WHITE PAPER

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A framework to build local ecosystems

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Executive Summary

Artificial intelligence is rapidly becoming a foundational layer of the global economy, with projections indicating that the AI market will reach $4.8 trillion by 2033 – approximately the size of Germany's entire economy. Yet this transformation is unfolding with stark inequality. While advanced economies aggressively invest in local AI capacity and infrastructure, low- and lower-middle-income countries (LLMICs) face systemic barriers that threaten to lock them into technological dependency. Recent announcements from governments and major technology firms show large AI funding commitments[1], but unclear governance and poor coordination risk turning these investments into deeper global AI inequality rather than lasting domestic capacity.

This white paper addresses a central challenge: **how to finance AI ecosystems in ways that allow LLMICs to move from passive adoption toward adaptation, co-creation, and meaningful participation in the global AI economy.**

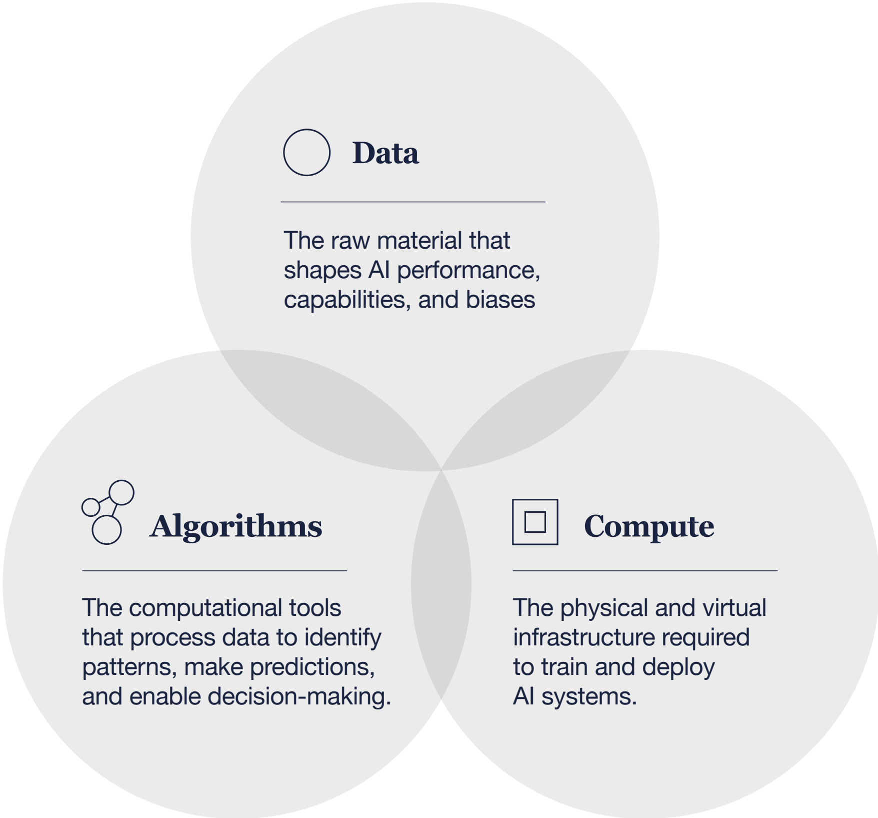
Methodology and Approach

Our analysis employed a two-stage approach. First, we conducted a broad cross-sectoral review of funding mechanisms in global health, climate finance, infrastructure, and technology to extract recurrent institutional features robust across domains. Second, we applied these factors in structured comparative assessment of nine flagship funds: Gavi; the Global Fund to Fight AIDS, Tuberculosis and Malaria; the Green Climate Fund (GCF); the Global Environment Facility (GEF); the UN Technology Bank; the Global Infrastructure Facility (GIF); the Global Financing Facility (GFF); the Adaptation Fund, and the Just Transition Transaction (JTT). We employed a "most-different systems" design, selecting funds that differ in sector and mandate but share the challenge of financing public goods in LLMICs. This allows us to identify institutional features that recur across heterogeneous contexts and therefore may be generalisable to AI financing.

1 We refer here to development-oriented funding commitments (including official development assistance, multilateral development bank financing, and philanthropic or corporate pledges earmarked for AI capacity in low- and lower-middle-income countries) rather than commercial capital expenditure on AI infrastructure.

Argument and Findings

First, this white paper introduces a comprehensive framework for financing AI ecosystems by focusing on three foundational technical pillars, collectively termed the "AI Triad":



Why it matters

Without robust data infrastructure, collection mechanisms, and governance frameworks, countries cannot generate, access, or govern high-quality representative datasets. This limits their ability to develop contextually relevant technologies and perpetuates dependence on externally developed solutions that may be poorly suited to local contexts.

Algorithmic innovation is currently concentrated in a handful of companies and countries, leaving most nations as consumers rather than producers or adaptors of AI technologies.

While the compute required to achieve specific AI capabilities has decreased over time due to efficiency gains, compute usage at the frontier (training the most advanced models) continues to increase exponentially, creating structural barriers for countries seeking to develop cutting-edge systems rather than deploy existing ones.

Second, each pillar evolves through three stages requiring different financing strategies: **foundation, enhancement,** and **integration.**

STAGE 1

Foundation
Laying the Groundwork

	PILLAR CONTENT	CHARACTERISTICS
Data	Foundation Building	Countries establish basic infrastructure (i.e., national data centres, research capacity, initial computing access). These public-sector-led efforts have limited commercial incentives and require patient, low-risk capital through sovereign loans and technical assistance grants.
Algorithms	Basic Research	
Compute	Core Infrastructure	

STAGE 2

Enhancement
Improving and Proving

	PILLAR CONTENT	CHARACTERISTICS
Data	Quality Enhancement	The focus shifts to making the initial assets work better: raising data quality, turning research into prototypes, or boosting energy efficiency in data centres. Blended or performance-linked finance may become viable because the projects now have clearer milestones and, in some cases, revenue signals.
Algorithms	Applied Development	
Compute	Enhancement and Optimisation	

STAGE 3

Integration
Scaling and Integrating

	PILLAR CONTENT	CHARACTERISTICS
Data	System Integration	Mature systems are linked together, exported to new sectors, or rolled out country-wide. Private capital becomes more prominent (VC, PPPs, commercial loans) and funding is usually tied to measurable market or policy outcomes.
Algorithms	Commercialisation	
Compute	Scaling and Specialisation	

Third, the paper identifies five institutional design principles that appear to distinguish more effective financing mechanisms from less successful ones based on comparative analysis of nine global funds and analysis[2] of the development finance literature.

Governance
Decision-making and authority distribution

Independent review bodies insulated from political pressure; no single contributor holds more than 20% of voting rights; diversification across donor types reduces risk that any single funder can impose divergent conditions.

Local Ownership
National prioritization and demand alignment

Countries prepare nationally endorsed AI investment cases integrating the three pillars into broader development strategies; external funding accelerates nationally agreed programs rather than substituting for domestic effort.

Finance & Predictability
Temporal stability and planning horizons

Replenishment cycles of 3–5 years; front-loaded disbursement options; liquidity reserves covering 12 months of projected outlays.

Outcome & KPIs
Performance measurement and adaptive learning

Streamlined performance indicators balance clarity with adaptability; avoids bureaucratic complexity.

Integrity & Risk Safeguards
System-wide integrity and risk controls

Real-time financial reporting; random forensic audits; whistleblower protections; conflict-of-interest rules.

2 The comparative analysis of nine funds employs a qualitative "most-different systems" design to identify institutional features that recur across heterogeneous contexts. This approach is suited to generating transferable design principles but does not permit statistical generalisation. The patterns identified should be understood as hypotheses informed by analogical reasoning, requiring empirical validation as AI-financing mechanisms mature

Recommendation

The framework distills three core insights that apply across diverse national contexts: (i) AI capacity should be coordinated and built as a system across data, algorithms, and compute; (ii) financing strategies should match development stages; and (iii) institutional design shapes outcomes.

