Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

The Infrastructure Paradox of AI Development in LMICs

Samuel T. Segun
samuel@globalcenter.ai

Global Center on AI Governance

Patrick Onodje
University of Ibadan

Ayantola Alayande
Global Center on AI Governance

Glory Oscar
University of Ibadan

Article

Keywords: AI, Infrastructure, Compute, Data, Internet, Electricity, LMICs, Innovation

Posted Date: March 31st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8965724/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

The regions that stand to benefit most from artificial intelligence are often the least equipped to develop it locally, a tension we term the "Infrastructure Paradox." This exploratory, cross-sectional study surveys 91 AI practitioners across 27 low- and middle-income countries (LMICs) to assess the availability, affordability, and reliability of four foundational AI infrastructure pillars: electricity, internet connectivity, computing hardware, and training data. Rather than a uniform deficit, the results reveal an income-stratified "Infrastructure Gradient" characterised by three non-linear dynamics: a Reliability Trap, wherein lower-middle-income countries report higher electricity service failure rates than low-income countries; a Data Quality Divide, where data accessibility remains constrained across income groups but quality improves markedly with income; and a Hardware Inversion, wherein AI interventions concentrate where hardware is most expensive, suggesting external financing rather than sustainable local markets drives current AI activity. Policy presence correlates with intermediate infrastructure capacity, implying governance frameworks emerge where capability and urgency coincide. These findings reframe infrastructure as a governance and equity determinant shaping where, how, and for whom AI develops, and suggest that technological leapfrogging in AI is conditional rather than categorical.

Introduction

A fundamental paradox defines the contemporary landscape of artificial intelligence: the countries where AI-driven solutions could yield the greatest developmental returns in healthcare delivery, agricultural productivity, financial inclusion, and climate adaptation are precisely those that lack the physical and economic infrastructure required to build, deploy, and sustain such systems locally[1]. We term this structural tension the "Infrastructure Paradox" of AI development. It reflects not merely a resource gap but a systemic misalignment between the geography of AI need and the geography of AI capacity, one that current global discourse on responsible AI governance has yet to address with sufficient empirical rigour. There is a notable disparity in AI innovation between low- and middle-income countries (LMICs) and high-income countries (HICs)[2], with HICs far out-pacing the global South in the development and deployment of AI[3, 4, 5]. A number of factors account for this gap such as a shortage of specialised talent, insufficient investment, weak institutional frameworks for AI governance, and infrastructural limitations[6]. This article focuses on one of these factors – infrastructural limitations in LMICs and seeks to contribute to the debate by considering the experiences of AI practitioners within the development context.

The classification “low- and middle-income countries (LMICs)” is used by the World Bank and other international organisations to group countries based on their gross national income (GNI) per capita[7], and this definition has been adopted for this article. LMICs represent about 122 countries, which is about 63% of the world’s countries. Table 1 shows the World Bank’s income classification (fiscal year 2024–2025) for the countries included in this study.

Table 1
LIMC countries' classification by World Bank GNI per capita thresholds

Low-income countries (GNI per capita ≤ US$1,145)	Lower-middle income countries (GNI per capita US$1,146 – US$4,515)	Upper-middle income countries (GNI per capita US$4,516 – US$14,005)
● Burkina Faso	● Ecuador	● Argentina
● Democratic Republic of Congo	● Bangladesh	● Brazil
● Ethiopia	● Bolivia	● Colombia
● Senegal	● Guyana	● Costa Rica
● Tanzania	● Ghana	● Dominican Republic
● Togo	● Indonesia	● Namibia
● Uganda	● Kenya	● South Africa
	● Jamaica	
	● Lebanon	
	● Morocco	
	● Nigeria	
	● Pakistan	
	● Palestine [WB: West Bank and Gaza)	

Within the last decade, AI has been considered one of the most consequential technologies of the 21st Century with significant impact on the global economy[8, 9, 10,]. Increasingly, the technology is deployed across a wide range of sectors, from healthcare, finance, education, to manufacturing and agriculture[11, 12], with projections of impact through enhancing productivity, improving ideation, and decision making[13]. AI is estimated to drive up global gross domestic product (GDP) by 3.5% and contribute about US$20 trillion to the global economy by 2030 according to data from the International Data Corporation[14]. Many low-and middle-income countries are prioritising the adoption of AI and seeking to build local AI industries by creating national strategies to support their ambition of participating in the projected economic prosperity of AI[15], but not without some challenges.

Low-and middle-income countries are often slow to adopt new technologies[16, 17]. The lack of critical infrastructure required to build or support such technologies is a standout issue for these countries[18, 19]. This is not a new issue, as the lack of critical infrastructure also inhibited the adoption of previous technologies[20, 21, 22]. In the case of artificial intelligence, several technical infrastructures are crucial to further advancing the technology – such as computing resources, reliable electricity, internet connectivity, and data availability[23, 24, 25]. Current literature on AI innovation in LMICs do not adequately account for all of these infrastructure deficits[26, 27]. Often, only one or two of these infrastructure issues are discussed as it is often taken as self-evident. We address this gap in this article, showing comprehensively how the lack of these infrastructure stifles AI innovation in LMICs, articulating the extent of the challenge and identifying opportunities to address them.

This exploratory study moves beyond the prevailing tendency to treat infrastructure as a monolithic "barrier" and instead conceptualises it as an "Infrastructure Gradient"—a multi-dimensional, income-stratified continuum along which different types of deficits dominate at different income levels[28]. In low-income settings, the primary constraints are access and affordability; in lower-middle-income countries, reliability and maintenance failures emerge as critical bottlenecks; and in upper-middle-income countries, the challenge shifts to the capital costs of sophisticated backup and

cloud systems. Understanding this gradient is essential for designing targeted, context-sensitive interventions rather than one-size-fits-all prescriptions. Considering the reality of infrastructure is important for contributing to discourses on emerging technologies in LMICs, and can add context to debates, for instance, on 'leapfrogging' in development. Key questions that this paper would address include: (i) How does the reliability and accessibility of infrastructure (electricity, compute resources, internet access) in LMICs affect AI development and deployment? (ii) In what ways do the economic milieu of LMICs influence their development and use of AI technologies? (iii) How do data limitations (quality, availability, and accessibility of training data) impact AI model development and implementation in LMICs?

Data and Methods

Research Design and Sampling Technique

The socio-political and economic milieu of a country influences its national strategy to AI development. In LMICs, innovators use AI to address multi-sector development challenges[29] such as improving access to healthcare[30,31], financial inclusion, education[32], agriculture[33, 34,].While the debate in higher-income countries trends towards agentic models, robotics, and the safety of techno-scientific progress toward artificial general intelligence (AGI), ongoing debates in LMICs are primarily focused on the role of AI in reshaping their economic opportunities[35, 36,] and solving developmental issues[37].

Therefore, for this study, we surveyed cross-sectoral AI experts (researchers, developers, industry stakeholders) working to develop AI-enabled solutions to developmental challenges in LMICs, to understand their experience of the availability, accessibility and affordability of AI infrastructure for innovation. We adopt an exploratory, cross-sectional, mixed methods design, with a survey capturing quantifiable metrics and open-ended questions. We also used a purposive sampling approach to ensure representation across the income groups and major geopolitical regions.

A total of 91 participants from 27 countries were represented across different LMICs, covering a broad range of regions, namely Asia, Africa, South America, and the MENA regions. The country distribution of survey participants is as follows.

- **Low Income**: Uganda, Ethiopia, Burkina Faso, Tanzania, Democratic Republic of Congo, Togo, Senegal
- **Lower-middle Income**: Nigeria, Kenya, Ghana, Bangladesh, Morocco, Jamaica, Palestine, Indonesia, Guyana, Pakistan, Bolivia, Ecuador, Lebanon
- **Upper-middle Income**: South Africa, Dominican Republic, Brazil, Costa Rica, Argentina, Colombia, Namibia

As shown in Fig. 1, the study included a diverse range of 13 roles across 11 sectors. The most frequently represented roles were Entrepreneur/Founder (28.9%), Academics (20.5%), and management/leadership positions (13.3%). Other roles that participated included Technical/Engineering, Policy/Governance/Legal, Other/Unspecified, Student, Research/Program Management, Both NGO executive manager and consultant, ISMS Coordinator, Consultant, Education/Teaching, and Technical Product Manager. This distribution highlights significant participation from both leadership and technical personnel in the survey.

Healthcare was the most represented sector at 25.6%, followed by Education/Research (20.9%) and Agriculture/Climate (16.3%). The remaining sectors included Technology/ICT, Government/Public Service, Civil Society/Development, Law/Legal, Financial/Commerce, Transport/Logistics, and a category for Other/Unspecified.

Data Collection and Challenges

Primary data were collected using online survey questionnaires disseminated through mailing lists, professional networks, AI research communities, and targeted outreach to AI organisations in the LMICs. The instrument contained closed-ended and multiple-choice questions that cover AI eco-system and strength., the presence and effectiveness of national AI policies, and a range of AI-related infrastructural factors including electricity reliability and cost, data availability and quality, hardware accessibility, cloud use and cost, and electricity reliability and cost. Where possible, respondents assessed the infrastructure factors in terms of availability, affordability, and reliability.

One key challenge with the data collection was the low response rate which is attributable to survey fatigue among target respondents and limited internet reach that is characteristic of LMICs[55, 56]. Our intended minimum sample size was 385 respondents which was derived using 95% confidence interval, 50% population proportion, and 5% margin of error. However, due to a lower response rate than anticipated, the final sample came to 91 completed surveys distributed across over 25 LMICs. Moreover, ongoing geopolitical instability in some of the LMICs posed significant hindrance to survey distribution and collection. To address these gaps, we analysed non-response patterns, and where appropriate, document missingness to identify potential bias sources, maintain transparency, and appropriately inform statistical handling[57]. Using this approach ensured the analysis accounts for systematic response gaps while helping to preserve the integrity of our analyses[58].

Our small sample size weakened the possibility of conducting a multivariate regression. This study is accordingly exploratory in its inferential scope. However, its analytical value lies in the density and diversity of perspectives captured. The sample spans 27 countries across four geopolitical regions, encompasses all three LMIC income classifications, and represents 13 professional roles across 11 sectors. This compositional breadth is uncommon in the existing literature, which has relied predominantly on single-country case studies or sector-specific assessments that, while achieving larger samples, cannot capture the cross-sectoral, multi-country practitioner perspective essential for understanding how infrastructure constraints operate across the heterogeneous LMIC landscape.

This diversity constitutes a form of representativeness complementary to that achieved by large-sample surveys. Non-significant associations should be interpreted as suggestive rather than null, while the significant associations that do emerge such as the Hardware Inversion ($p = 0.05$), the policy–infrastructure link ($p < 0.001$), and the data accessibility–policy association ($p = 0.03$) carry particular weight precisely because they achieve significance despite conservative sample size.

Data Analysis

Our research approach was informed by our hypothesis that differences in economic capacity (captured by GNI classifications) and technological infrastructure such as computing resources, electricity access, and internet connectivity explain variations in AI innovation.

To account for the reduced sample and associated missingness, we adopted a structured analytical strategy that combined descriptive distribution analysis with chi-square association tests, consistent with approaches validated for exploratory survey research under data constraints[59]. This allowed us to identify broad trends and examine associations between infrastructural factors and AI development outcomes.

