbone
Digital Superhighway plan	100,000 km fiber; 25,000 hotspots	Last mile
Renewable share of generation	$\approx 90\%$ (IEA); $>92\%$ (ITA)	Power supply
Electricity access, 2023/24	79% (IEA 2023); 77% (WDI 2024)	Connection
urban / rural (IEA 2023)	$\approx 100\%$ / $\approx 70\%$	Connection
KDEAP (World Bank)	\$390 million, from 2024	Access program
Adult mobile-money use	$>80\%$	Payments
Formal financial access, 2024	84.8% (FinAccess)	Payments
GDP through payment system	$\approx$ two-thirds (industry estimate)	Payments
Agriculture / GDP	$>20\%$ (KNBS); 22% (IEA 2023)	Structure
ICT-sector real growth (prior decade)	10.8% per year (BMI, via ITA)	Capability
Digital economy / GDP (2025 expectation)	9.24% (BMI, via ITA)	Capability
Startup funding, 2023	$\approx$ \$800 million	Capability
AI market, 2024	\$240 million; 28.22% CAGR (Statista, via ITA)	Vendor use
AI User Share (working-age)	7.83% (Misra et al.)	National <i>U</i>
AI User Share (internet-connected)	21.65% (Misra et al.)	National <i>U</i>
Oxford Insights 2024, Kenya	43.56 overall; gov. 56.20; tech. 30.98	Readiness
IoT market, 2024	\$670 million (Statista, via ITA)	Adjacent use
Cybersecurity market, 2024	$\approx$ \$56.13 million	Risk spend
Microsoft–G42 announcement, May 2024	\$1 billion, 1 GW campus	Compute
Digital services tax	1.5% of gross transactional value	Tax
Data-protection statute	Data Protection Act 2019; ODPC	Law
National AI strategy	Released 27 March 2025	Law

Notes: ITA [1]; KDEAP [12]; strategy date [6]; energy [36, 38]; FinAccess [25]; User Share [11]; Oxford Insights [10]. The GDP–payments ratio is the ITA’s industry estimate.

TABLE II
DOCUMENTARY CODING OF STRATEGY-PRIORITY SECTORS

Sector	<i>I</i>	<i>D</i>	<i>T</i>	<i>G</i>	<i>U</i>	Tightness / principal blocker
Financial services	H	H	M/H	M/H	H	H: model risk and DDoS on the rail [1]
Agriculture	L/M	L/M	L/M	M	M	H: farm records, last mile [8]
Healthcare	M	L/M	L/M	M	M	H: records, device prices [1]
Public services	M/H	M	M	M	M	H: outages, procurement [1]
Education	M	M	L/M	M	L/M	M: devices, teacher skill [8]
Security	M	M	M	L/M	M	H: oversight, dual use [8]
MSMEs	L/M	L	L	M	L/M	H: price, thin footprints [9]
Creative sector	M	L	L/M	L/M	L	M: compute, IP rules [9]

Notes: Anchors $L = 0.20$, $L/M = 0.35$, $M = 0.50$, $M/H = 0.65$, $H = 0.80$. Tightness is defined in Section III. Demand in the strategy text is absorbed into *G*, not scored as a sixth coordinate.

D. What the national series add

Oxford Insights and AIAI can be true at the same time. A government pillar of 56.20 is compatible with finance sitting near 1 after within-Kenya normalization, because the Oxford number compares Kenya to other states and AIAI compares Kenyan sectors to each other. The technology pillar of 30.98 is compatible with MSME and creative scores below 0.20. Misra et al.’s 7.83 percent User Share is a reminder that even the high *U* in finance is a high *relative to other Kenyan sectors*, not a claim that most clerks already live in a copilot.

V. DISCUSSION

A. Payments density is not AI density

M-PESA scaled because the action was short, cash-in/cash-out was local, and the regulator let a non-bank grow [2, 3].