The brief translates these principles into a practical operational workflow that transforms broad commitments into programs that evolve with evidence and changing contexts. This four-step process operationalises each of the five design levers: it embeds local ownership through country-led investment cases, ensures distributed governance through independent review, delivers finance predictability through structured funding tranches, anchors accountability through baseline-setting and evidence-based metric revision, and maintains integrity through ethics screening and results-based disbursement.

	What happens	Purpose
STEP 1 Investment case	Country teams prepare an AI investment case covering data, algorithms, and Compute, with budgets, indicators, and links to national priorities	**Define clear goals and funding needs**
STEP 2 Independent review	A parity board and independent experts review proposals for technical quality, ethics, and capture risks	**Ensure quality, fairness, and credibility**
STEP 3 Initial funding	Approved proposals receive first-round funding, usually for 12 months	**Start foundational work and set baselines**
STEP 4 Review and adjustment	Progress is reviewed regularly, metrics are updated, and further funding is released based on results	**Adapt funding based on evidence**

The framework presented here aims to offer policymakers, funders, and development partners a clear and operational pathway to finance the AI Triad in ways that are context-appropriate, sustainable, and equitable.

The pathway ahead is not about replicating Silicon Valley in every country. It is about enabling LLMICs to move step by step – from adoption, to adaptation, to co-creation, and eventually innovation – through smart, sequenced investments in data, algorithms, and compute. The framework provides the roadmap; implementation will require sustained political will, coordinated action across diverse stakeholders, and commitment to the principle that meaningful participation in the AI economy is not a privilege for the few but a development imperative for all.

Human capital development, though essential to realising value from AI investments, cuts across all three pillars and warrants dedicated analysis beyond the scope of this brief.

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Introduction

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Introduction

Background

Artificial intelligence (AI) is increasingly recognised as a general-purpose technology, like electricity or the internet (Crafts, 2021), with the potential to reshape global economic prospects and patterns of cooperation and development (Korinek & Stiglitz, 2021). Yet AI capacity is concentrated in a handful of countries, creating a divide that limits opportunities for the Global Majority – the nations representing most of the world's population but historically excluded from technological leadership. Within this broader challenge, low- and lower-middle-income countries (LLMICs) face the most acute barriers. Without deliberate investment in the foundational infrastructure – data, compute, and algorithms – these countries risk remaining or becoming consumers rather than establishing sovereign capacity. This paper focuses specifically on LLMICs, where resource constraints and structural barriers make strategic financing particularly critical.

An increasing number of initiatives are now funding AI development in LLMICs, from large-scale compute infrastructure to targeted dataset and algorithm support. But a question remains.

> What financing structures enable LLMICs to build foundational AI ecosystems that support sovereign capacity and equitable global participation in the global AI economy?

For purposes of this analysis, we define the *AI economy* as economic activities transformed by AI technologies, from productivity growth and industrial reorganisation to new forms of innovation and governance. Building on the AI Triad framework of data, compute, and algorithms (Buchanan, 2020; Sastry et al., 2024), this paper conceptualises these as the fundable bases – the three pillars of sovereign AI capacity. While talent and governance are essential enablers, our financing framework centres on the Triad.

As with previous general-purpose technologies like electricity and the internet (David, 1990; Jovanovic & Rousseau, 2005), AI's ability to generate broad economic and social benefits in LLMICs depends not only on the availability of the technology (Solaiman et al., 2025) but also on support for infrastructures and institutions that enable it be adopted and utilised for different needs (Aghion, Jones, & Jones, 2019;

Agrawal, Gans, & Goldfarb, 2019; Korinek & Stiglitz, 2021; Khan and Altun, 2025). The current concentration in a few economies constrains opportunities for LLMICs (UNCTAD, 2025).

Recent commitments underscore both the urgency and the opportunity. At the AI Action Summit in Paris, a coalition of governments, philanthropies, and technology companies launched Current AI with an initial $400 million[1] endowment to support the creation of AI "public goods" including high-quality datasets and open-source tools and infrastructure (Élysée, 2025). At the Global AI Summit on Africa in Kigali in April 2025, leaders proposed a $60 billion Africa AI Fund to invest in AI research, startups, infrastructure, and governance (Africa Declaration on Artificial Intelligence, 2025). Rwanda and the Gates Foundation also announced a $7.5 million pledge for an AI Scaling Hub focusing on solutions in healthcare, agriculture, and education (Centre for the Fourth Industrial Revolution Rwanda, 2025). Private sector commitments include Microsoft's investments – $300 million in South Africa (Shapshak, 2025), $1.7 billion in Indonesia, $1.3 billion in Mexico, and $14.7 billion in Brazil (Microsoft, 2024) – and Google's $37 million to support AI advancement across Africa (Benamara, 2025).

The Global Digital Compact (Global Digital Compact, 2024), adopted by 193 countries in September 2024, tasked the United Nations Secretary-General with developing a report on innovative voluntary financing options based on the recommendations of his High-level Advisory Body on AI (United Nations, 2024). The Secretary-General's 2025 report outlines three complementary mechanisms to address this mandate: a Global Fund for AI with innovative financing instruments, a coordination platform for funders, and a matching mechanism for in-kind contributions (United Nations Secretary-General, 2025).

1 All dollar amounts in this paper refer to U.S. dollars.

Methodology

This white paper synthesises insights from three bodies of evidence: development finance literature on infrastructure funding, innovation policy research on staged R&D investment, and documented practices from nine global funds operating in health, climate, and technology. Rather than offering a systematic comparison, we draw selectively on these cases to identify institutional features that appear to recur across successful mechanisms (while acknowledging that direct application to AI financing remains untested). The framework should be understood as a preliminary architecture informed by analogical reasoning, not a validated model.

Our analysis employed a two-stage approach. First, we conducted a broad cross-sectoral review of funding mechanisms in global health, climate finance, infrastructure, and technology. This wider scope allowed us to extract recurrent institutional features robust across domains. Through this comparative scan, supplemented by analysis of literature on these topics, we identified success factors (polycentric governance with independent review, locally embedded ownership, predictable and diversified financing, adaptive outcome measurement, and strong integrity safeguards) and failure modes (capture by narrow interests and volatility from concentrated donor bases). These factors were derived from both secondary literature and the systematic evidence collated in Annexes 1–6.

Second, we applied these factors in a structured comparative assessment of nine flagship funds. This stage served to (1) test whether the identified factors had explanatory power across varied institutional contexts and (2) assess how these factors manifest differently depending on governance mandates, sectoral priorities, and political economy conditions. In selecting cases, we employed a most-different systems design (Anckar, 2008), where diverse cases are examined to identify institutional features that recur across contexts and therefore may be generalisable.

Integrating these stages enabled us to move tentatively from descriptive comparison to institutional design. Specifically, the recurring institutional features distilled from this process are translated into five design levers for financing AI ecosystems: governance, ownership, finance, measurement, and integrity. These levers provide a scaffold for adapting lessons from global funds to financing AI ecosystems in LLMICs.

We acknowledge important limitations in applying lessons from these domains to AI ecosystem financing. Systematic empirical evidence on AI-specific financing mechanisms in LLMICs remains limited because AI as a development priority has emerged only recently (post-2018), providing insufficient longitudinal data on financing outcomes. No published research systematically examines which financing approaches succeed or fail in building AI capacity across low-income contexts, or validates optimal sequencing of investments across data, algorithms, and compute infrastructure. The framework presented in this paper should be understood as a proposed architecture informed by comparative evidence, requiring empirical validation as countries implement AI investments over the coming decade.

Contribution

> This paper argues that participation in the AI economy depends on building AI ecosystem foundations in LLMICs.

Our analysis shows first that building these foundations requires deliberate investment in the AI Triad: data, compute, and algorithms. Second, financing these foundations requires a staged approach as different instruments and strategies are suited to different phases of ecosystem development and one-size-fits-all approaches undermine sustainability. Third, evidence from global funds in health and climate suggests that institutional design may matter more than funding scale, though this hypothesis requires empirical validation as AI-financing mechanisms mature.

The remainder of this brief is structured as follows. Section 2 introduces the AI Triad as foundational infrastructure and its strategic importance. Section 3 maps financing instruments to developmental stages; Section 4 derives design principles from global fund experiences; Section 5 presents an operational framework for building AI ecosystems in LLMICs.

