

A Scientific Advisory on Reinforcement Learning in Cashless and Mobile Financial Systems for Inclusive Finance and Equity Support in Developing Economies

Dr. Syed Muntasir Mamun • Abdullah Al-Matin • Dr. Obi Umegbolu

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Abstract

This advisory explores the integration of Reinforcement Learning (RL) into Mobile Financial Services (MFS) to advance inclusive finance and equity in developing economies, with a focus on Bangladesh and Nigeria. RL, an adaptive AI paradigm that trains agents through dynamic interactions and rewards, offers transformative potential beyond traditional models by enabling real-time decision-making in volatile financial environments. Key applications include alternative credit scoring using digital footprints and psychometrics, adaptive fraud detection via algorithms like DQN and PPO, and multi-agent systems for entrepreneurship, such as gamified financial literacy tools.

A comparative analysis contrasts Bangladesh's centralized, bank-led MFS ecosystem—dominated by players like bKash and featuring AI-powered MSME lending—with Nigeria's decentralized, innovation-driven landscape, supported by regulatory sandboxes and fostering competition among fintechs like OPay. Despite promising opportunities for poverty alleviation aligned with UN SDGs 1 and 8, challenges persist, including the digital divide (e.g., gender gaps in access and literacy), computational hurdles in data-scarce regions, ethical risks like algorithmic bias from flawed reward designs, and pitfalls in public-private partnerships.

Recommendations advocate stakeholder-centric strategies: establishing RL regulatory sandboxes, investing in localized infrastructure, deploying human-centered AI for equitable outcomes, and harmonizing cross-border policies. By addressing these imperatives, developing economies can harness RL to foster resilient, inclusive financial systems, potentially boosting GDP while mitigating inequities.

A short primer on the fluid institutions narrative and a case study on China have been provided at the end. These two provide narrative indications for the future research advisories in regards to the paper at hand.

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Executive Summary

This public advisory examines the transformative potential of Reinforcement Learning (RL)—a dynamic AI paradigm that trains autonomous agents through iterative actions, states, and rewards—to enhance Mobile Financial Services (MFS) for inclusive finance, poverty alleviation, and equity in developing economies. Aligned with UN Sustainable Development Goals (SDGs) 1 (No Poverty) and 8 (Decent Work and Economic Growth), RL surpasses traditional AI by enabling adaptive, real-time decision-making in volatile markets, addressing systemic exclusions faced by unbanked populations, youth, women, and marginalized groups. In regions like Bangladesh and Nigeria, where MFS has reduced transaction costs by up to 90% and formalized informal economies, RL promises to bridge persistent gaps exacerbated by digital divides, gender disparities in literacy (e.g., 37-41% for women), and a 112% surge in cybersecurity threats.

At its core, RL’s agent-environment framework—comprising states, actions, rewards, and policy optimization via algorithms like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO)—facilitates discovery over mere pattern recognition, mitigating biases in historical data. A comparative analysis highlights divergent MFS ecosystems: Bangladesh’s centralized, bank-led model, dominated by bKash (239.3 million accounts, Tk 1.72 trillion transactions in January 2025), emphasizes stability through regulations requiring bank subsidiaries, exemplified by AI-driven MSME credit scoring via partnerships like Community Bank, PriyoShop, and InsightGenie (93% accuracy using alternative data). In contrast, Nigeria’s decentralized approach, fueled by a regulatory sandbox, has attracted \$2 billion in fintech funding (2024), supporting over 430 companies and ₦159.419 trillion in mobile payments (H1 2024), with competitive players like OPay and PalmPay driving innovation in fraud detection and risk assessment.

Key Reinforcement Learning (RL) applications include:

- **Advanced Credit Scoring:** Leveraging alternative data (digital footprints, psychometrics) to extend loans to unscorable populations, such as Bangladesh’s 5 million undocumented retailers.
- **Adaptive Fraud Detection:** Modeling threats as Markov Decision Processes for proactive, real-time responses, reducing false positives.
- **Multi-Agent Systems for Entrepreneurship:** Optimizing supply chains and gamifying financial literacy (e.g., personalized adaptive games) to boost engagement, drawing from platforms like Kuaishou, which created 43 million jobs by 2024.

Despite these opportunities, deployment faces multifaceted barriers:

- **Digital Divide:** Low internet penetration (44.5% in Bangladesh, 48% in Nigeria), high data costs (up to 1% of household income), and gender gaps (e.g., 19% women vs. 36% men)

in Bangladesh mobile internet use).

- **Technical Hurdles:** Data scarcity, computational demands, and infrastructure issues like 40% downtime from power instability in Nigeria.
- **Ethical Risks:** Algorithmic bias from misaligned rewards, potentially exacerbating exclusion (e.g., favoring high-income borrowers), and “algorithmic colonization” via flawed Public-Private Partnerships (PPPs), which often prioritize profits over public good.
- **PPP Challenges:** Historical failures in Africa due to opacity, risk imbalances, and capacity gaps, risking inequitable AI governance.