The analysis proceeded in two stages. First, descriptive statistics were used to summarise the distribution of responses across key variables, disaggregated by GNI classification. Missing data were quantified to highlight areas with particularly low reporting rates (e.g., internet speed, electricity affordability). Second, inferential analyses were performed to assess associations between infrastructural variables and AI innovation outcomes. Chi-square tests were used for categorical variables to evaluate the statistical significance of observed relationships, such as between electricity reliability and AI policy existence.

Variables demonstrating significant associations were further examined using cross-tabulations to explore patterns across income and regional classifications. Data cleaning, initial re-coding, and descriptive analysis were conducted with Python programming language due to its versatility and robust framework for data handling and manipulation[60, 61]. Subsequent crosstabulations and tests of association were performed with Stata.

Results

A. The Infrastructure Gradient: AI Infrastructure Gaps and Economic Capacity in LMICs

Our first level of analysis using descriptive data discusses key indicators of infrastructural capacity in electricity, internet, compute, and data infrastructure. The primary data collected identifies specific infrastructure limitations in LMICs that are impeding AI innovation.

Electricity

This section examines the quality of electricity available to respondents in the surveyed countries[38]. The data, shown in Fig. 2, supports the argument that electricity service failure operates along multiple, uncoupled axes of inequity: (i) Low-income countries suffer from affordability issues for the basic service; (ii) Lower-middle income countries suffer the highest rates of reliability failure, suggesting a critical gap in infrastructure investment or maintenance impacting that specific segment; (iii) Upper-middle income countries absorb the highest capital expenditures for sophisticated alternative systems to ensure consistent supply.

1. Electricity Affordability

The data on affordability demonstrates a clear regressive financial burden, where the perception of cost decreases steadily as income rises. The Low-income group experiences the most severe cost pressure, with nearly 57% of respondents classifying electricity as Expensive (42.9%) or Very Expensive (14.3%), and only 4.8% find it affordable. The proportion of respondents classifying electricity cost as Moderate, Affordable or Very Affordable increases from 42.9% in the Low-Income group to 51.8% in Lower-Middle Income group, and 61.1% in the Upper-Middle group. Conversely, the Expensive or Very Expensive category drops from 57.2% (Low) to 48.1% (Lower-Middle) and 39% (Upper-Middle), indicating that while costs remain substantial, the relative financial pain lessens significantly for higher income countries.

2. **Electricity Reliability**

The findings on reliability present counter-intuitive results, challenging the expectation that reliability improves linearly with income[39]. There was minimal difference between levels of reliability between the Low income and Lower-Middle income groups. Service quality is perceived as Poor or Very Poor by a third of respondents in both the Low-income group (33.4%, with 26.7% Poor and 6.7% Very Poor) and the Lower-middle income group (33.3% Poor). This perception of poor service quality improves in the Upper-Middle income group, where only 21.7% classify it as Poor.

The Low-Income group reported the highest proportion of "good/fair" ratings (67%), closely followed by the Lower-Middle income group (64.3%) and the Upper-Middle income group (65.2%). This suggests potential infrastructure issues such as maintenance problems, load shedding, or failures in these countries. Conversely, "excellent" service quality was reported by a small minority: 13% of the Upper-Middle income group and 3% of the Lower-Middle income group.

3. Alternative Electricity Cost

Here, we examine the cost of backup power supply, e.g., generators or solar solutions, used to mitigate the high unreliability. The results highlight that while these solutions are universally expensive, the highest costs are borne by the Upper-Middle income group.

Across all income groups surveyed, the cost of alternative electricity supply is overwhelmingly viewed as expensive[40]. Specifically, 91.6% of the Low-income group classified these alternatives as Expensive or Very Expensive, with only 8.3% finding them affordable. For both the Lower-Middle and Upper-Middle income groups, 100% considered auxiliary electricity supply to be Expensive or Very Expensive. The perception of "Very Expensive" is most pronounced among the Upper-Middle income group, where 54.5% placed the cost in this highest bracket. This contrasts sharply with the 17.6% recorded for the Lower-Middle group and the 8.3% for the Low-income group.

Internet

Figure 3 shows the analysis of internet infrastructure — affordability, reliability and speed — across income groups. There is a complex infrastructure gap defined by different challenges across income groups, with the Low-income group experiencing greater affordability issues and lower internet speed access. The Upper-Middle income group experiences high access to speed but reports surprisingly poor reliability. While speed correlates positively with income, the inverse relationship between income and reliability suggests that factors other than pure purchasing power, such as service-level agreements or specific network infrastructure saturation, are driving the unexpected lack of reliability in Upper-middle income countries.

1. Internet Affordability

The data from our study on affordability shows a clear inverse relationship between income and the perceived cost burden of internet access. Internet access costs are a substantial financial burden for the low-income group, with a significant majority (66.7%) finding it "Expensive" (50.0%) or "Very Expensive" (16.7%).

The perceived affordability of internet access demonstrates a strong correlation with income. The percentage of respondents classifying the cost as "Affordable" rises sharply from 6.7% in the Low-income group to 15.2% in the Lower-Middle income group. Similarly, those finding the cost "Moderate" increase from 26.7% (Low-income) to 42.4% (Lower-Middle income). Despite this increase in affordability perception, a substantial portion of the Lower-Middle income group (42.4%) still finds the cost challenging, categorizing it as either Expensive (39.4%) or Very Expensive (3%).

For the Upper-Middle income group, a significant majority (65.2%) perceives the cost of internet access as high, classifying it as either “Expensive” (52.2%) or “Very Expensive” (13%). Conversely, only a small portion (17.3%) finds the cost “Affordable” or “Very Affordable,” with the remaining 17.4% considering it Moderate.

2. Internet Reliability

The reliability data shows a varied assessment of service quality across income groups. In the Low-Income group, A significant portion (36.6%) classifies their internet as "Unreliable" (23.3%) or "Very Unreliable" (13.3%). Conversely, 23.3% report "Reliable" internet access, while 40% perceive it as "Moderate." The Lower-Middle group shows mixed results, with a majority reporting “Moderate” reliability (54.5%), and 21.2% “Reliable” and 3.0% “Very Reliable”. There is also a noticeable percentage reporting “Very Unreliable” (12.1%) or “Unreliable” (9.1%) service.

The Upper-Middle income group reports the highest perceived reliability, with 69.6% classifying their internet as "Reliable." An additional 26.1% report "Moderate" reliability, and only 4.3% classify their service as "Very Unreliable."

3. **Internet Speed**

The analysis of the speed metric reveals a strong, linear correlation between perceived internet speed and income level, with reported speeds consistently improving as income increases.

The Low-income group is overwhelmingly concentrated in the lower speed tiers, with 80% classifying their speed as either "Very Slow" (40%) or "Slow" (40%). Only 20% report "Fast" access. The Lower-Middle income group shows a mixed pattern. While 46.7% report "Fast" access, a significant portion still experiences slower speeds, with 33.3% reporting "Slow" and 20% reporting "Very Slow" access. The Upper-Middle income group reports the highest speeds, with 81.8% classifying their speed as "Fast" (63.6%) or "Very Fast" (18.2%). However, 18.2% still report "Slow" connections.

Data

We assessed the availability and quality of training data required to carry out AI research and development. The results in Fig. 4 indicate that while data accessibility challenges are widespread, there are distinct disparities in data quality, which correlate positively with income. Gaps in training data are shown to be primarily one of quality rather than just accessibility. While data accessibility is challenging for all groups, the quality of the data is starkly differentiated by income.

1. Data accessibility

For the low-income group, data was largely inaccessible or hard to obtain: 43.3% reported it as *partially accessible*, 40.0% as *difficult to access*, and 10.0% as *not accessible*. Only 3.3% found data for AI research to be *accessible*, reflecting severe barriers to access. In lower-middle income countries, accessibility improved with 24.2% reporting data as *accessible*, though 42.4% still found it only *partially accessible* and 24.2% described it as *difficult to access*. Upper-middle income countries showed a mixed outcome: while 43.5% still found data only *partially accessible* and 34.8% *difficult to access*, a small but notable 13.0% reported it as *accessible*, suggesting slightly better but still constrained access.

2. **Data quality**

Consistent with patterns observed for data access, training data quality varied systematically across income groups. In low-income countries, data quality was predominantly rated as moderate (40.0%) or low (33.3%), with relatively few respondents describing it as good (20.0%) or high (3.3%).

Lower-middle-income countries exhibited a similar distribution, indicating only marginal improvement. Most respondents rated training data as moderate (42.4%) or low (36.4%), while fewer than one in ten (9.1%) characterised data quality as good.

In contrast, upper-middle-income countries reported substantially stronger outcomes. More than half of respondents (52.2%) rated training data quality as good, although a sizeable proportion still described it as moderate (39.1%); only a small minority (8.7%) reported low-quality data. Together, these results indicate a pronounced income-related gradient in training data quality, with higher-income settings benefiting from more consistently high-quality data resources[41].

To contextualise the quantitative patterns in data access and quality, respondents were asked to describe the primary challenges associated with training data. Analysis of these responses revealed several recurring themes.

The most frequently reported challenges related to data availability. Respondents commonly cited an insufficient volume of usable data, reflecting persistent constraints in accessing adequately sized datasets for model development. Concerns surrounding data privacy and security were also prominent, underscoring widespread apprehension regarding regulatory compliance, data governance, and risks associated with sensitive information[42].

Issues of data quality and fragmentation emerged as additional, interrelated barriers. Respondents reported poor data quality and bias[43], alongside difficulties in consolidating datasets distributed across multiple sources and formats. Such fragmentation was described as a significant impediment to effective model training and system integration.

Technical and economic constraints were also repeatedly noted. Challenges related to data storage, collection, and broader technical infrastructure were common, while cost considerations, particularly those associated with data acquisition, annotation, and long-term maintenance, were identified as limiting factors.

Finally, respondents highlighted constraints related to dataset diversity and labelling. Limited representation across domains, insufficiently annotated data, and challenges in sourcing heterogeneous datasets were described as structural obstacles to the development of inclusive and generalisable AI systems.

Hardware

Consistent with disparities observed in data access and quality, pronounced differences were also evident in the accessibility and cost of computational hardware across income groups, as shown in Fig. 5.

1. Hardware accessibility.

In low-income countries, access to hardware was highly uneven. While one-third of respondents (33.3%) reported that hardware was easy to access, a comparable proportion experienced moderate (30.0%) or limited access (23.3%), and 13.3% reported no access. In lower-middle-income countries, accessibility was more constrained overall: only 21.2% reported easy access, whereas limited access was most common (39.4%), followed by moderate access (30.3%); 9.1% reported no access. Upper-middle-income countries exhibited a different distribution, with access more frequently described as moderate (39.1%) or limited (34.8%). Although a small minority reported wide access (8.7%), easy access remained uncommon (13.0%), and 4.3% continued to report no access.

Limited hardware access across lower-income settings likely reflects structural constraints in digital and research infrastructure. Insufficient investment in high-performance computing facilities, unreliable electricity and connectivity, and limited institutional capacity restrict the availability of advanced hardware, even where basic access exists. In many cases, hardware resources are shared across departments or institutions, resulting in fragmented or intermittent access that constrains sustained AI development and experimentation.

2. **Hardware cost**

Cost emerged as a pervasive barrier across all income groups, particularly in lower-income settings. In low-income countries, nearly three-quarters of respondents described hardware as expensive (36.7%) or very expensive (36.7%), while only a small fraction reported it as affordable or very affordable (3.3% each). Cost pressures were even more pronounced in lower-middle-income countries, where 45.5% rated hardware as expensive and 33.3% as very expensive; no respondents described hardware as very affordable. In upper-middle-income countries, cost constraints were comparatively less severe but remained substantial: 43.5% reported hardware as expensive and 17.4% as very expensive, while 30.4% described costs as moderate and 8.7% as affordable.