Foundations of the AI Economy

02

Foundations of the AI Economy

As previously mentioned, we use the term AI economy to describe a new layer of economic activity and value creation that is increasingly driven by AI. It encompasses not only AI technology development but also the transformation of traditional sectors through AI applications. Economic competitiveness is now increasingly linked to the ability to integrate AI across systems and industries as diverse as predictive analytics in agriculture and logistics, automated diagnostics in healthcare, and AI-enabled governance in public services.

This transformation requires access to core infrastructures: the AI Triad of data, compute, and algorithms. LLMICs differ widely in their contexts, resources, and development priorities, each arriving at AI development from different stages of digitalisation and with varying national priorities. Despite this diversity, the Triad remains foundational. Countries focused on adopting and localising existing AI need these pillars to adapt technologies to their contexts. Those with innovation ambitions require them to produce new ecosystems and contribute globally. Without strength across all three pillars, countries may face technological dependency, with limited ability to adapt technologies effectively or build sovereign capacity. This positions the AI Triad as a potentially critical foundation for economic resilience, strategic autonomy, and long-term development.

The AI Triad

The AI Triad represents the three potentially critical and interdependent pillars forming the foundation of AI ecosystems. Each component is necessary but insufficient alone: only when developed in concert can countries participate meaningfully in the AI economy.

Data: The Foundation of AI Systems

Data underpins the entire AI lifecycle from training to deployment, serving as raw material shaping model performance and as a contextual determinant of capabilities, limitations, and biases (OECD 2024). Without robust data infrastructure, collection mechanisms, and governance frameworks, countries face significant disadvantages. They cannot generate, access, or govern high-quality representative datasets. This limits their ability to develop contextually relevant technologies, risks perpetuating dependence on bias-prone foreign solutions, and reduces global competitiveness.

Data quality, representativeness, and accessibility significantly impact AI system performance, with major implications for fairness and inclusion. Poor data inputs can lead to opaque or inexplicable model outputs, which may undermine trust and accountability (Khan et al., 2022). These risks are acute in LLMICs, where data challenges are multifaceted: insufficient digital infrastructure, weak governance frameworks, and concerns about data sovereignty and colonialism (UNCTAD, 2021).

Africa, in particular, faces a significant data deficit that may constrain equitable AI development; researchers have argued that the predominance of Global North populations in training datasets risks perpetuating algorithmic biases and reducing effectiveness for African users (Pasipamire & Muroyiwa, 2024). This disparity is exacerbated by the limited internet access in the least developed countries: 27% connectivity vs 63% globally (UNCTAD, 2023; ITU 2023).

Moreover, equitable collection of representative data remains challenging (Evertsz et al., 2023). In resource-constrained countries, data collection is hampered by limited infrastructure, inconsistent data collection practices, and disregard or decontextualisation of local knowledge (Machuve, Ezinne, & Neema, 2021). Although open-data initiatives have gained momentum, power asymmetries, colonial legacies undermining trust, and disregard for local practice remain barriers to equitable data sharing in LLMICs (Arun, 2025).

External initiatives often overlook the importance of local norms and fail to adequately address the historical injustices that shape present-day mistrust. For example, in post-apartheid contexts, communities affected by forced land dispossession hesitate to share agricultural data. Abebe et al. (2021) lay out how this reluctance stems from a deeply rooted suspicion toward external actors and so-called open-data initiatives, which are perceived as potential threats to local autonomy.

These hurdles demand dedicated budget lines for data collection, distinct from broader AI funding, ensuring resources for infrastructural investments. Governments may increasingly provide data for AI, requiring financing to digitise existing datasets and improve interoperability.

Algorithms: The Technical Core

Algorithms, computational tools that process data to identify patterns, make predictions, generate content, optimise decisions, and enable human-machine interaction, form AI's technical core. Developing algorithms requires specialised expertise. Yet algorithmic innovation is concentrated in a handful of companies and countries, leaving most nations as consumers rather than producers of AI technologies.

The Stanford HAI AI Index (2025) shows that a small number of countries, particularly the U.S. and China, dominate global AI research output, patent filings, and state-of-the-art model development. In 2024, U.S. institutions produced 40 notable AI models[2] compared to China's 15 and Europe's 3, though Chinese models have rapidly closed the quality gap. Evidence also points to a comparative lack of AI tools available in developing countries relative to advanced economies (Alonso et al. 2022; Khan et

2 A notable AI model is generally understood as an AI system recognized for its significant impact – whether by advancing research, achieving state-of-the-art results, or shaping the direction of development. The Stanford AI Index 2025 uses this term to describe prominent models developed by leading institutions, noting that nearly 90% of such models in 2024 came from industry.

al., 2024). This concentration raises concerns that technologies designed primarily for a few economies' contexts may prove less effective elsewhere, potentially reinforcing patterns of dependency, though empirical evidence on cross-context performance gaps remains limited.

Geographic concentration mirrors institutional concentration: limited private firms drive most large-scale advances (Cottier et. al, 2023). Without adequate domestic funding, talented individuals in LLMICs may migrate to regions with more resources, which could constrain long-term domestic innovation capacity, though diaspora networks can also create opportunities for knowledge transfer.

Global algorithmic development must combine local expertise investment with international collaboration. Funding should support fundamental research at LLMIC universities and institutes, plus applied development through incubators, accelerators, and public-private partnerships. Such financing develops solutions reflecting local needs while ensuring that countries contribute to and benefit from global advances in the field.

Compute: The Infrastructure Backbone

The physical and virtual infrastructure required to train and deploy AI systems represents the third critical pillar. While efficiency gains have reduced the compute needed to achieve specific capabilities, making deployment and fine-tuning increasingly accessible, compute usage at the frontier continues to increase exponentially. Training state-of-the-art models now costs hundreds of millions of dollars, creating significant barriers for those seeking to compete at the cutting edge, though not necessarily for those focused on adapting and deploying existing systems.

Compute infrastructure is severely imbalanced. According to the African Data Center Association, Africa accounts for less than 1% of global data centre capacity despite comprising 17% of the world's population (ADCA, 2024), highlighting structural gaps in accessing computational power for sovereign AI capacity (Cottier, Besiroglu, & Owen, 2023).

High-performance hardware costs can be prohibitively expensive, especially for smaller or resource-constrained organisations. Ongoing operational overhead – such as energy consumption, cooling infrastructure, and hardware maintenance – strains local grids and conflicts with sustainability goals. In regions with scarce or expensive electricity, investing in computing requires strategic review of energy demands and infrastructure reliability.

But not every country needs local compute infrastructure for AI deployment or training. Cloud computing reliability solves expensive infrastructural demands of data centres. However, while offering scalability and reduced capital expenditure, cloud solutions lead to unpredictable operating costs and require robust internet. Reliance on hyperscalers' cloud infrastructure raises concerns about national autonomy, economic dependency, and value alignment, posing difficult choices: centralise nationally, pool regionally, or risk competing for foreign investment.

On-premises solutions, by contrast, grant direct control over hardware and data but come with an initial cost that is unattainable for most countries, complex maintenance, and underutilisation risk. Regional or shared infrastructure may provide sustainable middle paths, pooling resources to reduce costs, promote economic integration, and strengthen autonomy.

Computational infrastructure fundamentally influences the political economy of AI by determining who builds, what is created, and who profits, with implications for competition, industry concentration, and environmental impacts.

From Investment to Participation: Why Ecosystem Foundations Matter

Countries in this income group currently engage with AI in different ways: most adopt existing tools, while a few are beginning to develop their own solutions. But the fundamental gap is not between individual LLMICs. It is between high-income nations that control AI development and everyone else. Without coordinated, stage-appropriate investment in the AI Triad, these countries may remain dependent: purchasing AI systems built elsewhere and hosting infrastructure owned by foreign companies rather than building the capacity to adapt, customise, and eventually create AI technologies that serve their own needs.

However, sovereign capacity does not require building a fully indigenous technology stack. Countries can achieve meaningful progress by adapting foreign or proprietary technologies through localisation, custom training, and integration with local data and norms (Fournier-Tombs, 2023). This pathway is increasingly viable as efficiency improvements reduce the compute requirements for inference and fine-tuning, even as frontier training costs escalate. The barriers to adaptation are falling precisely as the barriers to frontier competition rise, a divergence that shapes the strategic calculus for LLMICs.

