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Powering Development? Chinese Energy Investment, Artificial Intelligence, and Local Electrification in Africa

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Abstract. Access to electricity is a prerequisite for modern economic life, yet in 2023 roughly 666 million people still lived without it, 85 percent of them in Sub-Saharan Africa [1]. This paper asks whether Chinese energy investment has powered local electrification in Africa, where the pay-as-you-go (PAYG) off-grid solar model can succeed where sovereign finance has been weak, and what artificial intelligence (AI) can add to both. Linking the complete loan record of the Chinese Loans to Africa (CLA) Database - 1,319 commitments, US$180.87 billion, 2000-2024 - to World Bank access indicators for 18 Sub-Saharan countries over 2000-2023, we find no detectable country-level association between cumulative Chinese energy finance and electricity-access gains, in the cross-section ($r = -0.08$, $p = 0.75$) or in two-way fixed-effects panels. The reason is structural: the portfolio is concentrated in hydropower and extraction-linked oil finance, and in a handful of borrowers - Angola alone absorbed 41 percent of energy lending. Meanwhile, PAYG off-grid solar expanded along exactly the affordability margin the megaprojects miss: its share of affiliate off-grid sales rose from 24 to 39 percent over 2018-2023, driving 94 percent of affiliate sales growth and supplying most of the region's new connections. Finally, we show that AI attacks the information margin that both channels lack: machine learning maps the unelectrified from satellite imagery, scores repayment from mobile-phone metadata, and verifies impacts cheaply enough to make results-based finance credible - even as AI's own data centres triple their electricity demand by 2030. The future of African electrification is 'pay as you go, power as you grow', with AI as the sensing and verification layer that makes the model investable.

Keywords: electricity access, Chinese development finance, Belt and Road Initiative, pay-as-you-go solar, off-grid energy, artificial intelligence, machine learning, Sub-Saharan Africa, SDG 7

1. Introduction

Electricity is the connective tissue of modern development. It powers health clinics, refrigerates vaccines, runs irrigation pumps, enables digital services - and increasingly, it powers computation itself: a country that cannot light a village cannot run an algorithm for it either. Yet in 2023, for the first time in a decade, the number of people without electricity in Sub-Saharan Africa rose again, to 588 million, even as the regional access rate doubled from 25.7 to 53.3 percent between 2000 and

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2023 [1, 2]. Closing this gap under SDG 7 requires roughly US$95 billion for decentralized solutions alone, against US$1.2 billion invested in 2022-23 [1, 3].

Over the same two decades, China became the continent's most important financier of energy infrastructure. The Chinese Loans to Africa (CLA) Database records 1,319 commitments worth US$180.87 billion over 2000-2024, and energy is the largest sectoral destination: US$66.08 billion, 36.5 percent of the total [4]. Has this money powered electrification? Our answer, on the best available loan-level evidence, is: it powered the grid, not the meter. Linking cumulative Chinese energy finance to household access across 18 Sub-Saharan countries, we find no association - Angola, the largest energy borrower, gained less access than the median country, while Kenya, the largest gainer, borrowed little. The megaproject model reaches the dam but not the last-mile household, for reasons the micro-electrification literature has made precise: connection costs, low take-up, and unreliable supply bind where generation does not [5, 6].

The alternative that did scale works the opposite margin. Pay-as-you-go (PAYG) off-grid solar turns a US$100-300 solar home system into daily micropayments of a few cents over mobile-money rails, using embedded metering and remote lockout as a collateral technology that substitutes for credit histories [7]. PAYG now dominates the off-grid market: its share of affiliate sales rose from 24 percent in 2018 to 39 percent in 2023, it drove 94 percent of affiliate sales growth, and decentralized renewables supplied 55 percent of new Sub-Saharan connections in 2020-22 [1, 3]. 'Pay as you go' is thus not a slogan but the binding affordability constraint, made visible and financeable.

This paper adds a third element: artificial intelligence. Both the sovereign channel and the PAYG channel are information-starved - lenders cannot see which villages lack power, providers cannot see which households will repay, donors cannot verify results cheaply enough to pay for them. Machine learning is closing exactly these gaps: convolutional networks map wealth and electrification from satellite imagery [8, 9], mobile-metadata models score repayment among borrowers without credit histories [10, 11], and ML-based causal inference verifies grid impacts at village scale [12]. Meanwhile AI itself is becoming an electricity consumer: the IEA projects AI-focused data-centre demand to triple by 2030 [13]. We argue that AI is best understood as the sensing, credit, and verification layer of a 'pay as you go, power as you grow' electrification strategy - not a substitute for capital, but the technology that lets capital find its last mile. Our contribution is to place sovereign finance, consumer-credit innovation, and the AI information margin in one account of African electrification, using real, fully reproducible data.