The persistently high cost of hardware across all income groups, including upper-middle-income countries, is plausibly driven by the capital-intensive nature of AI-relevant infrastructure. Dependence on imported hardware, exposure to currency fluctuations, and the concentration of global semiconductor supply chains increase acquisition and maintenance costs, particularly outside high-income economies. In lower-income settings, these pressures are amplified by limited procurement power and constrained public and private funding, making hardware affordability a systemic barrier rather than a marginal challenge.

Cloud Infrastructure

The use of cloud infrastructure varied substantially across income groups, revealing distinct patterns in reliance on global, local, mixed, and on-premises computing resources. Figure 6 details respondents' level of access to different types of cloud service providers, namely global cloud services, local cloud services, mixed cloud access, and on-premise infrastructure. Figure 7 shows respondents' perception of the affordability of cloud infrastructure.

1. Cloud use and accessibility

Reliance on global cloud providers increased monotonically with income level[44]. In low-income countries, use was distributed across categories: 19.2% identified global cloud as their primary source, while similar shares reported frequent (30.8%) or occasional use (30.8%); 19.2% reported rare use. In lower-middle-income countries, dependence was more pronounced, with nearly half of respondents (46.4%) relying primarily on global cloud services and a further 25.0% reporting frequent use. This reliance was strongest in upper-middle-income countries, where global cloud services constituted the dominant infrastructure: 70.0% reported primary reliance and the remaining 30.0% reported frequent use, with no respondents indicating occasional or rare use.

Use of local cloud infrastructure exhibited more heterogeneous and polarised patterns. In low-income countries, local cloud services played a substantive but uneven role, with comparable proportions reporting primary (4.8%) and frequent use (23.8%), alongside a sizable share reporting rare use (28.6%). In lower-middle-income countries, local cloud use declined and became more intermittent: the largest proportions reported rare (42.3%) or occasional use (26.9%), while relatively few relied on it as a primary source (19.2%). A similar pattern was observed in upper-middle-income countries, where local cloud services were most often sometimes used (27.8%) but less frequently served as a primary infrastructure (11.%).

Adoption of mixed cloud models was present across all income groups but did not dominate infrastructure choices. In low-income countries, reliance was fragmented, with 30.4% identifying mixed cloud as their primary source, while others reported occasional (26.1%) or rare use (17.4%); over one-fifth (21.7%) reported no use. Lower-middle-income countries showed broader but still secondary adoption, with mixed cloud most commonly used occasionally (40.7%) or as a primary source (22.2%). In upper-middle-income countries, mixed cloud configurations were more commonly used on an occasional basis (50.0%), with one-third (33.3%) relying on them as a primary source.

Meanwhile, on-premises solutions continued to play a role across income groups, though their prominence varied. In low-income countries, over one-third of respondents (35.0%) relied primarily on on-premises infrastructure, despite substantial shares reporting rare use (25.0%) or no use (20.0%). In lower-middle-income countries, reliance shifted toward intermittent use, with on-premises infrastructure most commonly used sometimes (30.8%) or rarely (26.9%), and fewer respondents identifying it as a primary source (19.2%). In upper-middle-income countries, on-premises systems remained relevant but less dominant, serving primarily as a complementary resource: 36.8% reported occasional use, while an equal proportion identified it as their primary source.

2. Cloud cost

We measure perceptions of cloud infrastructure costs among respondents. Figure 7 shows that perceptions of cloud costs varied markedly across income groups, indicating substantial differences in affordability.

In the lowest income group, cloud services were largely perceived as costly. Only 10.0% of respondents described cloud infrastructure as affordable, and 3.3% as very affordable. By contrast, half (50.0%) rated costs as expensive and a further 20.0% as very expensive, while 16.7% considered them moderate. Overall, approximately 70% of respondents in this group experienced cloud services as a significant financial strain. Cost pressures were most pronounced in lower-

middle-income countries. Just 3.0% of respondents reported cloud infrastructure as affordable, with none rating it as very affordable. The vast majority described costs as expensive (63.6%) or very expensive (21.2%), and only 12.1% considered them moderate, indicating that more than four-fifths faced substantial affordability constraints. Perceptions improved modestly in upper-middle-income countries but remained largely negative. While 8.7% reported cloud services as affordable, most respondents still characterised costs as expensive (60.9%), and 21.7% described them as moderate; 8.7% rated costs as very expensive. These findings suggest that, although cost burdens ease with income level, cloud infrastructure remains financially challenging for most respondents.

B. Infrastructure Factors and Innovation Outcomes

AI Policies in LMICs

The second level of analysis explores whether the presence of national AI policies is associated with different aspects of infrastructural capacity across income groups (lower-income, lower-middle income, upper-middle income). Variables examined include cloud cost, data accessibility, data quality, electricity affordability and reliability, hardware accessibility and cost, and internet affordability and reliability. Each variable is broken down by distribution across “No” and “Yes” (existence of policy), with p-values indicating the statistical significance of the association.

As shown in Table 2, the clearest association across income groups appears in low-income countries for data accessibility ($p = 0.03$). Policy presence is concentrated at the extremes of the access spectrum, with very high shares where data are reported as either difficult to obtain or easily accessible, and a notably low share when data are merely “accessible.” Although some cross-tabulated subgroups contain fewer observations, the pattern is consistent with a policy response that is mobilised in two situations, when gaps are conspicuous and when coordination capacity already exists. This result aligns with global guidance that stresses building sustainable, privacy-protective data access frameworks as a foundation for safe and effective AI governance[45].

In upper-middle income countries, electricity reliability is strongly associated with policy presence ($p < 0.001$). Policy is most prevalent at intermediate reliability levels (fair to good) and less visible at the extremes, suggesting that governments tend to formalise AI strategies where capability and urgency coincide, not where infrastructure is either prohibitive or already close to best-in-class. The policy–infrastructure link is consistent with comparative readiness assessments that treat information systems, data governance, and compute-adjacent infrastructure as core pillars of government AI readiness[46].

Other affordability variables for cloud, internet, and hardware do not reach statistical significance once stratified by income, though point estimates generally move in expected directions. Given the sample size, these should be read as suggestive rather than null. From a policy perspective, the results motivate staged investments in data governance and reliable power, both of which are repeatedly identified as enabling conditions for AI policy to translate into implementable plans.

Table 2
Association Between Infrastructural Capacity and the Existence of AI Policy

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.
Cloud Cost									
Very Expensive	0.00	100.00	0.33	71.43	28.57	0.17	50.00	50.00	0.35
Expensive	13.33	86.67	0.33	33.33	66.67	0.17	35.71	64.29	0.35
Moderate	40.00	60.00	0.33	25.00	75.00	0.17	60.00	40.00	0.35
Affordable	0.00	100.00	0.33	100.00	0.00	0.17	100.00	0.00	0.35
Very Affordable	0.00	100.00	0.33						
Data Accessibility									
Not Accessible	0.00	100.00	0.03	33.33	66.67	0.95			
Difficult	25.00	75.00	0.03	50.00	50.00	0.95	50.00	50.00	0.51
Partially Accessible	0.00	100.00	0.03	42.86	57.14	0.95	50.00	50.00	0.51
Accessible	100.00	0.00	0.03	37.50	62.50	0.95	66.67	33.33	0.51
Easily Accessible	0.00	100.00	0.03				0.00	100.00	0.51
Data Quality									
Very Poor	0.00	100.00	0.60	0.00	100.00	0.56			
Low	10.00	90.00	0.60	33.33	66.67	0.56	0.00	100.00	0.19
Moderate	25.00	75.00	0.60	50.00	50.00	0.56	66.67	33.33	0.19
Good	0.00	100.00	0.60	66.67	33.33	0.56	41.67	58.33	0.19
High	0.00	100.00	0.60	50.00	50.00	0.56			
Electricity Affordability									
Very Expensive	0.00	100.00	0.76	25.00	75.00	0.30	100.00	0.00	0.57
Expensive	22.22	77.78	0.76	77.78	22.22	0.30	66.67	33.33	0.57
Moderate	25.00	75.00	0.76	45.45	54.55	0.30	42.86	57.14	0.57
Affordable	0.00	100.00	0.76	50.00	50.00	0.30	75.00	25.00	0.57
Very Affordable				0.00	100.00	0.30			
Electricity Reliability									
Very Poor	0.00	100.00	0.90						
Poor	12.50	87.50	0.90	45.45	54.55	0.06	100.00	0.00	0.00
Fair	11.11	88.89	0.90	11.11	88.89	0.06	22.22	77.78	0.00

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.
Cloud Cost									
Good	18.18	81.82	0.90	66.67	33.33	0.06	16.67	83.33	0.00
Excellent				0.00	100.00	0.06	100.00	0.00	0.00
Hardware Accessibility									
Not Accessible	0.00	100.00	0.15	66.67	33.33	0.32	0.00	100.00	0.09
Limited	14.29	85.71	0.15	53.85	46.15	0.32	75.00	25.00	0.09
Moderate	33.33	66.67	0.15	20.00	80.00	0.32	22.22	77.78	0.09
Easy	0.00	100.00	0.15	42.86	57.14	0.32	33.33	66.67	0.09
Widely accessible							100.00	0.00	0.09
Hardware Cost									
Very Expensive	9.09	90.91	0.60	45.45	54.55	0.37	50.00	50.00	0.12
Expensive	9.09	90.91	0.60	46.67	53.33	0.37	60.00	40.00	0.12
Moderate	33.33	66.67	0.60	16.67	83.33	0.37	14.29	85.71	0.12
Affordable	0.00	100.00	0.60	100.00	0.00	0.37	100.00	0.00	0.12
Very Affordable	0.00	100.00	0.60						
Internet Affordability									
Very Expensive	20.00	80.00	0.57	0.00	100.00	0.07	66.67	33.33	0.41
Expensive	6.67	93.33	0.57	38.46	61.54	0.07	33.33	66.67	0.41
Moderate	25.00	75.00	0.57	64.29	35.71	0.07	75.00	25.00	0.41
Affordable	0.00	100.00	0.57	0.00	100.00	0.07	66.67	33.33	0.41
Very Affordable							0.00	100.00	0.41
Internet Reliability									
Very Unreliable	0.00	100.00	0.38	50.00	50.00	0.59			
Unreliable	14.29	85.71	0.38	33.33	66.67	0.59	100.00	0.00	0.27
Moderate	25.00	75.00	0.38	33.33	66.67	0.59	66.67	33.33	0.27
Reliable	0.00	100.00	0.38	57.14	42.86	0.59	37.50	62.50	0.27
Very Reliable				100.00	0.00	0.59			

AI Investments and interventions in LMICs

As used in this study, AI interventions or investments refers broadly to any structured allocation of financial, technical, or institutional resources directed toward advancing AI development, deployment, or capacity within a given country. This

encompasses both capital-oriented mechanisms such as government grants, equity investments, and loan schemes and non-financial forms of support, including technical assistance, capacity building, and public-private partnerships, sourced from domestic or international actors across government, private sector, academic, civil society, and intergovernmental entities.

The distribution of AI investment sources was examined to identify the most frequently cited contributors. The analysis in Fig. 8 indicates a clear concentration of funding among a small number of dominant actors.

The private sector emerged as the principal source of AI investment, underscoring the central role of technology firms, start-ups, and corporate research and development in advancing AI capabilities. Research institutions and higher-education organisations also featured prominently, highlighting the dual role of universities and academic research centres as both investors and key enablers of AI innovation.