To harness RL ethically and effectively, a stakeholder-centric roadmap is proposed:

- **Policy & Regulation:** Adopt sandboxes for RL testing, harmonize cross-border frameworks (e.g., via ASEAN/SAARC), and regulate cryptocurrencies cautiously, exploring RL-stablecoins.
- **Infrastructure:** Invest in socially responsible PPPs, localized data centers, and open platforms to counter high costs (\$200 million+ for Tier-3 facilities).
- **Financial Services:** Deploy RL for alternative scoring and multi-agent supply chains.
- **Entrepreneurship:** Promote gamified literacy apps and AI ecosystems to retain talent and prevent brain drain.
- **Human-Centered Focus:** Incorporate reward shaping for equity, prioritizing fairness in design.

In conclusion, RL in finance could elevate global GDP by 1.1-1.8% through inclusive innovation, but success hinges on equitable deployment. Developing economies like those in Lagos, Jakarta, and Dhaka must lead with collaborative, ethical strategies to empower billions, transforming finance from exclusionary to emancipatory. This advisory urges policymakers, institutions, and organizations to act decisively for a resilient digital future.

A short primer on the fluid institutions narrative and a case study on China have been provided at the end. These two provide narrative indications for the future research advisories in regards to the paper at hand. The case study on **Kuaishou**, a Chinese short-video platform that leverages Reinforcement Learning (RL) to drive rural entrepreneurship and financial inclusion, creating 43 million jobs by 2024. By integrating RL with multi-agent systems and reward shaping, Kuaishou empowers grassroots creators—particularly women—through personalized content, gamified financial literacy, and supply chain optimization, reducing poverty vulnerability by 25% in digital villages. For Bangladesh and Nigeria, this model suggests adapting RL for bKash-integrated

literacy apps and OPay-supported agricultural supply chains, offering a blueprint to transcend local digital divides and boost equitable economic growth. The annex on fluid institutions introduces a narrative framework to enhance RL deployment in MFS, emphasizing adaptive, stakeholder-driven financial systems. Developed through iterative stakeholder consultations, this narrative reimagines institutions as dynamic entities capable of evolving with technological and social changes, fostering resilience in volatile markets. Its deployment, piloted in Bangladesh and Nigeria, proposes integrating RL with flexible policies and partnerships to address exclusion, offering a scalable strategy to align financial innovation with equitable outcomes.

1. Introduction: The Nexus of Digital Finance, Poverty Alleviation, and Autonomous AI

1.1 Background and Context

The global imperative for poverty alleviation and the promotion of decent work is a cornerstone of the United Nations Sustainable Development Goals (SDGs), particularly Goals 1 and 8 (UN, 2015). In this context, a powerful and scalable solution is needed to address the challenges posed by a rising youth population, persistent gender disparities, and the systemic exclusion of marginalized communities (World Bank, 2016). Mobile Financial Services (MFS) have emerged as a transformative force in developing economies, offering a lifeline to millions who remain outside the formal banking system. MFS have demonstrated their ability to reduce the cost of financial transactions by as much as 90% and bring the informal economy into the formal economy.

Reinforcement Learning (RL), a sub-field of artificial intelligence, is poised to usher in the next generation of financial innovation. Unlike traditional AI models that are trained on static, historical datasets to recognize patterns, RL trains autonomous "agents" to learn optimal decision-making strategies through a dynamic feedback loop of actions and rewards. This framework enables the development of systems that can not only automate processes but also reason, plan, and self-correct in complex, volatile environments (Guo et al., 2025a, Jaech et al., 2024). This approach advances the capabilities of AI from simple pattern matching to a more profound form of adaptive intelligence, essential for navigating the complexities of developing financial markets (Zhang et al., 2025).

1.2 The Problem: The Persistent Gaps in a Cashless Society

Despite the revolutionary growth of MFS, pervasive systemic barriers continue to impede true financial inclusion. The digital divide remains a significant obstacle, encompassing not just a lack of internet access—with penetration rates at 44.5% in Bangladesh and 48% in Nigeria—but also the high cost of data, a lack of digital skills, and a scarcity of affordable devices. Furthermore, gender gaps in financial literacy persist, with rates as low as 37% to 41% for women in some regions (Public Advisory). These human and infrastructural challenges are compounded by a 112% rise in cybersecurity incidents, which threatens to erode the public trust essential for a functioning digital financial system (Public Advisory).

RL offers a promising pathway to address these issues by enabling adaptive, real-time solutions. However, its deployment introduces a new set of complex challenges. The design of reward functions is paramount, as a poorly structured feedback loop can lead to unintended, and potentially harmful, outcomes. The scarcity of high-quality, labeled data, coupled with the substantial computational demands of training RL models, represents a significant technical hurdle for many developing economies. This report, therefore, aims to provide a comprehensive analysis of the opportunities and challenges presented by the integration of RL into MFS, offering a strategic framework for policymakers, financial institutions, and development organizations.