Predictive and generative systems fail those tests. They need orderly data, complementary skill, and someone who is liable when the score is wrong [4, 18]. Kenya’s unusual complements (dense payments, English in the formal sector, green generation for campuses) raise returns in finance-adjacent uses first. Table III is that asymmetry written as two rankings.

B. Law, tax, and a training pipeline

At strategy launch Kenya still had no comprehensive AI statute. The working law is the Data Protection Act 2019, the Computer Misuse and Cybercrimes Act 2018, intellectual-property statutes, and the Consumer Protection Act 2012 [9, 28, 29]. Cross-border transfers require “appropriate safeguards” and comparable protection. The Act does not list the documents that count as proof [1]. Until ODPC publishes an adequacy

TABLE III
COMPUTED AIAI AND RANKS

Sector	AIAI ^E	Rank ^E	AIAI ^U	Rank ^U
Financial services	0.998	1	0.998	1
Public services	0.574	2	0.549	2
Education	0.399	3	0.349	6
Security	0.391	4	0.424	3
Healthcare	0.362	5	0.412	4
Agriculture	0.279	6	0.362	5
Creative sector	0.150	7	0.100	8
MSMEs	0.125	8	0.175	7
Equal-weight mean	0.410		0.421	
VA-tilted mean	0.395		0.415	

Notes: $\varepsilon = 10^{-3}$. Kendall $\tau(\text{AIAI}^E, \text{AIAI}^U) = 0.71$. VA-tilted λ puts 0.22 on agriculture. Monte Carlo 5–95 percent bands (cell jitter ± 0.05 , Dirichlet weights) keep finance first and MSME/creative last in every draw; education and agriculture swap inside the middle of the pack.

list or standard clauses aimed at model training, a defensible interim path is: register as a controller or processor; run a data-protection impact assessment that names the training purpose; contract for comparable protection in the receiving jurisdiction; keep raw logs of Kenyan residents out of open training dumps; and log any onward transfer. The 1.5 percent digital services tax on gross transactional value still applies to a marketplace sale of the resulting service. The ITA recorded talk of a significant-economic-presence replacement; no replacement is treated as enacted here [1]. The 2025–2030 strategy asks for impact assessments and sector standards [8]. The 2026 draft AI and emerging-technologies policy is the next instrument in that line, not a finished code.

C. Language, price, and counties

Swahili is comparatively well covered in African LLM surveys. Kikuyu, Dholuo, Kalenjin, Somali, and the rest of the county list are not [22, 23]. Misra et al. put a number on that gap: low-resource-language countries sit about 20 percent below their socioeconomic baseline on AI User Share [21]. A Nairobi English chatbot can raise U in finance and leave U in agriculture unchanged. I would put a later language score into D (training text) and G (whether a public-service chatbot is allowed to run only in English).

Price works the same way. ITA notes that Kenyan private buyers are price-sensitive [1]. The Communications Authority’s 143 percent mobile penetration and 80.8 percent smartphone share mean a screen is common, not that a \$15 monthly copilot clears a hardware stall in Gikomba [37]. Viable near-term models are USSD or thin-app front ends on the payment rail, with the model in a regional hall and a fallback when the packet drops. Adewusi et al. write that path down as SIM-plus-PIN-plus-JWT session binding, with reported gains in authentication time and success under poor networks relative to smartphone SSO [35]. After the 2023 outages, the relevant test is whether an AI-scored overdraft or an eCitizen queue can fail over and roll back a model without taking the rail with it. That test belongs to the Central Bank, ODPC, and MICDE together.

County means are not scored in Table III. The IEA urban–rural electricity split (about 100 percent versus 70 percent in 2023) is the cleanest published cut I trust [36]. Nairobi’s services-heavy gross county product, set against the arid and semi-arid counties, is the economic version of the same cut. Last-mile fiber and county innovation hubs in the strategy are the official response. They do not yet appear as a county AIAI. SAIDI and SAIFI are not published here at county resolution; until they are, I should not be filled with the national generation mix.