International and intergovernmental organisations were identified as significant contributors, reflecting the importance of cross-border collaboration, regional partnerships, and global development initiatives in supporting AI research and infrastructure. National governments remained visible but comparatively less prominent sources of investment — though it is worth noting that governments remain the main source of funding for research institutions and universities in many LMIC countries. Non-governmental organisations and civil society groups appeared less frequently, yet represent meaningful contributors, particularly in initiatives focused on social impact, ethics, and inclusive AI deployment.

The forms through which AI investment is channelled were also analysed in Fig. 9 to capture prevailing funding mechanisms.

Public–private partnerships and technical assistance were the most frequently cited forms of investment, indicating a strong emphasis on cross-sector collaboration and capacity strengthening. Capacity-building initiatives were also prominent, suggesting that investments often prioritise human capital development and institutional readiness alongside technical infrastructure.

Direct financial mechanisms, including government grants and subsidies, featured consistently, reflecting policy-driven efforts to reduce adoption barriers and stimulate AI innovation. International and intergovernmental frameworks further highlight the cooperative nature of many AI investments

The relationship between AI interventions or investments and infrastructural factors (Table 3) reveal two results that merit emphasis. First, in low-income countries, hardware cost is associated with intervention presence ($p = 0.05$). Strikingly, the highest intervention shares appear where hardware is reported as very expensive, while more affordable categories are sparse. This inversion is consistent with donor-financed pilots and externally supported procurements that decouple local affordability from execution, a dynamic well documented in digital programs in low-resource settings. The implication is that beyond infrastructure prices, financial architecture, shapes where interventions materialise and persist.[47 48]

Second, in lower-middle income countries, internet reliability correlates with intervention incidence ($p = 0.05$), but the distribution places many observations with reliable or very reliable connectivity in the no-intervention column. Two mechanisms are plausible in cross-section. Routine, institutionalised projects in better-connected settings may be less likely to be labelled as “interventions” by respondents, while projectised, donor-funded efforts may cluster where connectivity remains uneven. Either way, the finding emphasises that the incidence of AI interventions reflect both infrastructure and program design choices, including how initiatives are financed, branded, and reported.

Table 3
Association between infrastructural capacity and existence of AI interventions or investments

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.
Cloud Cost									
Very Expensive	25.00	75.00	0.14	100.00	0.00	0.55	50.00	50.00	0.32
Expensive	63.64	36.36	0.14	81.25	18.75	0.55	66.67	33.33	0.32
Moderate	100.00	0.00	0.14	100.00	0.00	0.55	100.00	0.00	0.32
Affordable	100.00	0.00	0.14	100.00	0.00	0.55	100.00	0.00	0.32
Data Accessibility									
Not Accessible	33.33	66.67	0.22	66.67	33.33	0.46			
Difficult	50.00	50.00	0.22	100.00	0.00	0.46	87.50	12.50	0.39
Partially Accessible	87.50	12.50	0.22	88.89	11.11	0.46	57.14	42.86	0.39
Accessible	100.00	0.00	0.22	83.33	16.67	0.46	100.00	0.00	0.39
Easily Accessible							100.00	0.00	0.39
Data Quality									
Very Poor	0.00	100.00	0.09	50.00	50.00	0.48			
Low	37.50	62.50	0.09	87.50	12.50	0.48	100.00	0.00	0.48
Moderate	85.71	14.29	0.09	92.31	7.69	0.48	85.71	14.29	0.48
Good	100.00	0.00	0.09	100.00	0.00	0.48	66.67	33.33	0.48
High	100.00	0.00	0.09	100.00	0.00	0.48			
Electricity Affordability									
Very Expensive	33.33	66.67	0.32	100.00	0.00	0.25	0.00	100.00	0.18
Expensive	55.56	44.44	0.32	100.00	0.00	0.25	83.33	16.67	0.18
Moderate	85.71	14.29	0.32	80.00	20.00	0.25	71.43	28.57	0.18
Affordable	100.00	0.00	0.32	50.00	50.00	0.25	100.00	0.00	0.18
Very Affordable				100.00	0.00	0.25			
Electricity Reliability									
Very Poor	0.00	100.00	0.17						
Poor	66.67	33.33	0.17	87.50	12.50	0.94	60.00	40.00	0.59
Fair	60.00	40.00	0.17	85.71	14.29	0.94	83.33	16.67	0.59
Good	85.71	14.29	0.17	90.91	9.09	0.94	75.00	25.00	0.59

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.	No (%)	Yes (%)	p-val.
Cloud Cost									
Excellent							100.00	0.00	0.59
Hardware Accessibility									
Not Accessible	25.00	75.00	0.26	66.67	33.33	0.36	100.00	0.00	0.59
Limited	66.67	33.33	0.26	90.91	9.09	0.36	62.50	37.50	0.59
Moderate	77.78	22.22	0.26	100.00	0.00	0.36	75.00	25.00	0.59
Easy	100.00	0.00	0.26	75.00	25.00	0.36	100.00	0.00	0.59
Wide							100.00	0.00	0.59
Hardware Cost									
Very Expensive	40.00	60.00	0.05	90.00	10.00	0.77	50.00	50.00	0.32
Expensive	80.00	20.00	0.05	81.82	18.18	0.77	75.00	25.00	0.32
Moderate	100.00	0.00	0.05	100.00	0.00	0.77	100.00	0.00	0.32
Affordable				100.00	0.00	0.77	100.00	0.00	0.32
Internet Affordability									
Very Expensive	20.00	80.00	0.10				66.67	33.33	0.57
Expensive	80.00	20.00	0.10	84.62	15.38	0.74	70.00	30.00	0.57
Moderate	75.00	25.00	0.10	90.00	10.00	0.74	100.00	0.00	0.57
Affordable	100.00	0.00	0.10	100.00	0.00	0.74	100.00	0.00	0.57
Internet Reliability									
Very Unreliable	33.33	66.67	0.30	50.00	50.00	0.05			
Unreliable	50.00	50.00	0.30	66.67	33.33	0.05	0.00	100.00	0.07
Moderate	77.78	22.22	0.30	100.00	0.00	0.05	100.00	0.00	0.07
Reliable	100.00	0.00	0.30	100.00	0.00	0.05	72.73	27.27	0.07
Very Reliable				100.00	0.00	0.05			

Innovation strength, measured as weak versus moderate or strong, is most clearly aligned with data quality in upper-middle income countries ($p = 0.04$) from results reported in Table 4. Where data quality is “good” or “high,” the share of moderate or strong innovation dominates, whereas “low” quality is associated with weak innovation. This pattern is consistent with the idea that, once basic access and affordability barriers are alleviated, the returns to quality curation, standardisation, and representativeness become the binding constraint for model development and integration. In low-income countries, electricity affordability shows a suggestive, although not significant, gradient ($p = 0.10$) where more affordable electricity aligns with stronger innovation. Other inputs, including cloud and internet affordability, tend to move in the expected directions but do not reach significance in this sample, which is again consistent with limited cell sizes (low observation counts within individual response categories) and the study’s exploratory focus.

Table 4
Association between infrastructural factors and existence of AI innovations

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.
Cloud Cost									
Very Expensive	50.00	50.00	0.37	16.67	83.33	0.18	50.00	50.00	0.72
Expensive	36.36	63.64	0.37	62.50	37.50	0.18	33.33	66.67	0.72
Moderate	0.00	100.00	0.37	33.33	66.67	0.18	40.00	60.00	0.72
Affordable	0.00	100.00	0.37	0.00	100.00	0.18	0.00	100.00	0.72
Data Accessibility									
Not Accessible	33.33	66.67	0.37	66.67	33.33	0.81			
Difficult	50.00	50.00	0.37	50.00	50.00	0.81	62.50	37.50	0.13
Partially Accessible	12.50	87.50	0.37	44.44	55.56	0.81	14.29	85.71	0.13
Accessible	0.00	100.00	0.37	33.33	66.67	0.81	0.00	100.00	0.13
Easily Accessible							0.00	100.00	0.13
Data Quality									
Very Poor	100.00	0.00	0.37	100.00	0.00	0.07			
Low	37.50	62.50	0.37	75.00	25.00	0.07	100.00	0.00	0.04
Moderate	28.57	71.43	0.37	30.77	69.23	0.07	42.86	57.14	0.04
Good	0.00	100.00	0.37	0.00	100.00	0.07	11.11	88.89	0.04
High	0.00	100.00	0.37	0.00	100.00	0.07			
Electricity Affordability									
Very Expensive	33.33	66.67	0.10	75.00	25.00	0.67	0.00	100.00	0.82
Expensive	55.56	44.44	0.10	44.44	55.56	0.67	33.33	66.67	0.82
Moderate	0.00	100.00	0.10	40.00	60.00	0.67	42.86	57.14	0.82
Affordable	0.00	100.00	0.10	50.00	50.00	0.67	25.00	75.00	0.82
Very Affordable				0.00	100.00	0.67			
Electricity Reliability									

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.
Very Poor	50.00	50.00	0.19						
Poor	50.00	50.00	0.19	50.00	50.00	0.18	20.00	80.00	0.17
Fair	40.00	60.00	0.19	71.43	28.57	0.18	33.33	66.67	0.17
Good	0.00	100.00	0.19	27.27	72.73	0.18	75.00	25.00	0.17
Excellent							0.00	100.00	0.17
Hardware Accessibility									
Not Accessible	50.00	50.00	0.69	66.67	33.33	0.73	100.00	0.00	0.44
Limited	33.33	66.67	0.69	45.45	54.55	0.73	25.00	75.00	0.44
Moderate	22.22	77.78	0.69	50.00	50.00	0.73	50.00	50.00	0.44
Easy	0.00	100.00	0.69	25.00	75.00	0.73	33.33	66.67	0.44
Wide							0.00	100.00	0.44
Hardware Cost									
Very Expensive	30.00	70.00	0.12	50.00	50.00	0.58	50.00	50.00	0.64
Expensive	60.00	40.00	0.12	54.55	45.45	0.58	37.50	62.50	0.64
Moderate	0.00	100.00	0.12	25.00	75.00	0.58	25.00	75.00	0.64
Affordable				0.00	100.00	0.58	0.00	100.00	0.64
Internet Affordability									
Very Expensive	40.00	60.00	0.87				66.67	33.33	0.47
Expensive	30.00	70.00	0.87	53.85	46.15	0.39	30.00	70.00	0.47
Moderate	25.00	75.00	0.87	30.00	70.00	0.39	33.33	66.67	0.47
Affordable	0.00	100.00	0.87	66.67	33.33	0.39	0.00	100.00	0.47
Internet Reliability									
Very Unreliable	33.33	66.67	0.81	50.00	50.00	0.24			
Unreliable	33.33	66.67	0.81	66.67	33.33	0.24	0.00	100.00	0.49
Moderate	33.33	66.67	0.81	57.14	42.86	0.24	50.00	50.00	0.49
Reliable	0.00	100.00	0.81	0.00	100.00	0.24	27.27	72.73	0.49

Variable	Lower-Income			Lower-Middle Income			Upper-Middle Income		
	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.	Weak (%)	Moderate or Strong (%)	p-val.
Very Reliable				0.00	100	0.24			

Discussion

This study set out to provide a comprehensive, practitioner-grounded assessment of the infrastructure landscape for AI development across LMICs. The findings challenge several prevailing assumptions in global AI discourse and yield three principal insights that merit sustained attention from researchers, policymakers, and development practitioners.