2. Data and framework

Our loan-level source is the CLA Database (2025 update), with sector, energy source, and sub-sector tags for each commitment [4]; electrification outcomes come from the World Bank's World Development Indicators for 18 Sub-Saharan countries spanning the full range of Chinese energy-finance exposure, from zero recorded energy loans (Mozambique) to US$27.3 billion (Angola) [2]. Off-grid market data are from the Off-Grid Solar Market Trends Report 2024 and Tracking SDG 7 [1, 3]. The AI evidence base is the peer-reviewed machine-learning literature on satellite-based development mapping [8, 9, 14, 15], mobile-metadata credit scoring [10, 11], ML-based impact evaluation [12], and the IEA's Energy and AI series [13, 16].

Why do billions in generation finance leave household access flat? Household i gains access if the grid reaches it and the fixed connection cost is paid, or if it adopts a decentralized system. For a PAYG system with monthly installment m over n months at collection rate rho, the provider break-even and household affordability conditions are:

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$$m \geq \frac{C}{\rho \sum_{t=1}^{n} \delta^t} \, and adopt_i = 1\{m_i \leq \lambda y_i\} . \tag{1}$$

Sovereign megaproject finance shifts generation capacity but touches none of these terms: not the installment m, not the system cost C, not the collection rate rho. PAYG lowers m by converting a lump sum into metered installments. AI enters through the remaining parameters: satellite mapping of unelectrified settlements cuts the information cost inside C [14, 8]; ML credit scoring on phone metadata raises rho by screening borrowers without credit histories [10, 11]; and ML-based outcome verification [12] makes results-based financing - subsidies that buy down C - contractible at scale. We estimate the sovereign channel with a two-way fixed-effects panel (country and year effects, country-clustered errors) and benchmark it against the demand and information margins below.

3. Findings

3.1. Finance without electrification

Figure 1 sets the scene: Sub-Saharan access doubled to 53.3 percent by 2023, yet the unelectrified population grew from 506 to 588 million because population outpaced connections; 84 percent of those without power are rural [1, 2]. Chinese energy finance, meanwhile, was enormous but oddly shaped. Of US$66.08 billion over 2000-2024, hydropower took US$23.85 billion (36.1 percent) and oil US$20.75 billion (31.4 percent); wind, solar, and geothermal together took under 3 percent. The portfolio is an extraction-and-generation portfolio: more than half of Chinese DFI energy lending in Africa supported fossil-fuel projects, and even hydropower was partly captive to metals extraction [17]. It is also geographically extreme: Angola alone absorbed 41 percent of energy lending, while Nigeria and the Democratic Republic of Congo - the two largest unelectrified populations - received about US$1.2 billion each. After 2019 the flow collapsed: no Chinese energy loan commitments to Africa were recorded in 2022, and the cautious 2023 return took the form of three small renewable projects worth US$502 million [18].

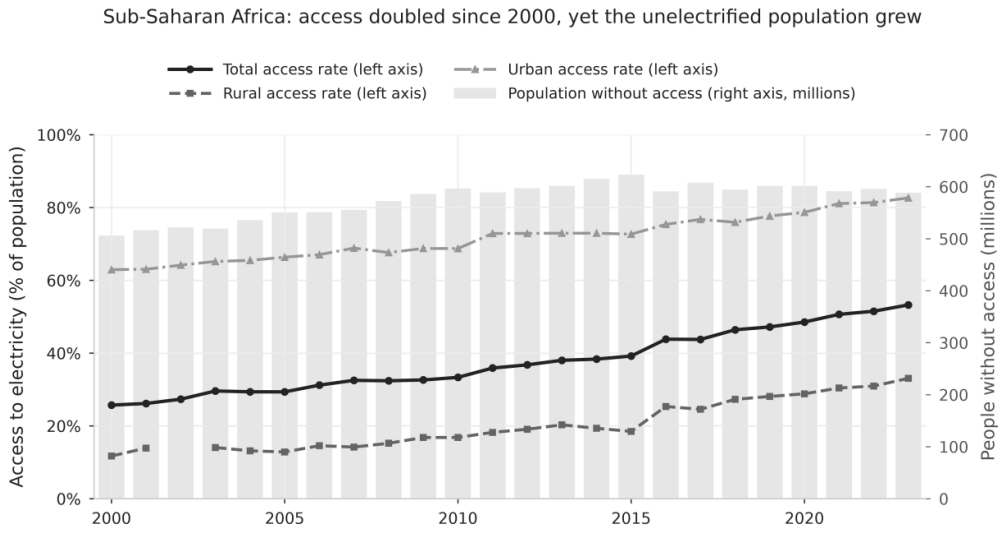


Figure 1. Sub-Saharan Africa, 2000-2023: access doubled, yet the unelectrified population grew. Left axis: access rate (% of population); right axis and bars: people without access (millions). Source: World Bank, World Development Indicators (accessed October 2026) [2]; SDG 7 (2025) [1]