On farm data, Vedamurthy et al.’s four tests (decision-cycle latency, a shared geocode, a machine-readable API, consent) are the right checklist for Kenya’s agricultural data-sharing platform [34]. Identifiers and an API are cheap relative to a campus. They are also the items that move D .

D. A short work program

Table V is a work program, not a budget law. Costs are orders of magnitude against two published anchors: KDEAP at \$390 million and the Microsoft–G42 campus at \$1 billion [1, 12]. Registry APIs, ODPC clauses, and a failover drill sit in the low six figures or below (a rounding error on KDEAP). A bilingual ministry chatbot and evaluated procurement sit in the high six to low seven figures. A county AIAI is a statistics exercise. None of these lines is a campus.

E. Limits

The ITA block mixes official series, BMI, Statista, and industry estimates. I left the provenance in Table I. Sector codes are single-author documentary codes. λ_s is a sensitivity, not a national accounts identity. County SAIDI/SAIFI and device-price indices are not used. Equation (5) still wants a firm file with county fixed effects and a payments interaction.

VI. CONCLUSION

Kenya enters this period with dense mobile money, a named AI strategy, green generation that a campus can buy, a 2019 data statute with a sitting commissioner, and a World Bank digital project already in execution [1, 7, 12, 28]. It does not enter with measured, economy-wide AI use. The vendor market is still in the low hundreds of millions of dollars [1]. Microsoft-telemetry User Share is 7.83 percent of the working-age population [11]. Production use, on the coding in Table III, concentrates on the payment rail. Agriculture, health, public services, and MSMEs are the strategy’s targets and the thin cells on data and complementary skill.

The practical implication is local. Ministries can publish the five coordinates once a year. Firms can price for a market that is digitally dense and cash-constrained, with a USSD door on the front and a model in a regional hall. Equation (5) is the next estimation, on firms and counties. This paper leaves that estimator a target, a reproducible index, and a first set of sector ranks.

TABLE IV
PUBLISHED PROXIES BESIDE THE THREE-SECTOR CODING

	Finance	Health	Public services
<i>I</i> proxy	Payment rail; urban power	Clinic last mile; rural access $\approx 70\%$	eCitizen scale; 2023 outage
<i>D</i> proxy	Transaction logs	Thin interoperable records	Administrative registries
<i>U</i> proxy	Production fraud/credit models (ITA)	Named telemedicine (ITA)	National portal, no model census
National <i>U</i> ceiling	0.2165 (online User Share)	0.0783 (working-age User Share)	0.0783
Documentary <i>U</i>	H (0.80)	M (0.50)	M (0.50)

TABLE V
NEAR-TERM WORK PROGRAM, COST ORDER, AND EXPECTED AIAI COORDINATE

Step	Horizon	Cost order	Moves
Machine-readable farm and facility registries, with consent	12 months	$\ll$ KDEAP	<i>D</i>
ODPC standard clauses for training transfers	12 months	staff time	<i>G</i>
USSD / JWT fallback on public chatbots [35]	12 months	$\ll$ KDEAP	<i>I, U</i>
Joint failover and model-rollback drill on one rail service	12 months	drill budget	<i>G</i>
Swahili plus one county language in one ministry chatbot	18 months	small procurement	<i>D, G</i>
Evaluated procurement (accuracy, failover, price)	24 months	process, not capex	<i>G, U</i>
County AIAI on CA and KNBS files	24 months	statistics desk	all

APPENDIX A CODING RULE

Continuous items in Table I are taken from the cited source. Ordinal cells in Table II use the anchors $L = 0.20$, $L/M = 0.35$, $M = 0.50$, $M/H = 0.65$, $H = 0.80$. Tightness is High if two or more independent sources name the same present blocker of production use, Medium if the blocker is named once or is partial, and Low if none is documented. Monte Carlo bands use 2,000 draws, cell jitter of ± 0.05 , and Dirichlet weights centered on (4). Missing coordinates are dropped and remaining weights are renormalized. No cell is imputed. Coding is single-author.

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