The first and perhaps most consequential finding is what we term the “Reliability Trap.” Conventional development logic assumes that infrastructure quality improves monotonically with national income. Our data contradicts this assumption: lower-middle-income countries report electricity reliability failures at rates comparable to, and in some dimensions exceeding, those of low-income countries. This pattern is consistent with a scenario in which rapid urbanisation, expanding demand, and ageing grid infrastructure outpace maintenance investment and institutional capacity. For AI systems that depend on continuous power for training, inference, and data centre operations, intermittent reliability is arguably more disruptive than consistent absence, because it introduces unpredictable failure modes that undermine both operational continuity and user trust[49]. Policymakers and donors should therefore resist the temptation to allocate infrastructure investment solely on the basis of income-level proxies and instead prioritise reliability diagnostics at the sub-national and sectoral level[50].

The second insight concerns the quality and accessibility of data. Our results demonstrate that while data accessibility remains constrained across all income groups, data quality improves markedly with income. This finding reframes the “Big Data” narrative; the binding constraint for AI development in LMICs is not the volume of available data but rather the quality of its curation, standardisation, and representativeness. In low-income settings, respondents reported data that was not merely scarce but fragmented across incompatible formats, poorly labelled, and subject to significant privacy and governance concerns. These qualitative dimensions of data infrastructure are frequently overlooked in quantitative assessments of AI readiness, yet they determine whether locally relevant AI models can be developed at all. Investment in data governance frameworks, annotation capacity, and interoperability standards may yield greater returns for AI capability than investments in raw data collection[51].

The third insight, the “Hardware Inversion,” carries profound implications for the sustainability of AI development in the Global South. Our analysis reveals that AI interventions are most prevalent in settings where hardware is reported as most expensive ($p = 0.05$ in low-income countries). This counter-intuitive pattern is consistent with a model of donor-financed, project-based deployment in which the presence of an AI intervention reflects the availability of external capital rather than the emergence of a local market. Such dynamics create what development economists term “aid dependency”, which is a temporary capability that dissipates when project funding ends[52]. The concentration of AI interventions in high-cost environments, coupled with the absence of interventions where hardware is more affordable, suggests that current development financing is not cultivating the enabling conditions for locally sustainable AI ecosystems.

The Hardware Inversion reflects a structural misalignment between development financing and LMIC hardware markets. In low-income countries, AI hardware costs are inflated by high import duties, volatile currency fluctuations, and the absence of local semiconductor supply chains, a systemic cost driver that international donors typically fail to address. Hardware procurement is treated as a discrete project expenditure rather than a recurring systemic cost, decoupling the presence of equipment from the economic conditions necessary to maintain and scale it[53].

The resulting dependency distorts local AI ecosystems, incentivising practitioners to orient work around donor priorities rather than locally identified needs, while suppressing indigenous hardware maintenance and distribution markets essential for long-term sustainability.

Addressing this requires reorienting development financing from hardware procurement toward market-enabling interventions: reducing import tariffs on computing equipment, establishing regional shared-compute facilities, supporting currency-hedged procurement mechanisms, and investing in local technical capacity for hardware lifecycle management.

The association between national AI policy and infrastructure capacity adds a governance dimension to these findings. Policy presence is strongest at intermediate levels of infrastructure quality — neither at the extremes of deprivation nor at levels approaching high-income-country standards. This pattern suggests that AI governance frameworks emerge where institutional capability and perceived urgency coincide, implying that governments with minimal infrastructure may lack the bureaucratic capacity or political incentive to formulate AI strategies, while those with near-adequate infrastructure may perceive less urgency. This “policy window” has practical implications for international organisations seeking to support AI governance in LMICs: capacity-building efforts may be most effective when targeted at countries approaching but not yet reaching intermediate infrastructure thresholds[54].

These findings also speak directly to the “leapfrogging” debate that pervades development discourse on emerging technologies. The mobile telephony experience, in which many LMICs bypassed fixed-line infrastructure, is frequently invoked as a template for AI adoption. Our data suggest that this analogy is structurally misleading. Unlike mobile telephony, which requires relatively modest infrastructure (cell towers and handsets), AI development demands a convergent stack of electricity, connectivity, compute, and data—each of which is subject to distinct economic and governance constraints at different income levels. The Infrastructure Gradient we document implies that leapfrogging is not a binary possibility but a conditional one: certain layers of the AI stack (such as cloud compute) may be partially leapfrogged through global services, while others (such as reliable electricity and high-quality local data) cannot be substituted by external provision and require sustained domestic investment. Development strategies premised on wholesale leapfrogging risk underinvesting in these non-substitutable foundations.

Several limitations of this study should be acknowledged. A survey sample of 91 respondents, though geographically diverse, falls substantially below the intended target of 385 and constrains the robustness of the inferential analyses. The results should therefore be interpreted as exploratory rather than confirmatory, and the non-significant associations should be read as suggestive rather than as evidence of null effects. Additionally, the reliance on practitioner perceptions introduces subjectivity; objective infrastructure metrics from sources such as the International Telecommunication Union or the World Bank could complement and validate these self-reported assessments in future research. The cross-sectional design precludes causal inference, and the sampling strategy, while purposive and diverse, may not fully represent the heterogeneity within LMIC categories. Future research should pursue larger, longitudinal samples and incorporate mixed-methods case studies to explore the mechanisms underlying the non-linear patterns identified here.

Conclusion & Recommendations

This study documents the Infrastructure Paradox of AI development: the countries where AI could deliver the greatest developmental impact face the most severe and structurally differentiated infrastructure constraints. Through a cross-sectional survey of 91 AI practitioners across 27 LMICs, we demonstrate that infrastructure gaps are not uniform but follow an income-stratified gradient characterised by the Reliability Trap, the Data Quality Divide, and the Hardware Inversion, each of which demands distinct policy responses.

Our findings carry several actionable implications. First, infrastructure investment for AI readiness should be disaggregated by income level and by infrastructure dimension. Electricity reliability in lower-middle-income countries, data quality and standardisation in low-income countries, and the capital costs of compute in upper-middle-income countries each represent distinct binding constraints requiring targeted interventions. Second, the Hardware Inversion underscores the need for development financing to shift from project-based hardware procurement toward building sustainable local markets for AI compute—through regional data centre initiatives, shared compute facilities, and procurement pooling mechanisms. Third, data governance must be elevated from a secondary concern to a primary pillar of AI strategy in LMICs. Investment in annotation infrastructure, interoperability standards, and privacy-protective data sharing frameworks is essential for transforming raw data availability into usable training resources.

Regarding the leapfrogging debate, our evidence suggests that while certain layers of the AI infrastructure stack (particularly cloud compute) may be partially bypassed through global platform services, foundational layers such as reliable electricity and high-quality, locally representative data cannot be substituted by external provision. Leapfrogging in AI is therefore conditional, not categorical, and development strategies must invest in these non-substitutable foundations to avoid building AI capabilities on structurally fragile ground.

Finally, the observed association between AI policy and intermediate infrastructure capacity suggests a governance window that international organisations and national governments should seek to exploit: the point at which institutional capacity is sufficient to design and implement policy, and infrastructure gaps are severe enough to create political will. Identifying and supporting countries at this inflection point may represent the most efficient allocation of AI governance assistance.

We call for larger, longitudinal studies that combine practitioner perspectives with objective infrastructure metrics, and for the development of an “Infrastructure Gradient Index” that can guide context-sensitive AI policy and investment across the diverse landscape of LMICs[62]. The Infrastructure Paradox will not resolve itself through market forces alone; it demands deliberate, differentiated, and sustained policy action grounded in the kind of empirical evidence this study begins to provide.

Data Availability

To support reproducibility, datasets generated and analysed (datasets, survey instruments, code guide) during the current study are available from the the following platforms:

Dataverse via https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VJY5QV

Ethics Declarations

Declarations

Data Availability

To support reproducibility, datasets generated and analysed (datasets, survey instruments, code guide) during the current study are available from the the following platforms:

Dataverse via https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VJY5QV

Competing interests

The authors declare no competing interests.

Ethical Approval Statement

This study was reviewed by the Research Ethics Committee (REC) of the Global Center on AI Governance (GCG), an independent institutional research ethics body. The REC determined that the study qualifies for exemption from formal ethics review and approval (Reference: GCG-REC-2025-003, dated 1 April 2025).

All research was designed and conducted in accordance with the ethical principles of the Declaration of Helsinki (World Medical Association, 2024 revision), with particular regard to informed consent (Paragraph 26) and the protection of participants' privacy (Paragraph 24). The study further aligns with the principles of the Belmont Report (1979) concerning respect for persons, beneficence, and justice, as well as the Human Sciences Research Council (HSRC) Research Ethics Policy Framework for minimal-risk social research.

Exemption was granted on the following grounds: (i) the study employed a fully anonymous online survey collecting no personally identifiable information, making re-identification risk very low; (ii) the subject matter, professional assessments of AI infrastructure conditions in low- and middle-income countries, poses no foreseeable risk of harm, embarrassment, legal liability, or professional disadvantage to participants; (iii) the target population comprised adult AI practitioners, researchers, industry stakeholders, and policymakers, none of whom constitute a vulnerable population under applicable ethical guidelines; and (iv) participation was entirely voluntary, with informed consent obtained through a disclosure statement presented to all participants prior to survey completion.

References

1. Mutiso RM (2025) Beyond the binary: Navigating AI's uncertain future in Africa. Science 388(6742):eadw9439. 10.1126/science.adw9439
2. Ahmed N, Wahed M, Thompson NC (2023) The growing influence of industry in AI research. 379(6635):884–886. 10.1126/science.ade2420. Science
3. Nestor Maslej L, Fattorini R, Perrault V, Parli A, Reuel E, Brynjolfsson J, Etchemendy K, Ligett T, Lyons J, Manyika JC, Niebles Y, Shoham R, Wald, Clark J (2024) The AI Index 2024 Annual Report, AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA, April
4. Adams R (2024) The new empire of AI: the future of global inequality. Wiley
5. Adams R, Adeleke F, Florido A, de Magalhães Santos LG, Grossman N, Junck L, Stone K (2024) Global Index on Responsible AI 2024 (1st Edition). South Africa: Global Center on AI Governance. Available at: https://coral-trista–52.tiiny.site/
6. Adams R, Adeleke F, Junck L et al (2026) Mapping the potential and limitations of using generative AI technologies to address socio-economic challenges in LMICs. Nat Comput Sci. https://doi.org/10.1038/s43588-026-00960-8
7. Metreau E, Young KE, Eapen SG (2024) World Bank country classifications by income level for 2024–2025. World Bank. https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025. Accessed April 7, 2025
8. Djama RM (2024) The Impact of Artificial Intelligence on the Global Economy: Opportunities and Challenges. International Journal for Multidisciplinary Research (IJFMR). Volume 6, Issue 3