With targeted investment in the AI Triad and supportive policy frameworks, LLMICs may be better positioned to leverage, govern, and shape imported AI systems, potentially enabling a gradual shift from passive adoption toward active co-creation or localised innovation. Consistent with literature on incremental innovation, diffusion, and learning (Viotte, 2002, Khan, 2022), this approach offers a pathway toward technological sovereignty without requiring immense upfront resource commitments.

Achieving this sovereignty through adaptation requires financing strategies that recognise the interdependence of the AI Triad. Each element has distinct funding needs but remains highly interdependent with the others. Robust datasets fuel algorithmic development, though realising their potential typically requires sufficient compute. Compute capacity benefits only with curated datasets and algorithmic expertise. Underinvestment in any element creates bottlenecks, dampening overall effectiveness.

Understanding this interdependence is critical given current investment patterns. Major technology companies like AWS, Microsoft, and Google have begun investing in AI infrastructure in regions like Africa, Latin America, and South Asia. Amazon's $4 billion3 cloud investment in Chile (Cambero, 2025) illustrates how such investments may position countries as both infrastructure hosts and consumers, though whether these arrangements translate into lasting benefits for host countries remains an open question.

While Morgan Stanley (2025) calculates that AI could lead to $40 trillion in operational efficiencies globally and Goldman Sachs (2023) predicts up to $7 trillion in global GDP gains from AI over the next 10 years, and McKinsey (2023) projects generative AI could add $2.6-4.4 trillion annually to the global economy, these benefits will likely concentrate in advanced economies with the resources and ecosystems to harness them quickly, potentially deepening rather than narrowing global divides.

However, these potential gains must be weighed against immediate opportunity costs. Building AI ecosystems implies trade-offs for low-income countries facing urgent developmental needs (Frimpong, 2025). Large AI investments risk diverting scarce resources from health, education, and basic infrastructure where returns may be more predictable and address more immediate needs (Farlow et al., 2023). Returns from AI investment remain uncertain, and technology costs typically decrease over time; waiting may allow for more effective, lower-cost adoption later. Over-investing now in the hope of catching up could inadvertently "kick away the development ladder", where advanced economies climb to success using certain tools and then remove those tools, making it harder for others to follow (Strusani and Houngbonon, 2019). In the case of AI, the traditional ladder (labour-intensive manufacturing, cheaper exports, incremental technological adoption) may vanish, making fundamental needs harder to address and potentially deepening dependency (Korinek, Schindler & Stiglitz, 2021).

Yet the risks of underinvestment are also substantial. Evidence suggests that insufficient investment could widen global economic inequalities, particularly in regions with slower digital development (Korinek & Stiglitz, 2019; Korinek, Schindler & Stiglitz, 2021), potentially causing permanent decline in trade terms between advanced and developing economies.

These competing pressures underscore why equitable AI development requires strategically balancing current investments, laying the groundwork for future adoption, and ensuring that any capacity-building is context-appropriate and responsive to local priorities so that AI becomes an enabler of sustainable development rather than another costly missed opportunity. Uncoordinated or fragmented investment risks deepening the concentration patterns documented in Section 2.1, further limiting the ability of developing nations to participate in the AI economy.

Addressing these challenges requires coordinating diverse funding sources. Multilateral institutions, development finance organisations, governments, private sector investors, and philanthropic foundations each have distinct incentives for supporting AI development in LLMICs. Multi-stakeholder coordination may enable different investments to reinforce one another across economic, social, and technological dimensions.

3 Most comparable projects – like Microsoft Azure's expansion in South Africa – are usually hundreds of millions of dollars, not billions. This makes Amazon's investment in Chile stand out and signals major interest in building global digital infrastructure (Boltt, 2025).

Development Stages and Financing Options Across the AI Triad

Building an AI economy is not an overnight transformation. The European Union, despite substantial resources, has faced challenges in matching the scale of U.S. and Chinese AI ecosystems. If wealthy regions with substantial resources face such difficulties, LLMICs likely face even steeper challenges, suggesting that strategic prioritisation may be particularly important. Rather than competing across all fronts, these countries should prioritise removing bottlenecks to AI diffusion, strengthening governance frameworks, and selecting investment areas with meaningful returns (Khan et al., 2024).

While systematic empirical evidence on AI ecosystem financing in LLMICs remains limited due to the recent emergence of AI as a development priority, we draw on three bodies of established evidence: (1) infrastructure financing literature demonstrating that stage-financing mismatches consistently fail (World Bank & OECD, 2022; Bhattacharya et al., 2015), (2) innovation policy research showing that different funding mechanisms suit different R&D maturity levels (Mazzucato, 2013; OECD, 2015), and (3) technology diffusion studies documenting staged adoption patterns (Rogers, 2003).

We identify three recurring stages (foundation, enhancement, and integration) within each pillar of the AI Triad. This staged approach reflects patterns observed in digital infrastructure programmes (World Bank, 2024) and R&D maturity models (OECD, 2015), where financing needs evolve as projects progress from establishing basic capacity to optimisation and finally to scaled deployment.

Each stage presents distinct levels of institutional maturity, technical complexity, and revenue potential. Financing strategies should therefore align not only with the specific pillar (data, algorithms, compute), but also with its stage of development.

Drawing on the infrastructure financing and innovation policy literature cited above, as well as documented practices from development finance institutions, we identify a spectrum of financing instruments suited to different stages of ecosystem development. Early-stage investments with high uncertainty and long time horizons have typically relied on public or concessional financing. As projects mature and demonstrate clearer outcomes, blended finance mechanisms that combine public and private capital become viable (OECD, 2025). At advanced stages with proven revenue potential, commercial financing can play a larger role (Puerta et al., 2023; World Bank & OECD, 2022). The financing instruments mapped below fall into three broad categories: public financing (sovereign loans, development bonds, technical assistance grants), blended finance (structured funds, performance-based contracts, impact bonds that combine public guarantees with private capital), and commercial financing (venture capital, public-private partnerships, commercial lending). The table below maps these instruments across each pillar and stage, illustrating how financing approaches should evolve alongside ecosystem development.

TABLE 1

Development stages of AI Triad

Stage	Data	Algorithms	Compute	Characteristics
Foundation Laying the Groundwork	Foundation Building	Basic Research	Core Infrastructure	Countries put the prerequisites in place: physical facilities, research labs, governance rules, and initial human capital programmes. Funding here is long term and often public because there is little immediate revenue.
Enhancement Improving and Proving	Quality Enhancement	Applied Development	Enhancement and Optimisation	The focus shifts to making the initial assets work better: raising data quality, turning research into prototypes, or boosting energy efficiency in data centres. Blended or performance-linked finance may become viable because the projects now have clearer milestones and, in some cases, revenue signals.
Integration Scaling and Integrating	System Integration	Commercialisation	Scaling and Specialisation	Mature systems are linked together, exported to new sectors, or rolled out country-wide. Private capital becomes more prominent (VC, PPPs, commercial loans) and funding is usually tied to measurable market or policy outcomes.

The following subsections detail how these financing instruments apply to each pillar of the AI Triad. The financing instruments in Tables 2–4 draw on practices documented by development finance institutions (Puerta et al., 2023; World Bank & OECD, 2022).

Data Infrastructure

At the foundation stage, countries establish national data centres, improve connectivity, and create data governance frameworks. These efforts are often public sector led, given limited near-term commercial incentives. Low-risk, long-horizon financing (sovereign loans and technical assistance grants) is commonly used for these efforts. Rwanda's National Data Centre is an example of the strategic use of concessional financing (World Bank, 2021). The country has relied heavily on concessional sovereign loans and technical assistance to finance core digital public infrastructure, including data centres and shared platforms, through the World Bank's Digital Acceleration Project co-financed with AIIB (World Bank, 2021), and through a joint-venture model for the National Data Center with Korea Telecom (World Bank, 2019).