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Table 1 (online appendix) shows the result plainly: regressing the 2000-2023 change in access on log cumulative Chinese energy lending across 18 countries yields a slightly negative, insignificant slope (OLS -1.44 points per log-billion; Pearson r = -0.08, p = 0.75; Figure 2). Angola, the largest borrower, gained 26.9 points - below the sample median - while Kenya, the top gainer (+61.0 points), received modest Chinese energy finance. In the two-way fixed-effects panel (414 country-years), lagged cumulative electrification-track lending per capita enters at 1.15 points per US$100 (SE 7.68, p = 0.88): statistically indistinguishable from zero, as are all-energy lending and the rural-access outcome. This null is not proof that projects failed - geocoded studies find local gains around completed infrastructure [19], and ML-based evaluation of Uganda's grid expansion finds village-level asset-wealth gains up to 0.15 standard deviations [12]. It is evidence that the aggregate household-access margin - the one SDG 7 counts - did not move with the money, because connection cost, take-up, and reliability bind where generation does not [5, 6].

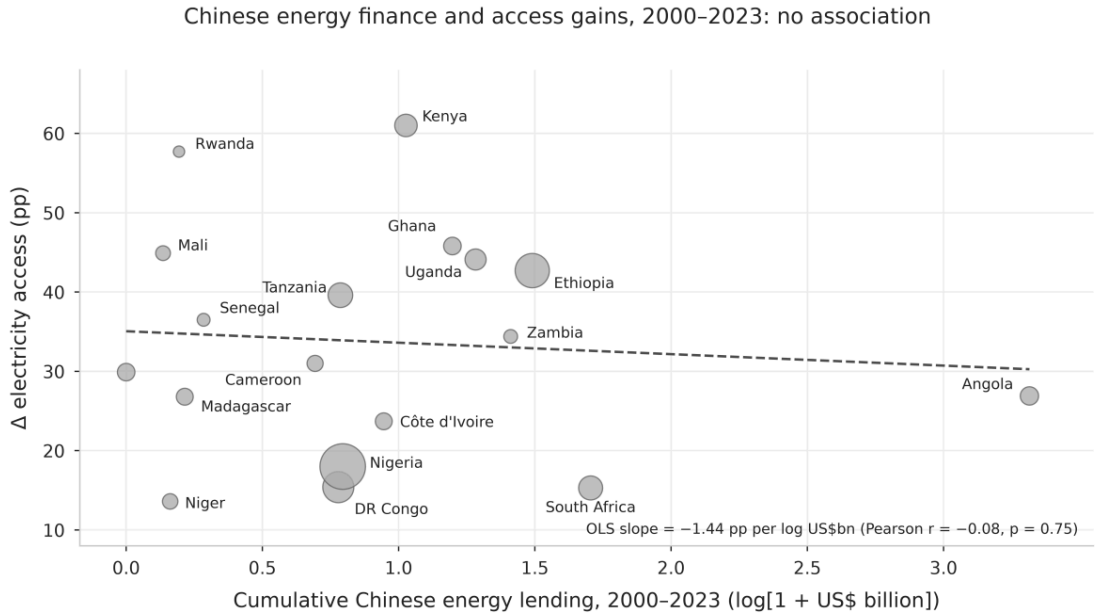


Figure 2. Electricity-access gains (2000-2023, percentage points) against cumulative Chinese energy lending (log scale), 18 Sub-Saharan countries; bubble size is proportional to 2023 population. The fitted line is insignificant (r = -0.08, p = 0.75). Source: authors' calculations on CLA and WDI data

3.2. The complementary margin: pay as you go, power as you grow

PAYG works the affordability margin directly. The technology is unglamorous - a solar home system with an embedded GSM meter that unlocks on payment - but the financing logic is transformative: it converts a lump sum into daily micropayments, aligns repayment with usage, and gives the lender remote lockout as collateral [7]. Riding East Africa's mobile-money rails, whose poverty impacts are themselves well documented [20], PAYG lifted its share of affiliate off-grid sales from 24 percent (2018) to 39 percent (2023) and accounted for 94 percent of affiliate sales growth; 96 percent of larger solar home systems are now sold on PAYG terms [3]. Off-grid solar benefited an estimated 561 million people by 2023, decentralized renewables supplied 55 percent of new Sub-Saharan connections in 2020-22, and off-grid solar is the least-cost route for 41 percent - 398 million - of those who must gain access by 2030 [1, 3]. Yet PAYG is also an affordability frontier: only 22

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percent of unelectrified households can afford a Tier 1 kit at current prices, and collection rates hovered near 62 percent in 2023 [3]. The binding constraint is no longer hardware - solar LCOE fell 90 percent over 2010-2023 [21] - but consumer credit, subsidy, and distribution.