9. Davoyan A (2024) A Review on Artificial Intelligence and the Global Economy. In Proceedings of the Future Technologies Conference, pp. 599–605. Cham: Springer Nature Switzerland
10. Abbas Khan M, Khan H, Omer MF, Ullah I, Yasir M (2024) Impact of artificial intelligence on the global economy and technology advancements. In Artificial General Intelligence (AGI) Security: Smart Applications and Sustainable Technologies (pp. 147–180). Singapore: Springer Nature Singapore
11. Espina-Romero L, Noroño Sánchez JG, Gutiérrez Hurtado H, Conde D, Solier Castro H, Cajo YC, L. E., Corredoira R, J (2023) Which industrial sectors are affected by artificial intelligence? A bibliometric analysis of trends and perspectives. Sustainability, 15(16), 12176
12. Palliyil V, Cai M, Karam H, Phatthanachaisuksiri L, Suhre N, Kaßens-Noor E (2025) Artificial intelligence use cases adopted by people and their impact on achieving sustainable development goals: a systematic review. Open Res Europe 5:117
13. Al-Surmi A, Bashiri M, Koliousis I (2022) AI based decision making: combining strategies to improve operational performance. International Journal of Production Research, 60(14), 4464–4486
14. Fioretti L, La Croce C, Siviero A, Clemmons E, Lemaire E (2024) The Global Impact of Artificial Intelligence on the Economy and Jobs. International Data Corporation (IDC). https://www.idc.com/getdoc.jsp?containerId=US51057924
15. Jaldi A (2023) Artificial Intelligence Revolution in Africa: Economic Opportunities and Legal Challenges. Policy Cent. New South
16. Bergoeing R, Loayza N, Piguillem F (2010) Why are developing countries so slow in adopting new technologies? The aggregate and complementary impact of micro distortions. *The Aggregate and Complementary Impact of Micro Distortions (August 1, 2010). World Bank Policy Research Working Paper*, (5393)
17. Mobarak M (2016) March 3 What Keeps the Poor from Adopting New Technology? Yale Insights. https://insights.som.yale.edu/insights/what-keeps-the-poor-from-adopting-new-technology
18. Fan RY, Nguyen H, Arezki R (2019) June 29 Technology adoption and the middle-income trap: Lessons from the Middle East and East Asia. Vox. https://cepr.org/voxeu/columns/technology-adoption-and-middle-income-trap-lessons-middle-east-and-east-asia
19. Duggal M, Ayadi AE, Duggal B, Reynolds N, Bascaran C (2023) Challenges in implementing digital health in public health settings in low- and middle-income countries. 10:1090303Frontiers in public health
20. Adhikari R, Tesfachew T (2024), March 27 The Least Developed Countries are falling behind on digital transformation — here's what to do. World Economic Forum. https://www.weforum.org/stories/2024/03/unleashing-digital-transformation-in-the-least-developed-countries/
21. Biana HT, Joaquin JJ (2024) The irony of AI in a low-to-middle-income country. 40(1):225–226. 10.1007/s00146-023-01855–2. AI & Society
22. Dinh M, Ngoc J, Nygate C, Louise Thwaites, and Global Grand Challenges Event Vietnam Group (2020). New technologies to improve healthcare in low-and middle-income countries: global grand challenges satellite event, Oxford University clinical research unit, Ho Chi Minh City, 17th–18th September 2019. Wellcome Open Research 5
23. Taylor S, O'Neil S, Sivasankaran A Start with the Basics for Data Equity in Low- and Middle-Income Countries. Mathematica. https://www.mathematica.org/blogs/start-with-the-basics-for-data-equity-in-low-and-middle-income-countries (2022 April 8).
24. de Vries A (2023) The growing energy footprint of artificial intelligence. Joule 7(10):2191–2194. 10.1016/j.joule.2023.09.004
25. Rozenberg J, Fay M (eds) (2019) Beyond the gap: How countries can afford the infrastructure they need while protecting the planet. World Bank

26. Ciecierski-Holmes T, Singh R, Axt M (2022) Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review. 5:162. https://doi.org/10.1038/s41746-022-00700-y. .npj Digit. Med.
27. Khan MS, Umer H, Faruqe F (2024) Artificial intelligence for low income countries. 11:1422. https://doi.org/10.1057/s41599-024-03947-w. Humanit Soc Sci Commun
28. Hung K-H (2024) Artificial intelligence as planetary assemblages of coloniality: The new power architecture driving a tiered global data economy. 11(4). 10.1177/20539517241289443. Big Data & Society
29. Dixit S, Gill IS (2024) AI, the New Wingman of Development. Background paper prepared for World Development Report. https://thedocs.worldbank.org/en/doc/20ca38de6ebb3fc55a9c6a2883bffda8–0050022024/original/AI-the-new-wingman-of-development-Siddharth-Dixit-and-Indermit-Gill.pdf
30. Mollura, D. J., Culp, M. P., Pollack, E., Battino, G., Scheel, J. R., Mango, V. L.,… Dako, F. (2020). Artificial intelligence in low-and middle-income countries: innovating global health radiology. Radiology, 297(3), 513–520.
31. Williams D, Hornung H, Nadimpalli A, Peery A (2021) Deep learning and its application for healthcare delivery in low and middle income countries. Frontiers in Artificial Intelligence, 4, 553987
32. Pune DAC (2022) AI in Farming, Education and Healthcare. Future Skills Prime. https://futureskillsprime.in/knowledge-center/tech-simplified/ai-farming-education-and-healthcare
33. Ciecierski-Holmes T, Singh R, Axt M (2022) Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review. 5:162. https://doi.org/10.1038/s41746-022-00700-y. .npj Digit. Med.
34. Finnegan, A., Potenziani, D. D., Karutu, C., Wanyana, I., Matsiko, N., Elahi, C.,… Vota, W. (2022). Deploying machine learning with messy, real world data in low-and middle-income countries: Developing a global health use case. Frontiers in big Data, 5, 553673.
35. George AS (2024) Artificial Intelligence and the Future of Work: Job Shifting Not Job Loss. Partners Universal Innovative Research Publication, 2(2), 17–37
36. Rahman MA, Akter S (2024) The transformative role of AI in reshaping employment trends across South Asia. Romanian Journal of Economics, 59(2 (68)), 48–71
37. Lipcsey RA (2024) AI Diffusion to Low-Middle Income Countries; A Blessing or a Curse? arXiv preprint arXiv:2405.20399
38. Debus C, Piraud M, Streit A, Theis F, Götz M (2023) Reporting electricity consumption is essential for sustainable AI. 5:1176–1178. 10.1038/s42256-023-00750–1. Nature Machine Intelligence
39. Colangelo P, Coskun AK, Megrue J, Roberts C, Sengupta S, Sivaram V, Tiao E, Vijaykar A, Williams C, Wilson DC, Records B, MacFarland Z, Dreiling D, Morey N, Ratnayake A, Vairamohan B (2025) AI data centres as grid-interactive assets. 10.1038/s41560-025-01927–1. Nature Energy
40. Ding T, Li H, Liu L, Feng K (2024) An inquiry into the nexus between artificial intelligence and energy poverty in the light of global evidence. 136:107748. 10.1016/j.eneco.2024.107748. Energy Economics
41. Schwabe D, Becker K, Seyferth M, Klaß A, Schaeffter T (2024) The METRIC-framework for assessing data quality for trustworthy AI in medicine: a systematic review. 7:203. 10.1038/s41746-024-01196–4. npj Digital Medicine
42. Alderman JE, Palmer J, Laws E, McCradden MD, Ordish J, Ghassemi M, Pfohl SR, Rostamzadeh N, Cole-Lewis H, Glocker B, Calvert M, Pollard TJ, Gill J, Gath J, Adebajo A, Beng J, Leung CH, Kuku S, Farmer L-A, Matin RN, Mateen BA, McKay F, Heller K, Karthikesalingam A, Treanor D, Mackintosh M, Oakden-Rayner L, Pearson R, Manrai AK, Myles P, Kumuthini J, Kapacee Z, Sebire NJ, Nazer LH, Seah J, Akbari A, Berman L, Gichoya JW, Righetto L, Samuel D, Wasswa W, Charalambides M, Arora A, Pujari S, Summers C, Sapey E, Wilkinson S, Thakker V, Denniston AK, Liu X

(2025) Tackling algorithmic bias and promoting transparency in health datasets: the STANDING Together consensus recommendations. 7(1):e64–e88. 10.1016/S2589–7500(24)00224–3. The Lancet Digital Health

43. Chen RJ, Wang JJ, Williamson DFK, Chen TY, Lipkova J, Lu MY, Sahai S, Mahmood F (2023) Algorithmic fairness in artificial intelligence for medicine and healthcare. 7(6):719–742. 10.1038/s41551-023-01056–8. Nature Biomedical Engineering
44. Editorial (2025) Localizing AI in the global south. 7:675. 10.1038/s42256-025-01057-z. Nature Machine Intelligence
45. UNESCO (2021) Recommendation on the ethics of artificial intelligence. UNESCO. https://www.ohchr.org/sites/default/files/2022–03/UNESCO.pd
46. Oxford Insights (2024) Government AI Readiness Index 2024. Oxford Insights. https://oxfordinsights.com/wp-content/uploads/2024/12/2024-Government-AI-Readiness-Index–2.pdf
47. Labrique AB, Wadhwani C, Williams KA, Lamptey P, Hesp C, Luk R, Aerts A (2018) Best practices in scaling digital health in low and middle income countries. 103. https://doi.org/10.1186/s12992-018-0424-z. Globalization and Health 14
48. Forslund M, Mathieson K, Djibo Y, Mbindyo C, Lugangira N, Balasubramaniam P (2024) Strengthening the evidence base on the use of digital health technologies to accelerate progress towards universal health coverage. oqae033. https://doi.org/10.1093/oodh/oqae033. Oxford Open Digital Health 2
49. Goldberg CB, Adams L, Blumenthal D, Brennan PF, Brown N, Butte AJ, Cheatham M, deBronkart D, Dixon J, Drazen J, Evans BJ, Hoffman SM, Holmes C, Lee P, Manrai AK, Omenn GS, Perlin JB, Ramoni R, Sapiro G, Sarkar R, Sood H, Vayena E, Kohane IS (2024) To do no harm — and the most good — with AI in health care. 30(3):623–627. 10.1038/s41591-024-02853–7. Nature Medicine
50. Kane S (2024) Leveraging digital health initiatives to enhance the effectiveness, equity and responsiveness of health systems. 9(8):e014626. 10.1136/bmjgh–2023–014626. BMJ Global Health
51. Cáceres Rivera DI, Paredes Suárez SM, Cardenas Herrera MS, Ruiz Sandoval JP, Rincón Romero MK, López-Romero LA (2024) Use of artificial intelligence to address health disparities in low- and middle-income countries: a thematic analysis of ethical issues. 235:134–151. 10.1016/j.puhe.2024.06.033. Public Health
52. Muldoon J, Cant C, Graham M, Ustek Spilda F (2023) The poverty of ethical AI: impact sourcing and AI supply chains. 40(2):529–543. 10.1007/s00146-023-01824–9. AI & Society
53. Irihamye E, Hadad J, Ali N, Holthof B, Wafula F, Paton C, English M, Nagraj S (2025) Sustainable by design: digital health business models for equitable global health impact in low-income and low-middle-income countries. Mayo Clinic Proceedings: Digital Health, 3(4), 100261. 10.1016/j.mcpdig.2025.100261
54. Ayana G, Dese K, Nemomssa HD, Habtamu B, Mellado B, Badu K, Yamba E, Faye SL, Ondua M, Nsagha D, Nkweteyim D, Kong JD (2024) Decolonizing global AI governance: assessment of the state of decolonized AI governance in Sub-Saharan Africa. 11(8):231994. 10.1098/rsos.231994. Royal Society Open Science
55. Dakhil ZA, Cader FA, Banerjee A (2024) Challenges in Clinical Research in Low and Middle Income Countries: Early Career Cardiologists' Perspective. 113. https://doi.org/10.5334/gh.1293. Global Heart19
56. Lau C (2021) Survey Research in Low- and Middle-Income Countries (LMICs) During the COVID–19 Pandemic
57. Davern M (2013) Nonresponse Rates are a Problematic Indicator of Nonresponse Bias in Survey Research. 3905–912. https://doi.org/10.1111/1475–6773.12070. Health Services Research48
58. Brick JM, Tourangeau R (2017) Responsive Survey Designs for Reducing Nonresponse Bias. 3735–752. https://doi.org/10.1515/jos–2017–0034. Journal of Official Statistics33
59. Wærsted M, Børnick TS, Twisk JWR, Veiersted KB (2018) Simple descriptive missing data indicators in longitudinal studies with attrition, intermittent missing data and a high number of follow-ups. 1123. https://doi.org/10.1186/s13104-018-3228–6. BMC Research Notes11