In the enhancement stage, the focus shifts to improving data quality, expanding interoperability, and building trusted sharing platforms. Blended finance tools (structured funds, sustainability-linked bonds) become viable (IEEFA, 2023). For example, India's Aadhaar ID system combined World Bank loans (which paid out only after meeting data quality targets) with private vendor financing. Meanwhile, innovation awards can incentivise startups to solve specific data processing challenges.

At the integration stage, data systems are embedded across sectors and increasingly involve private providers. Public-private partnerships (PPPs), commercial lending, and revenue-linked instruments (e.g., royalties, data licensing contracts) can support deployment at scale. PPPs dominate capital formation, commercial loans fund specialised expansions, and results-based contracts tie payments to integration metrics such as utilisation rates or cross-border data-flow compliance. Estonia's X-Road platform,[4] financed by a mix of EU structural funds and domestic PPPs, shows how an initially public asset can evolve into a commercial backbone for digital-service industries.

TABLE 2

Data Infrastructure

Stage	Focus Areas	Potential Financing Options
Foundation Foundation Building	Infrastructure: Core systems, storage, collection; Governance: Frameworks, security standards	Sovereign loans, Development bonds; Technical assistance grants
Enhancement Quality Enhancement	Data quality, interoperability, accessibility, privacy	Performance contracts, Structured funds, Impact bonds, Innovation awards
Integration System Integration	Ecosystems, analytics, cross-sector, international standards	Public-private partnerships, Commercial financing, Specialised data funds, Results-based financing

Algorithm Development

At the foundation stage, the key is building basic research and teaching capacity, primarily through universities and research institutes. Direct public funding is typically necessary since commercial applications are distant and uncertain. Levy (2011) argues that non-repayable public grants and stable, university-centred funding mechanisms may be particularly well-suited to building research capacity and institutional infrastructure required for long-term innovation. However, in many LLMICs where immediate development needs are pressing, universities serve less as pure research centres and more as practical training grounds for AI talent and testing sites for locally relevant applications. Public grants and technical assistance from development partners support faculty training, curriculum development, and basic computing resources for students.

4 Estonia's X-Road is an open-source software platform and ecosystem that enables secure, standardized, and seamless data exchange between both public and private sector organizations. It acts as the backbone of Estonia's renowned digital government infrastructure, playing a central role in delivering hundreds of electronic services to citizens and businesses.

At the enhancement stage, the focus shifts from theory to practice, developing prototypes that address specific local challenges. Innovation prizes offer an alternative mechanism, paying only for successful outcomes: Brazil's AI for the Amazon challenge, for instance, pays research teams only after their algorithms achieve specified accuracy in detecting illegal deforestation from satellite images. Impact bonds can fund social applications, where private investors provide upfront capital for AI health or education solutions, and governments or donors repay them only if predetermined outcomes are achieved. Philanthropic organisations like the Gates Foundation and technology companies like Meta offer grants for applying AI to development challenges, providing more flexible funding than traditional government sources do.

At the integration stage, successful prototypes scale into commercial products or widely deployed public services. Venture capital funds invest in AI startups with proven products and revenue potential. Mezzanine finance (combining elements of debt and equity) helps companies transition from grant funding to commercial operations without giving up excessive ownership. Kenya's Safaricom Digital Innovation Fund exemplifies this approach, providing graduated support from early grants through to growth capital. Additionally, crowdfunding platforms have emerged as important early-stage funding sources, allowing AI startups to raise capital while simultaneously testing market demand.

Adapting financing strategies to local circumstances, including longer-term grants for capacity-building, targeted awards for applied problem-solving, and blended finance for scaling, may help countries develop more sustainable innovation ecosystems, reduce dependence on external expertise, and address local priorities while creating inclusive economic opportunities.

TABLE 3

Algorithm Development

Stage	Focus Areas	Potential Financing Options
Foundation Basic Research	Research capacity, infrastructure, talent	Technical assistance grants, Equity investments
Enhancement Applied Development	Application design, testing, integration	Innovation awards, Impact bonds, Mezzanine finance
Integration Commercialisation	Scaling, business models, market presence	Venture capital, Structured funds, Commercial loans

Compute Infrastructure

In LLMICs, establishing foundational computing infrastructure (such as data centres or cloud nodes) typically requires first addressing the critical precondition of reliable electricity access. Most face severe national and regional power supply constraints, often making large-scale server facilities impractical without parallel investments in the energy sector. Consequently, digital infrastructure development should typically be sequenced behind, or bundled with, new energy projects, particularly electricity generation and grid expansion. Sovereign loans, syndicated loans, and technical assistance grants are commonly used financing instruments at this stage. Multilateral banks, donors, and governments may jointly finance integrated programs combining power plants (especially renewables) with digital facilities or provide dedicated mini-grids for critical digital assets. For example, modular or micro data centres powered by off-grid solar, wind, or hydro can serve as interim solutions, supporting priority sectors like health or education until large-scale grid access is established.

As the digital ecosystem matures, enhancement efforts focus on distributed and resilient approaches that optimise efficiency and sustainability. This includes micro-grids and renewable-powered data facilities designed to support ongoing digital operations where grid reliability is limited. Performance-based and climate-linked finance are emerging tools to incentivise energy efficiency and ensure operational continuity. As seen in the Democratic Republic of the Congo, large-scale solar hybrid mini-grids, developed in partnership with the World Bank and other international financiers, are bringing electricity not only to households and businesses but also to digital and telecommunications hubs in remote and underserved regions, highlighting how digital and electrification investments must go hand in hand. Africa Data Centres has also pioneered the integration of renewable-powered data centres, signing long-term power purchase agreements to deliver solar energy directly to their facilities, alleviating stress on unreliable national grids while supporting sustainability.

At the integration stage, countries expand beyond basic capacity to advanced facilities and sector-specific applications (Alonso, 2016). Here, public-private partnerships, specialised funds, and results-based financing become critical tools for scaling and specialisation. Participation may include accessing compute remotely through regional cloud platforms or "compute-as-a-service" models that allow countries to leverage advanced capabilities hosted abroad. This enables participation in the global AI economy while circumventing some local infrastructure and power limitations. Regional data parks and initiatives (such as cross-border renewable investments and digital substations in West Africa) suggest how public-private partnerships and regional cooperation can deliver sustainable, scalable, and inclusive digital capacity.

Over time, some countries may also seek regional dominance or niche specialisms (e.g., biotech computing) as part of their strategic positioning in the global AI economy.

TABLE 4

Development Stages and Financing Options – Compute Infrastructure

Stage	Focus Areas	Potential Financing Options
Foundation Core Infrastructure	Facilities, energy systems, technical capacity	Sovereign loans, Syndicated loans, Technical assistance grants
Enhancement Enhancement and Optimisation	Efficiency, capacity, sustainability	Structured funds, Performance-based financing, Green bonds
Integration Scaling and Specialisation	Advanced facilities, sector-specific applications	Public-private partnerships, Specialised funds, Results-based financing

These development stages across the AI Triad illustrate how financing needs evolve as countries build their AI ecosystems. The progression from foundation through enhancement to integration is neither linear nor uniform; countries may be at different stages across different pillars, requiring careful coordination of financing instruments.

The framework suggests three insights for policymakers and development partners:

First, sequencing matters: attempting to deploy sophisticated financing instruments before foundational capacity exists often wastes resources and may create unsustainable dependencies, as infrastructure financing literature suggests (World Bank & OECD, 2022; Bhattacharya et al., 2015). Countries should assess their current stage across each pillar and resist pressure to leap ahead prematurely.

Second, coordination across pillars is important. A country with excellent data infrastructure but limited capacity to develop or adapt algorithms may face significant constraints in participating in the AI economy. Financing strategies should therefore address all three pillars in parallel, even if at different speeds.

Third, the rapid evolution of AI technologies requires financing mechanisms with built-in flexibility. Unlike traditional infrastructure, where technical specifications remain stable over decades, AI ecosystems face continuously shifting computational requirements and data governance norms. Rigid long-term commitments without adjustment mechanisms risk locking countries into approaches that become obsolete or misaligned with emerging opportunities.