3.3. The third margin: artificial intelligence

Artificial intelligence relaxes the information constraints that sit inside every term of Eqn. (1). Table 1 organizes the evidence along the electrification chain. For mapping and planning, machine learning manufactures data where registries are missing: convolutional networks trained on daytime satellite imagery predict local wealth across Africa [8, 9], nighttime lights validate village-level connection status [14], and a gridded electrification dataset now covers all of Sub-Saharan Africa from free satellite, population, and land-cover layers [15] - while satellite tracking shows that recent connection gains cluster near existing infrastructure, which is exactly why national access rates stay flat even when projects succeed locally [22]. For credit and repayment, ML scoring on mobile-phone metadata predicts loan repayment among borrowers with no credit history, outperforming conventional scorecards [10], and the same metadata predict wealth directly [11] - the digital twin of the PAYG lockout, raising the collection rate rho in Eqn. (1). For evaluation, Ratledge et al. [12] combine satellite imagery with ML-based causal inference over Uganda's grid expansion and show that verified outcomes can be produced cheaply enough to anchor results-based financing - the instrument most likely to replace part of megaproject lending. Two cautions apply: models can misclassify the poorest, most remote households they are meant to find, and phone-metadata scoring raises consent and privacy concerns [10, 14]. And AI is itself an electricity consumer - data-centre demand rose 17 percent in 2025 and AI-focused consumption will triple by 2030 [13] - so for Africa, electricity access is a precondition for the AI economy, not a consequence of it. The asymmetry is nonetheless favorable: mapping, scoring, and verification models are cheap to import, which is why the information margin is the one margin Africa can adopt faster than it can build dams.

Table 1. Artificial intelligence across the electrification chain: applications and evidence. IEA figures from the Energy and AI series [13, 16]

Chain link	AI application	Representative evidence	Key finding / implication
Mapping & planning	CNNs on satellite imagery predict village wealth and electrification; nighttime-light validation	Jean et al. [8]; Yeh et al. [9]; Min and Gaba [14]; Falchetta et al. [15]	Village-scale electrification maps for all of Sub-Saharan Africa from free data; targeting becomes computable
Distribution diagnostics	Satellite tracking of who actually gains connections	Falchetta et al. [22]	Gains cluster near existing grids; national rates stay flat even when projects succeed locally

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Table 1. (continued)

Credit & repayment	ML credit scoring on mobile-phone metadata	Björkegren and Grissen [10]; Blumenstock et al. [11]	Raises the collection rate in Eqn. (1); substitutes for credit bureaus in PAYG expansion
Impact evaluation	Computer vision + ML-based causal inference on grid expansion	Ratledge et al. [12]	Uganda grid access raised village asset wealth up to 0.15 SD; cheap verification enables results-based finance
System operations	AI for grid management, demand forecasting, industrial efficiency	IEA [13, 16]	Could cut energy costs 3-10% in energy-intensive industries; skills and data are the barriers
Demand side (caution)	Data centres powering AI consume electricity	IEA [13]	Demand +17% in 2025, tripling by 2030 - access is a precondition for, not a consequence of, AI

Note: CNN = convolutional neural network; ML = machine learning; SD = standard deviations. Eqn. (1) is the PAYG break-even and affordability condition in Section 2.

4. Conclusion

Has Chinese energy investment powered local electrification in Africa? It powered the grid, not the meter: US$66 billion of generation- and extraction-heavy finance shows no detectable association with household access gains across 18 countries. What did move access was the demand-side innovation that treats affordability, not capacity, as the constraint: pay-as-you-go solar, which drove 94 percent of recent off-grid sales growth and most new connections [3, 1]. Artificial intelligence is the emerging third margin - sensing the unelectrified from space [8, 15], scoring repayment from phone metadata [10], and verifying impacts at village scale [12] - and it is the layer that can make a redirected, 'small-is-beautiful' Chinese energy finance investable at the household level: concessional results-based financing and local-currency credit lines for PAYG distributors, targeted by satellite maps and verified by machine learning. Pay as you go, power as you grow - and let AI find, finance, and verify the households on the other side of the meter. Our country-level estimates are descriptive associations over 18 countries; commitments are not disbursements; and ML measures themselves carry bias against the poorest. The priority for future work is geocoding Chinese energy loans against subnational access and nighttime-light panels - the satellite-plus-ML stack now makes that feasible at low cost [12, 15] - and evaluating whether results-based finance shifts the affordability frontier of Eqn. (1).

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