60. Nagpal A, Gabrani G, Technical Applications (2019) Python for Data Analytics, Scientific and. 2019 Amity International Conference on Artificial Intelligence (AICAI), 140–145. https://doi.org/10.1109/AICAI.2019.8701341
61. Teoh TT, Rong Z (2022) Python for Data Analysis. In T. T. Teoh & Z. Rong (Eds.), Artificial Intelligence with Python (pp. 107–122). Springer. https://doi.org/10.1007/978-981-16–8615–3_7
62. Ciecierski-Holmes T, Singh R, Axt M, Brenner S, Barteit S (2022) Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review. 5:162. 10.1038/s41746-022-00700-y. npj Digital Medicine

Figures

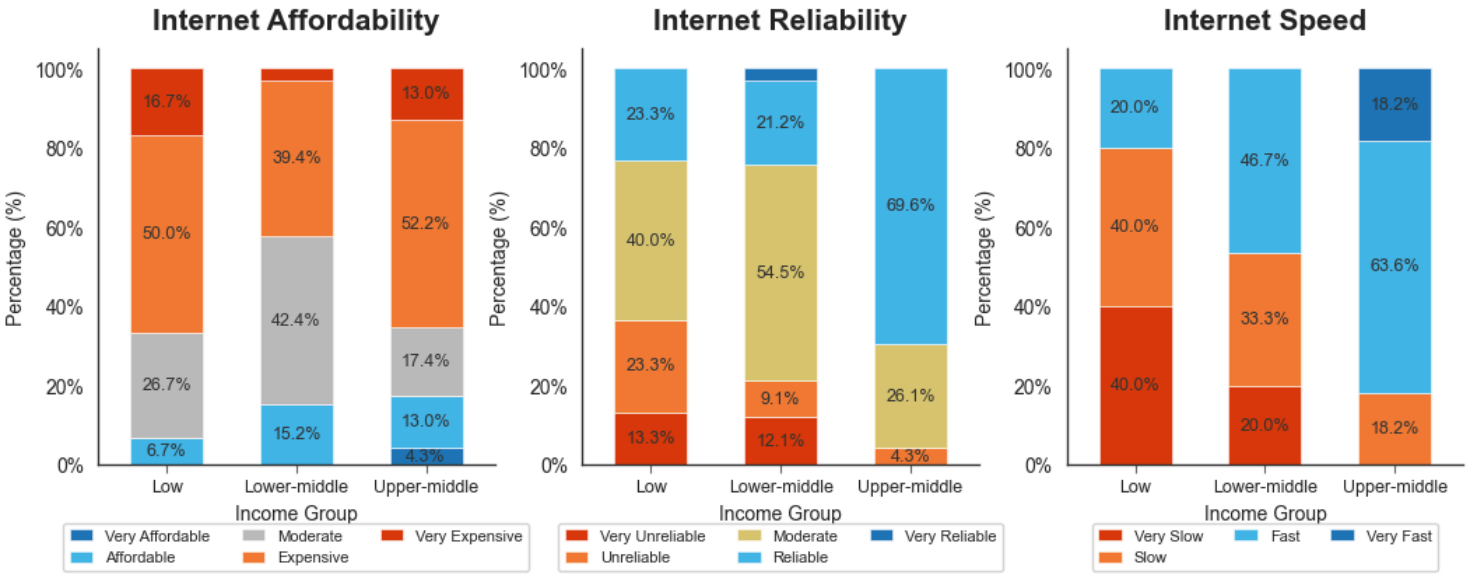


Figure 1

Representation of respondents by role category and primary work sector

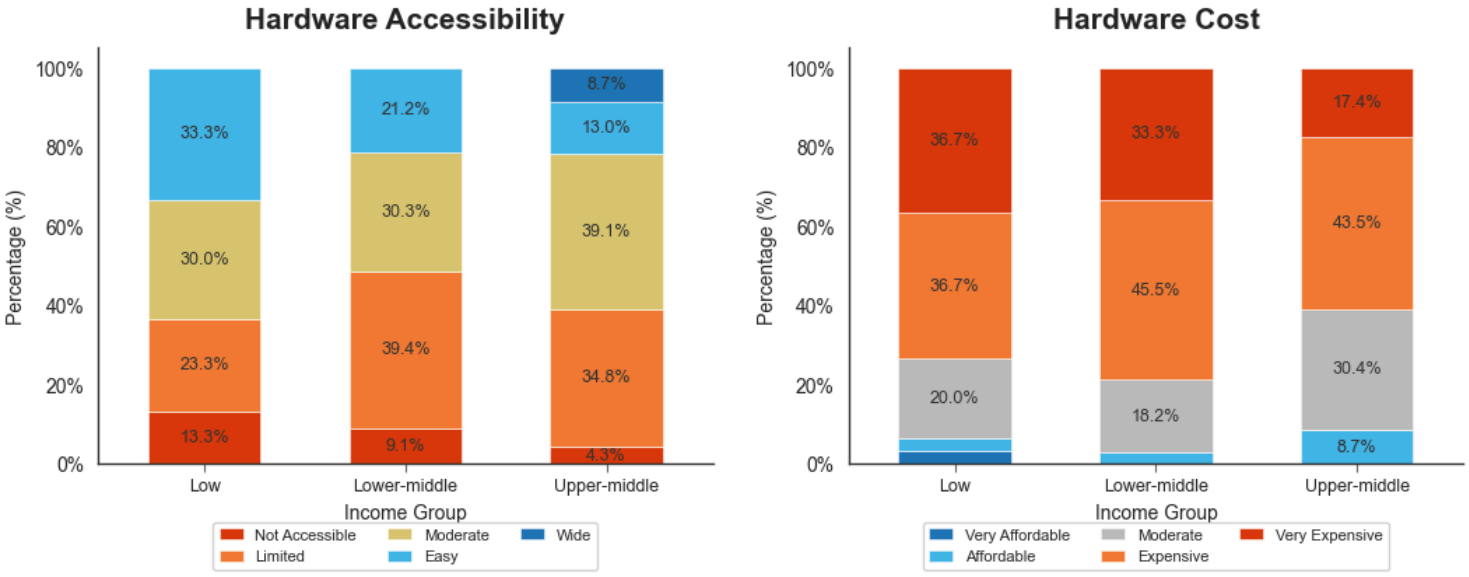


Figure 2