Institutional Design for Financing the AI Triad

03

Institutional Design for Financing the AI Triad

Over the past two decades, global health, climate, infrastructure, and technology funds have collectively deployed over $100 billion in support of public goods (UN IATF, 2022). While results have varied, these vertical funding mechanisms offer instructive lessons for institutional design – particularly in LLMICs, where equitable access and innovation remain constrained. Global initiatives such as Gavi and the Global Fund suggest how vertical funds can mobilise capital at scale, pool risk, and address collective-action challenges, features that resemble those now emerging in AI. This section especially draws on nine flagship funds – including Gavi, the Global Fund, the Green Climate Fund (GCF), the Global Environment Facility (GEF), and the UN Technology Bank – to identify recurrent patterns in governance, financial structure, country ownership, performance measurement, and risk mitigation. These comparative insights are translated into design principles that can guide the creation of effective and equitable financing architectures for AI ecosystems.

This section proceeds in three steps: First, we examine lessons from global funds, identifying what distinguishes successful mechanisms from failed initiatives across five dimensions: governance structure, alignment with local priorities, financing sustainability and predictability, outcome measurement and adaptation, and risk management. Second, we translate these lessons into five operational design levers specifically adapted for AI ecosystem financing. These levers, governance, local ownership, finance and predictability, outcome and KPIs, and integrity and risk safeguards, form the institutional scaffold for effective AI financing. Third, we demonstrate how these levers apply differently across the three pillars of the AI Triad (data, algorithms, and compute), providing a diagnostic framework that policymakers and funders can use to design context-appropriate financing mechanisms.

Lessons from Global Funds: Success Factors and Failure Modes

The first success factor is **governance that distributes authority across multiple constituencies.** Funds where formal authority is shared among donor countries, recipient governments, civil society, and technical experts appear to perform more effectively than those dominated by a single group, based on the cases examined (see Annex 2). Gavi's 28-member board, for instance, is divided into eight voting blocs: donors, implementing countries, civil society, multilateral agencies, foundations, the private sector, research institutions, and two independents (Gavi, 2025). Every grant must first be approved by an Independent Review Committee insulated from political pressure (Gavi, 2025). This arrangement has mobilised over $23 billion (Kaiser Family Foundation, 2024). In climate finance, the Adaptation Fund's 16-seat board balances regional groups, least-developed countries and small-island states, while an expert accreditation panel certifies entities seeking direct access – resulting in the approval of 183 local projects in 54 countries (Adaptation Fund, 2024). Meanwhile the Global Environment Facility overlays a dual-majority rule that needs 60% of contributions and 60% of countries for any decision, preventing domination. Between fiscal years 2022 and 2024, GEF funding supported 130 million ha of protected areas, improved land management on 25 million ha, and averted 840 million t CO_2-e (Global Environment Facility, 2024). These cases suggest that distributing decision-making authority across diverse blocs, reinforced by independent review mechanisms, may help reduce the risk of capture by any single donor, government, or vendor.

A second factor is **local ownership**. Successful initiatives were grounded in comprehensive local needs assessments and demand-driven design, ensuring projects were relevant and context-specific (see Annex 3). For example, Gavi employed a demand-driven approach by aligning vaccine priorities with national immunisation plans, ensuring that funded projects met actual local health needs.

Similarly, the Global Fund promotes country ownership through Country Coordinating Mechanisms (CCMs), which engage local governments, civil society, and community organisations in strategic planning, implementation, and monitoring (Global Fund, 2023). The Global Infrastructure Facility (GIF) actively includes representatives of emerging markets and developing economies (EMDE) in strategic decision-making processes, ensuring that infrastructure projects align with local economic priorities. Moreover, the Green Climate Fund (GCF) adopts a country-driven model, requiring National Designated Authorities (NDAs) to approve projects, ensuring alignment with national climate strategies (Green Climate Fund, 2024). By contrast, donor-driven agendas often resulted in strategic misalignment and diminished local ownership. Taken together, these mechanisms suggest that funds are more effective when they embed national strategies and local community priorities into design and disbursement rather than relying on donor-driven agendas.

A third factor is **finance and predictability**, which proved important for strategic planning, operational stability, and program scalability (see Annex 4). Multi-year commitments provided certainty, enabling initiatives to design and implement long-term interventions. Gavi established a First Response Fund, allocating up to $500 million to enable rapid vaccine procurement during health emergencies (Gavi Staff, 2024), such as the mpox outbreak in Africa. Furthermore, the expansion of vaccine bonds through IFFIm continues to strengthen Gavi's financial sustainability by raising capital from international markets while distributing donor commitments over time (IFFIm, 2026). The Green Climate Fund (GCF), on the other hand, set long-term funding targets ($100 billion by 2030) to provide predictable funding for climate adaptation and mitigation projects.

Innovative financial instruments, such as guarantees, bonds, and blended finance mechanisms, leverage private capital and enhance sustainability. The Global Infrastructure Facility uses blended finance, including guarantees and concessional loans, to de-risk infrastructure investments, attracting private investors. Gavi's Advance Market Commitments stimulate vaccine markets and guarantee future purchases, securing long-term manufacturer commitments and reducing price volatility. These approaches suggest that predictability and diversification reduce volatility, enhance trust, and enable long-term planning.

Fourth, **outcome and KPI frameworks** underpin stronger performance (see Annex 5). The Global Fund links primary indicators to epidemiological outcomes; AIDS-related deaths in supported countries declined 73% between 2002 and 2023. Gavi conditions disbursements on vaccination-coverage targets and revises metrics each funding cycle, allowing new evidence to inform allocation decisions. Tying funding to measurable outcomes while regularly revising metrics creates both accountability and flexibility, as illustrated by the Global Fund and Gavi models.

Fifth, **integrity and risk safeguards** help prevent financial mismanagement and strategic disruptions (see Annex 6). For example, the Global Fund implements comprehensive risk assessments, real-time monitoring, and mitigation strategies. Gavi integrates risk management into performance-based funding, using real-time data and financial audits to monitor risks. Proactive frameworks covering financial, operational, and reputational risks help prevent mismanagement and enable adaptation to shocks, though no system eliminates these risks entirely.

Two failure modes also surface repeatedly. The first is capture by profit-seeking actors. For example, pharmaceutical seats on Gavi's board kept pricing data opaque; during the first year of COVID-19 vaccine rollout, more than 80% of Pfizer-BioNTech doses were channeled through bilateral deals with high-income countries, side-stepping COVAX. A parallel hazard exists for AI-capacity funds if large technology firms dominate without adequate checks. The second failure mode is a concentrated donor base leading to agenda volatility. In the Global Fund's seventh replenishment, 92% of resources came from just 50 donors, enabling conditionalities that sometimes diverged from recipient priorities – most notably in Liberia, where donor-selected indicators displaced local health targets. A similar misalignment could occur if AI funds lean heavily on a small group of government or corporate sponsors.

Translating Lessons into Design Principles: Five Levers for AI Ecosystem Financing

Building on these lessons, we outline an operational framework for financing AI capacity across the three pillars. Our comparative analysis suggests five institutional features that distinguish more effective financing mechanisms in health, climate, and infrastructure domains: (1) governance structures that distribute authority and prevent capture, (2) local ownership to ensure relevance to national priorities, (3) finance and predictability through stage-appropriate instruments, (4) outcome and KPI frameworks focused on results, and (5) integrity and risk safeguards to reduce mismanagement.

We propose that these principles may transfer to AI financing, though with important adaptations given AI's distinct characteristics: rapid technological change, concentrated industrial structure, dual-use concerns, and nascent governance frameworks.

The table below summarises how each of the five institutional levers applies across the AI Triad. It is intended as a diagnostic tool, rather than a prescriptive blueprint, helping policymakers and funders visualise how common principles of governance, ownership, finance, measurement, and integrity can be adapted to the specific contexts of data, algorithms, and compute. By making these differences explicit, the framework supports more coherent, balanced, and transparent approaches to financing AI capacity.

TABLE 5

The five levers apply differently across the three pillars of the AI Triad

Institutional lever / risk guard	Algorithms (Talent, R&D, Scaling)	Compute	Data
Governance	AI institutes propose; Parity Board approves; Scientific Council may veto.	Oversight Panel certifies procurement; utilisation dashboards; vendor cap 25%.	Data Councils license exchanges; ethics review; public dataset registry.
Local Ownership	Investment Case sets research themes; domestic co-funding required.	Credits released against Investment-Case milestones; regional hubs under consortium MOUs.	Dataset road-maps co-authored with statistics offices; 10% budget for stewardship skills.
Finance and Predictability	Public grants matched 1:1 by private labs; four-year pledges; 12-month liquidity reserve.	Concessionary cloud, lease-to-own GPUs, PPPs; donor vote ≤20%.	Revolving data-trust fund recycles licence fees; core upkeep in replenishment cycle.
Outcome and KPIs	Workforce share in AI roles; support: checkpoints, energy per run.	Median inference compute-hours; utilisation, diversity index.	% datasets FAIR+Secure; refresh rate, user-access count.
Integrity and Risk Safeguards	Corporate ownership cap; disclosure; open-access for publicly funded models; real-time grant dashboard; whistle-blower hotline; fraud ratio <0.1%.	Audit of prices; contract disclosure in 72 h; competitive bidding; random audits; supplier blacklist.	Reciprocity rule on data use: users of national data contribute back or document local benefits; public ledger of data-sharing agreements; periodic multi-stakeholder review.

These provisions create a modular, adaptive structure aligned with global best practice. They may enable actors in LLMICs to attract diverse capital while safeguarding public interest, ensuring national agency, and maintaining ecosystem integrity by enabling LLMICs to participate as producers, not merely consumers, in the AI economy.

This workflow, drawn from Gavi and Global Fund lessons, operationalises the five design levers into a practical sequence. Structured review cycles, independent oversight, and tranche-based disbursement maintain accountability while enabling flexibility.

1 Drafting the Investment Case

Drafting the Investment Case: Country teams prepare an AI Investment Case integrating the three pillars into broader digital strategy, including budgets, KPIs, and national priorities.

2 Independent Review and Approval

The Parity Board and Independent Scientific Council review the case, ensuring proposals are technically sound, ethically robust, and capture-resistant.

3 Initial Disbursement

Approved cases receive Tranche 1 (12-month funding) for foundational activities while establishing KPI baselines.

4 Mid-term Review and Adjustment

At month 12, structured review adjusts activities and KPIs as needed, updates risk registers, and releases Tranche 2 based on performance and continued alignment.

This sequencing balances predictability with adaptability, transforming broad commitments into enforceable programs that evolve with evidence and changing contexts.

Conclusion

04

Conclusion

This white paper has presented a framework for financing AI ecosystems in low- and lower-middle-income countries (LLMICs). Artificial intelligence is rapidly becoming embedded in the global economy, yet this transformation is unfolding unevenly. U.S. institutions produced 40 notable AI models in 2024 compared to China's 15 and Europe's 3 (Stanford HAI, 2025); Africa hosts less than 1% of global data centre capacity despite comprising 17% of the world's population (ADCA, 2024); and the least developed countries maintain only 27% internet connectivity compared to 63% globally (UNCTAD, 2023).

These disparities matter because meaningful participation in the AI economy likely requires building integrated ecosystems where technology, human capital, institutions, and markets reinforce each other. At the core lies the AI Triad: three foundational pillars that benefit from developing in concert. Without capacity across all three, countries risk lasting dependencies rather than building the foundations that sovereign AI capacity may require.

For LLMICs, the challenge is not whether to compete in frontier AI development, but how to allocate scarce resources strategically. Our analysis suggests that each pillar of the Triad evolves through distinct phases (foundation, enhancement, and integration), each suited to different financing instruments. Foundation-building typically demands patient public capital. Enhancement may benefit from blended finance. Integration can attract commercial investment. Attempting to deploy sophisticated financing before foundational capacity exists risks wasting resources, as infrastructure financing literature suggests (World Bank & OECD, 2022; Bhattacharya et al., 2015).

Our comparative analysis of nine global funds identified institutional features that appear to distinguish more successful financing mechanisms: distributed governance, demand-driven design, predictable funding, outcome-linked measurement, and safeguards against mismanagement. These principles derive from analogical reasoning across sectors, and their applicability to AI financing remains to be tested empirically.

Rather than proposing a maturity ladder that assumes uniform development, we advocate for a building-block approach. This means starting with minimum viable foundations: digitising priority datasets, piloting localisation projects, and accessing compute through cloud credits or regional hubs. Countries can then sequence investments, moving from adaptation to co-creation when talent and validated use cases warrant.

We found further that three insights should guide implementation. First, the AI Triad should be financed as a system. Second, financing strategies should match development stages. Third, institutional design shapes outcomes and should be addressed from the outset.

The stakes are high. Recent commitments, from the $400 million Current AI initiative to Africa's proposed $60 billion fund, signal growing recognition of AI's potential. The framework proposed here offers one route toward ensuring that investments reinforce rather than undermine local capacity. Whether it proves sufficient to ensure that no country is left behind remains an open question, one that will depend on political will, resource mobilisation, and learning from experience.

Annexes

05

Annex 1
Overview of Case Studies Analysed

This annex provides a summary of all case studies, including goals, funding amounts, years, and funding types.

Initiative	Goals and Objectives	Funding Amount (USD)	Year	Funding Type
UN Technology Bank	Bridge digital divide and build STI capacity in LDCs	~$40 million/ year (Voluntary)	2018 - Ongoing	Grants, voluntary contributions
Global Infrastructure Facility (GIF)	Mobilise private capital for sustainable infrastructure	$1.2 billion (Project Prep and TA)	2014 - Ongoing	Blended finance, PPPs
Green Climate Fund (GCF)	Climate adaptation and mitigation in developing countries	$10 billion initial; $100 billion target	2015 - Ongoing	Grants, loans, equity, guarantees
Gavi, the Vaccine Alliance	Equitable vaccine access and health system strengthening	$21 billion (Cumulative)	2000 - Ongoing	Grants, IFFIm, AMCs
Global Fund	Fight AIDS, tuberculosis, and malaria; strengthen health systems	$55.4 billion (Cumulative)	2002 - Ongoing	Grants, performance-based funding
Global Financing Facility (GFF)	Improve reproductive, maternal, newborn, child, and adolescent health and nutrition through health system financing	$2.6 billion; $8.5 billion leveraged	2015 - Ongoing	Blended finance, grants, concessional loans
Global Environment Facility (GEF)	Environmental protection (biodiversity, climate change)	$21 billion; $107 billion leveraged	1991 - Ongoing	Grants, concessional loans, blended finance
Adaptation Fund (AF)	Climate adaptation for vulnerable communities	$923 million (CDM levy and voluntary)	2001 - Ongoing	CDM levy, voluntary contributions
Just Transition Transaction (JTT)	Support South Africa's energy transition	$8.5 billion (Pledged)	2021 - Ongoing	Blended finance, grants, concessional loans

Annex 2
Governance Structure Across Case Studies

Governance Sub-Factor	Clear Division of Strategic Oversight and Operational Management	Multi-Stakeholder Representation and Balanced Decision-Making	Independent Accountability Mechanisms and External Oversight	Adaptive and Flexible Governance Models	Transparent Decision-Making and Conflict-of-Interest Policies
UN Technology Bank	Strategic Council lacked operational insight	Balanced representation	External audits lacked enforcement power	Adaptive reforms enhanced strategic alignment	Initial lack of transparency, improved through reforms
GIF	Clear role separation	EMDE representation	Independent evaluations and reporting	Flexible decision-making	Clear role separation and transparency
Gavi	Effective separation, minor inefficiencies	Power imbalances with donor influence	Strong oversight, direct reporting	Slow adaptation to emerging challenges	Private sector influence in procurement
Global Fund	Strategic influence on operations	Donor dominance	Alleged conflicts of interest	Adaptive planning with feedback loops	Alleged conflicts of interest
GCF	Centralised decision-making	Power asymmetry	Limited enforcement in strategic decisions	Rigid strategic framework	Insufficient transparency mechanisms
Adaptation Fund (AF)	Clear Board–Accreditation Panel separation; Direct Access strengthens operational clarity	Balanced developed/developing representation; dedicated LDC and SIDS seats	Independent Accreditation Panel; multi-level evaluation framework	Results-Based Management; evolving resource mobilisation strategy	Initial trustee reliance (World Bank) raised concerns; transparency strengthened over time
GFF	Donor-driven strategic oversight	Donor-driven priorities	Limited independence in evaluations	Inflexible donor conditions	Donor influence affected transparency
GEF	Strategic misalignment	Donor influence on strategic decisions	Donor influence affected transparency	Slow strategic adaptations	Inconsistent transparency measures
JTT	Overlap in strategic and operational roles	Imbalance in international donor influence	Lack of independent audits	Iterative feedback and strategic agility	Inadequate conflict-of-interest policies