Electricity infrastructure gap across income groups

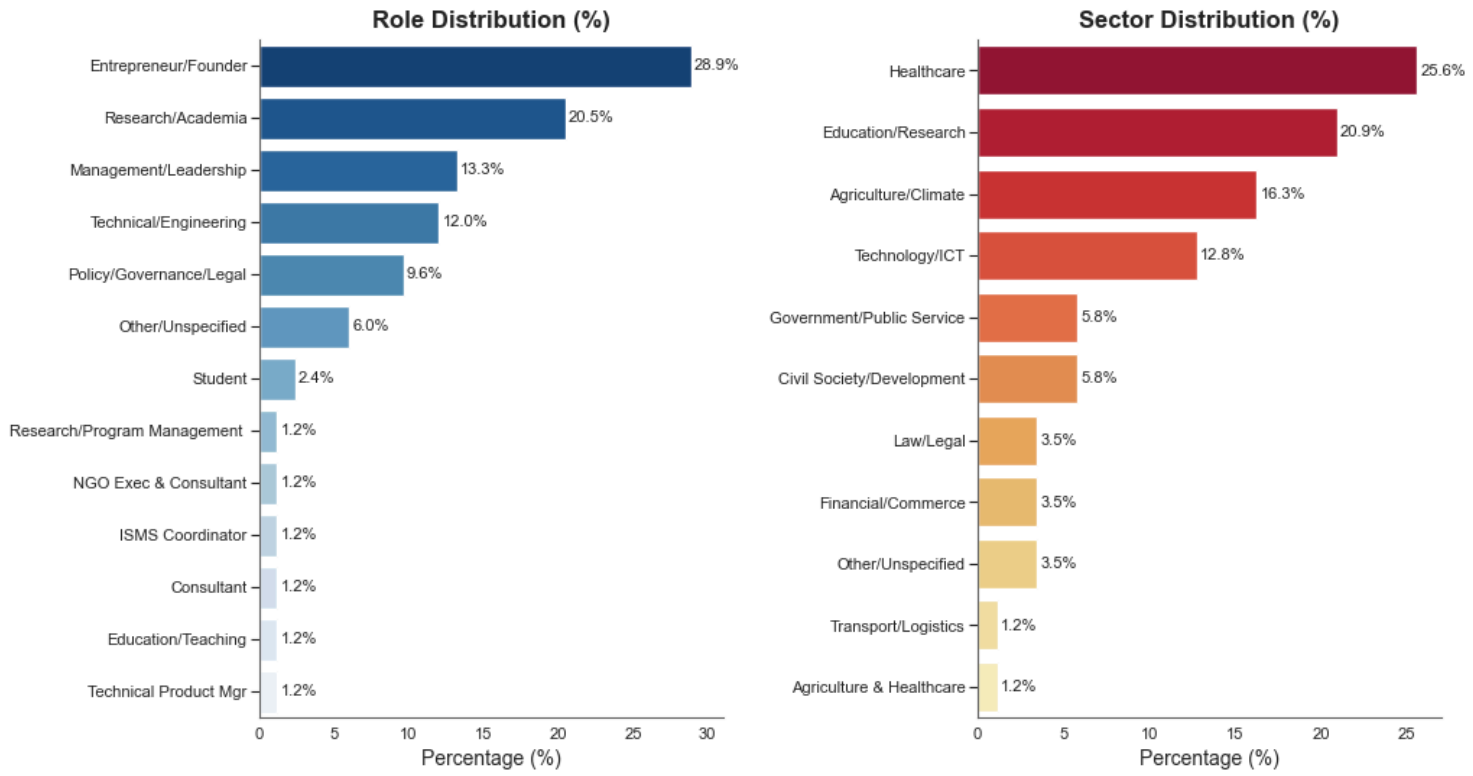


Figure 3

Internet infrastructure gap across income groups

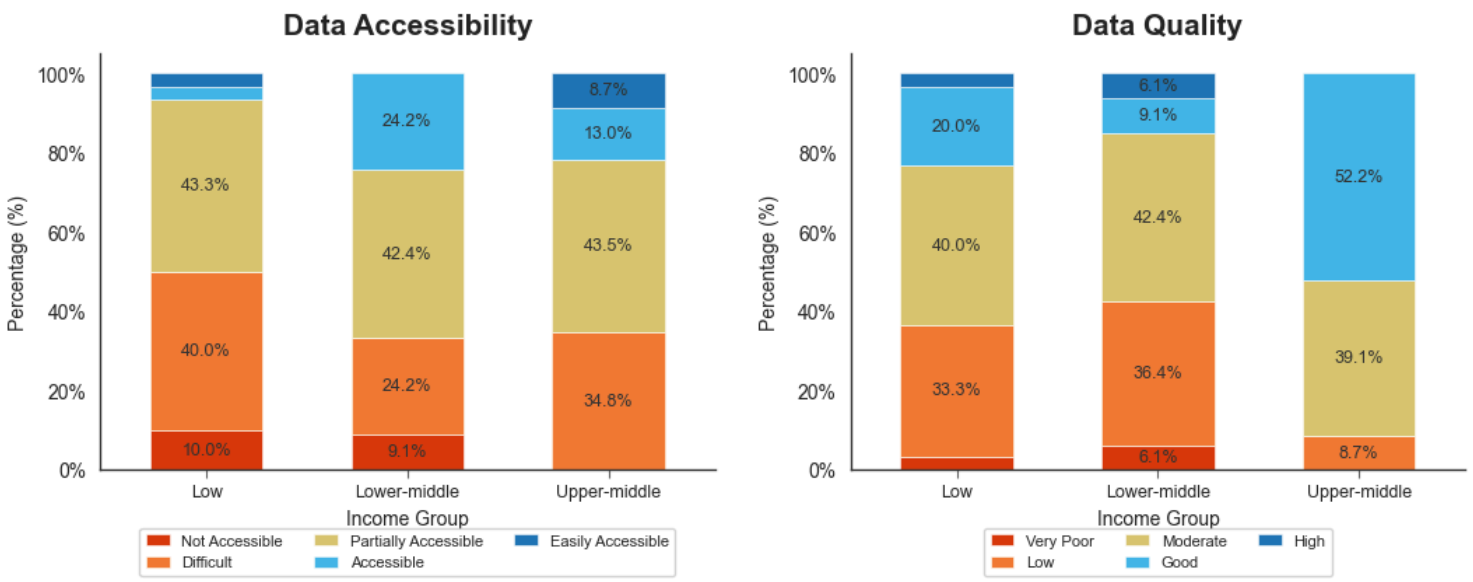


Figure 4

Training data gap across income groups

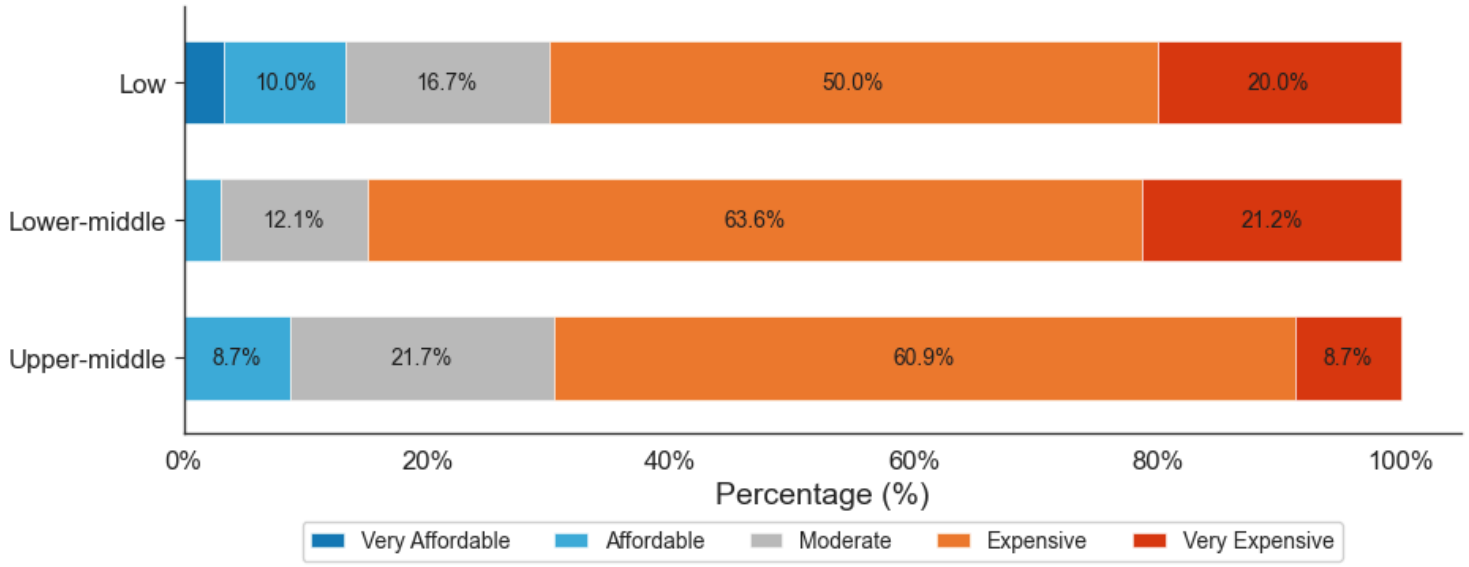


Figure 5

Hardware infrastructure gap across income groups

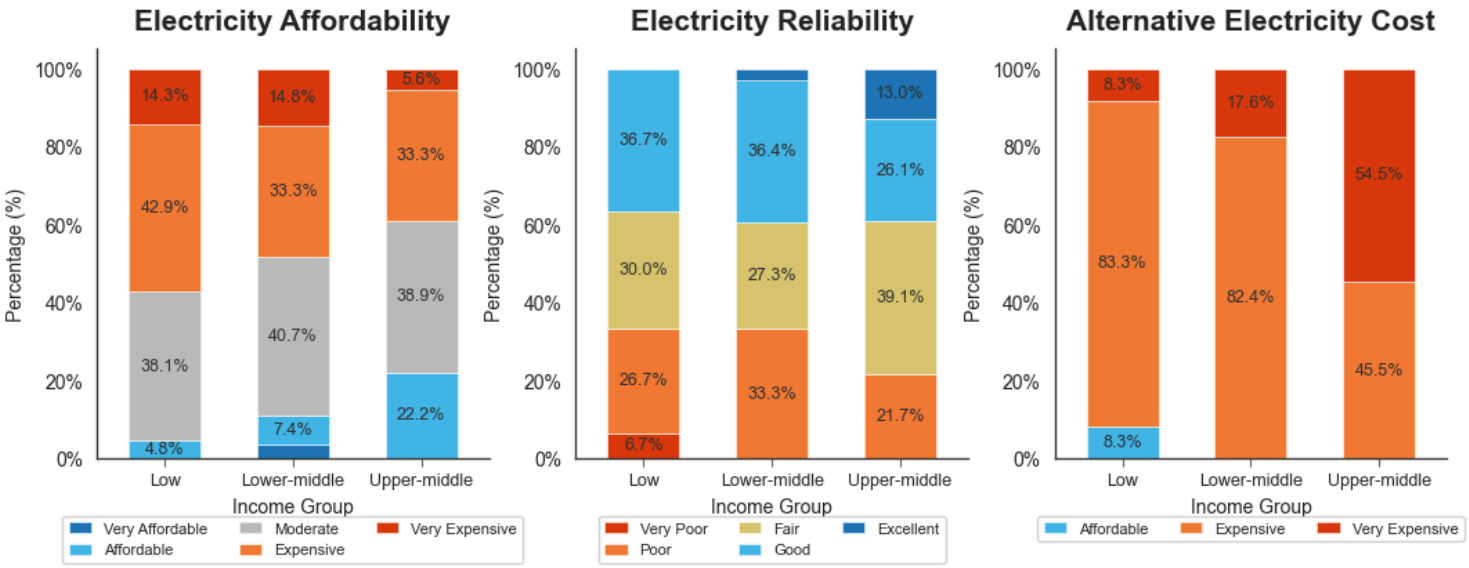


Figure 6

Cloud infrastructure gap across income groups

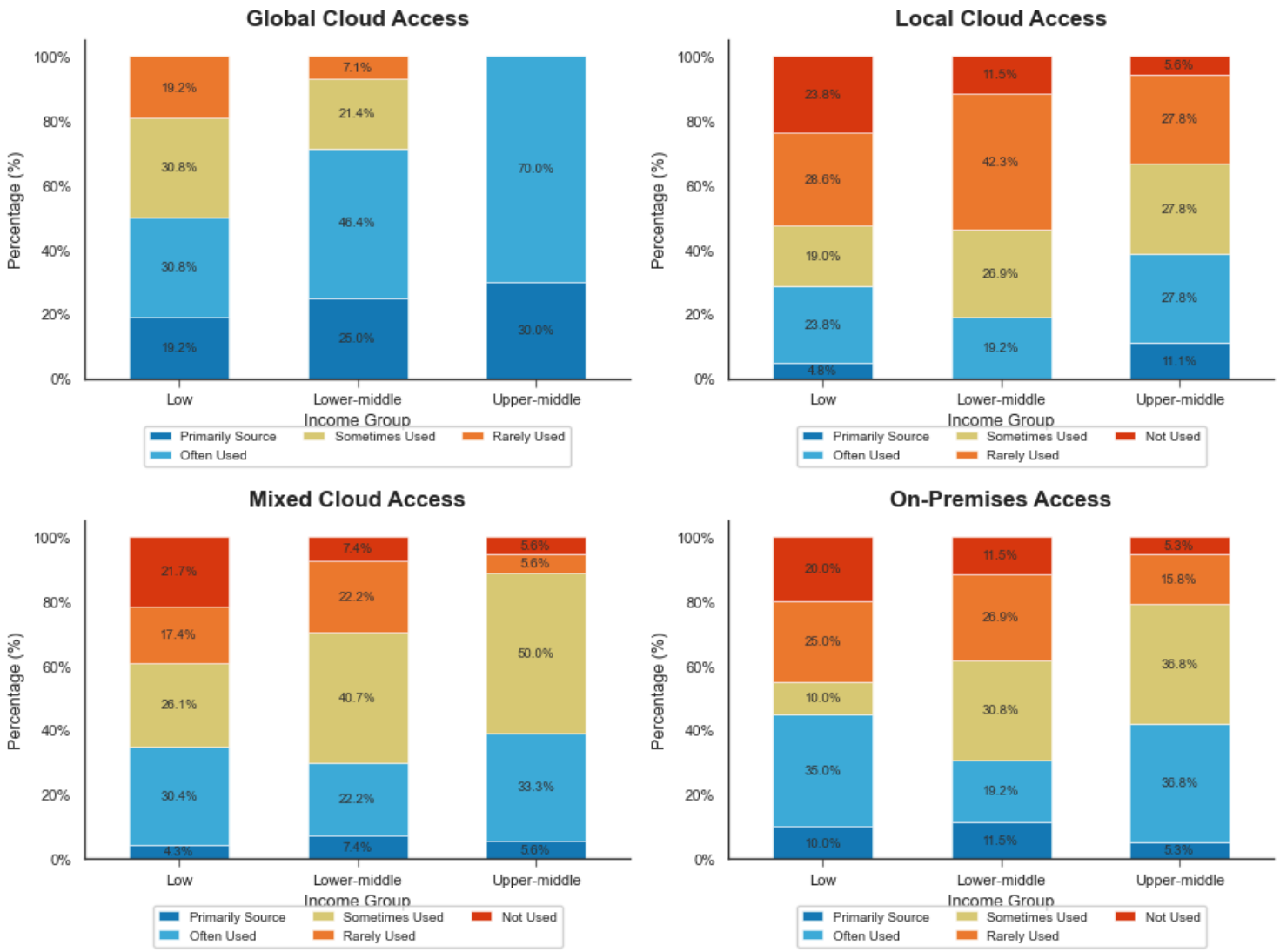


Figure 7

Cloud infrastructure cost perception across income groups



Figure 8

Word cloud representation of AI investment sources



Figure 9

Word cloud representation of AI investment forms

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- InformedConsentStatement.pdf
- DataAvailabilityStatement.pdf
- ResearchEthicsCommittee.pdf