Annex 3
Local Ownership Performance Across Case Studies

Local Ownership Sub-Factor	Demand-Driven Project Design and Contextual Relevance	Country-Led Implementation and Leadership Development	Capacity-Building and Institutional Strengthening	Alignment with Local Priorities and National Development Plans
UN Technology Bank	Needs assessments ensured contextual relevance	Limited leadership development, but locally led projects	Technical training and STI capacity-building programs	Aligned with national technology strategies
GIF	EMDE input shaped project priorities	Partial local implementation, but strategic decisions centralised	Limited capacity-building focus	Aligned with local economic priorities
Gavi	Aligned with national immunisation plans	Co-financing promoted country-led implementation	Health system strengthening supported local institutions	Integrated with national health plans
Global Fund	Contextual relevance varied by country	CCMs empowered local actors	Governance capacity-building through CCMs	Aligned with national health priorities
GCF	Country-driven approach ensured local relevance	International entities dominated implementation	Capacity-building limited to project management	Aligned with national climate strategies
Adaptation Fund (AF)	Direct Access + locally-led adaptation emphasis strengthened contextual fit	National Implementing Entities (NIEs) led delivery	Accreditation support built national institutions, but capacity constraints affected implementation quality in some contexts	Strong alignment via national/local policy coherence requirements and relevance criteria
GFF	Investment cases varied in alignment with local needs	Donor conditions limited leadership autonomy	Institutional reforms and capacity-building	Variable alignment with national development plans
GEF	Mixed success in contextual adaptation	Mixed success in local leadership development	Limited capacity-building, focus on technical assistance	Alignment varied by country and sector
JTT	Limited local adaptation in project design	Limited local leadership, reliance on international partners	Inconsistent capacity-building efforts	Strategic alignment inconsistent with national plans

Annex 4
Financial Sustainability and Predictability Performance Across Case Studies

Financial Sustainability Sub-Factor	Diversified Funding Sources and Multi-Donor Contributions	Innovative Financial Instruments and Blended Finance	Multi-Year Funding Commitments and Predictable Cycles	Risk Mitigation and Financial Safeguards
UN Technology Bank	Over-reliance on voluntary contributions	Limited use of innovative instruments	Inconsistent disbursements	Limited financial safeguards, later improved
GIF	Multi-donor and PPPs	Guarantees and concessional loans for de-risking	Multi-year cycles for strategic continuity	Comprehensive fiduciary controls
Gavi	Blended public, private, and philanthropic sources	AMCs and IFFIm for predictable commitments	Multi-year commitments for sustained programs	Rigorous anti-corruption and audits
Global Fund	Multi-donor contributions with co-financing	Performance-based funding	Predictable disbursement schedules	Real-time financial reporting and audits
GCF	Delays in donor pledges impacted funding cycles	Blended finance for climate resilience	Delays in multi-year pledges impacted timelines	Insufficient enforcement in risk management
Adaptation Fund (AF)	Initial CDM levy provided innovation, but later reliance on voluntary contributions increased volatility	2% CDM share-of-proceeds model; early example of automatic climate finance mechanism	Carbon market decline disrupted predictability; increasing reliance on replenishment-style pledges	Fiduciary standards, accreditation requirements, multi-level evaluation and reporting framework
GFF	Variable co-financing commitments	Blended finance with concessional loans	Unpredictable cycles due to donor conditions	Variable fiduciary controls by country
GEF	Dependency on GEF Trust Fund contributions	Limited use of blended finance	Inconsistent funding cycles	Inconsistent risk management frameworks
JTT	Over-reliance on international donors	Blended finance challenges in leveraging private capital	Uncertainty in long-term commitments	Limited anti-corruption measures

Annex 5
Accountability and Impact Measurement Performance Across Case Studies

Accountability and Impact Measurement Sub-Factor	Robust Monitoring and Evaluation Systems	Clear and Measurable Key Performance Indicators (KPIs)	Independent Oversight and Auditing	Adaptive Feedback Mechanisms and Strategic Learning
UN Technology Bank	Inconsistent M&E systems, later improved through reforms	Vague KPIs limited strategic alignment	External audits lacked enforcement power	Limited feedback loops, improved with strategic reforms
GIF	Comprehensive M&E with regular reporting	Clear, measurable KPIs linked to strategic objectives	Independent evaluations with direct reporting	Adaptive decision-making with strategic feedback loops
Gavi	Quantitative and qualitative indicators for holistic evaluation	Well-defined KPIs for health system strengthening	Office of the Inspector General ensuring impartiality	Real-time adjustments based on evidence-based feedback
Global Fund	Results-based M&E linked to performance-based funding	Country-specific KPIs linked to strategic objectives	Independent oversight with direct Board reporting	Strategic learning integrated into planning processes
GCF	Sector-specific M&E linked to national strategies	Sector-specific KPIs aligned with NDCs	Independent oversight, but limited enforcement	Strategic feedback loops for policy refinement
Adaptation Fund (AF)	Results-Based Management project-, portfolio-, Fund-level evaluations	Strategic Results Framework with defined impact, outcome, and output indicators	Independent evaluation mechanisms, but enforcement authority more limited	Periodic evaluations and mid-term reviews integrated into strategic adjustments
GFF	Variable M&E frameworks by country	Inconsistent KPIs across countries	Limited independence in evaluations	Variable feedback integration by country
GEF	Mixed success with qualitative assessments	Output-based KPIs varied in strategic relevance	Donor influence impacted transparency	Slow adaptation to strategic lessons learned
JTT	Inconsistent M&E systems, reliance on donor reporting	KPIs focused on short-term outputs, lacking long-term impact metrics	Limited independent audits, reducing financial accountability	Inconsistent integration of feedback loops

Annex 6
Risk Management and Conflict Mitigation Performance Across Case Studies

Risk Management and Conflict Mitigation Sub-Factor	Comprehensive Risk Assessment Frameworks	Conflict-of-Interest Policies and Governance Safeguards	Anti-Corruption Measures and Financial Safeguards	Transparent Decision-Making and Stakeholder Trust
UN Technology Bank	Inconsistent risk assessments, improved with strategic reforms	Initial lack of clear role definitions, improved through reforms	Limited financial safeguards, later enhanced with audits	Limited transparency in early stages, improved through public reporting
GIF	Proactive risk monitoring and mitigation strategies	Clear role definitions, advisory roles without decision-making power	Rigorous fiduciary controls and anti-corruption measures	Transparent project selection and public reporting
Gavi	Real-time risk monitoring integrated with performance-based funding	Comprehensive conflict-of-interest policies	Real-time financial reporting and anti-corruption mechanisms	Transparent decision-making with public disclosures
Global Fund	Comprehensive risk management framework	Mandatory disclosures and recusal procedures	Whistleblower protection and external audits	Public reporting and stakeholder consultations
GCF	Inconsistent risk assessments by country	Perceived conflicts due to international dominance	Inconsistent enforcement of anti-corruption policies	Insufficient public transparency
Adaptation Fund (AF)	Fiduciary standards requirements; structured evaluation framework	Balanced Board representation, but trustee reliance created perceived influence concerns	Accreditation-based fiduciary controls; financial reporting and evaluation oversight	Direct Access modality strengthened local trust; public reporting and evaluation disclosures
GFF	Variable risk management practices by region	Inconsistent conflict-of-interest disclosures	Variable fiduciary controls across countries	Inconsistent transparency measures
GEF	Mixed success in risk monitoring	Donor influence affected governance integrity	Inconsistent financial safeguards	Limited stakeholder engagement
JTT	Limited risk assessments and mitigation strategies	Limited governance safeguards against conflicts	Limited anti-corruption frameworks	Inadequate transparency in decision-making

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