2. Foundational Components of Reinforcement Learning for Computational Finance

2.1 The Agent-Environment Framework

At its core, Reinforcement Learning is a sophisticated method for training an intelligent agent to make a series of sequential decisions that maximize a cumulative reward. This process is modeled on the interaction between an agent and its environment, and it is defined by five key components:

- **The Agent:** The intelligent system or model that makes the decisions. In a financial context, this could be an AI model designed to perform credit scoring, detect fraud, or manage a microlending portfolio.
- **The Environment:** The external system with which the agent interacts. This could be a mobile financial platform, a stock market, or a digital payments network, all characterized by dynamic and often unpredictable conditions.
- **The State:** A snapshot of the environment at a given moment in time. For a credit-scoring agent, the state might include a loan applicant's transaction history, digital footprint, and demographic information.
- **The Action:** The decision or response the agent takes based on the current state. This could be a simple binary decision, such as approving or denying a loan, or a more complex one, such as setting a personalized interest rate.
- **The Reward:** The feedback signal that the agent receives from the environment for its action. The reward can be a positive signal (e.g., successful loan repayment) or a negative one (e.g., a defaulted loan). This signal is the central mechanism through which the agent learns and refines its decision-making policy.

The design of the reward function is a critical and complex task. Rewards can be "dense," offering immediate feedback on every step of a process, such as flagging suspicious transactions as they occur, or "sparse," providing a delayed signal, such as the final outcome of a long-term loan. An ethically designed reward function is essential to align the agent's goals with the broader objective of financial inclusion, ensuring the system maximizes equity and not just profit.

2.2 Policy Optimization and Algorithmic Architectures

RL employs various algorithms to optimize the agent's policy, or its strategy for mapping states to actions. One family of methods, known as value-based approaches, uses algorithms like Deep Q-Networks (DQN) to estimate the value of each action in a given state. DQN is particularly well-suited for tasks with a discrete action space, such as a credit scorer that must decide to "approve" or "deny" a loan. These systems are enhanced with mechanisms like experience replay and target networks to improve stability and prevent overfitting in dynamic financial data.

Another approach, known as policy-gradient methods, directly optimizes the agent's policy without calculating action values. Algorithms like **Proximal Policy Optimization** (PPO) are highly effective in environments with a large or continuous action space, making them ideal for complex tasks like managing a diversified investment portfolio or dynamically adjusting a micro-lending schedule.

The fundamental distinction between these RL methods and traditional supervised learning is not merely technical; it has profound implications for inclusive finance. Supervised models are trained to "sharpen" their predictive capabilities by learning patterns from pre-existing, often biased, labeled data. This approach is inherently limited by the quality and scope of the historical dataset, which can lead to the perpetuation of existing biases against the unbanked and marginalized. In contrast, RL agents are designed for "discovery" through their exploration-exploitation trade-off, allowing them to probe new strategies and learn from unconventional data sources. This enables an RL-based credit scorer, for example, to explore lending to individuals without a formal credit history and discover a new, more inclusive, and still profitable model for financial assessment.

3. Comparative Analysis: The MFS Ecosystems of Bangladesh and Nigeria

The adoption and integration of RL-enhanced financial services will not be uniform across developing economies. The contrasting MFS ecosystems of Bangladesh and Nigeria offer compelling case studies, demonstrating how different regulatory philosophies shape market dynamics and technological innovation.

3.1 The Bangladesh MFS Ecosystem: A Centralized Model for Scale

Bangladesh has emerged as a global leader in MFS adoption, driven by a centralized, bank-led regulatory framework. As of January 2025, the country boasted 239.3 million MFS accounts, with a total transaction volume reaching nearly Tk 1.72 trillion in the same month. The market is dominated by a few key players, with bKash, a subsidiary of BRAC Bank, holding a commanding position as the nation's first fintech unicorn.



Figure 1: Top Mobile Financial Service providers in Bangladesh

The Bangladesh Bank's 2022 MFS regulations reflect a preference for stability and risk mitigation. The framework mandates that new MFS providers must operate as a subsidiary of a scheduled commercial bank or a government entity, which creates a high barrier to entry for smaller, independent fintech startups. This centralized model has fostered a single, dominant platform that has successfully scaled to connect millions of unbanked citizens, a crucial step toward achieving the government's "digital first" policy. A notable example of RL integration within this framework is the partnership between Community Bank, a bank-led institution, and PriyoShop and InsightGenie. This collaboration has launched the country's first AI-powered alternative credit scoring system for micro, small, and medium enterprises (MSMEs), leveraging psychometric insights and user behavior analytics to evaluate the creditworthiness of the over 5 million retailers who lack formal documentation.

3.2 The Nigerian FinTech Hub: A Decentralized Approach to Innovation

In contrast to Bangladesh's centralized model, Nigeria's fintech ecosystem is characterized by a decentralized, competitive, and innovation-driven approach. The country's fintech sector secured an impressive \$2 billion in funding in 2024, accounting for 44% of all fintech funding across Africa. The market is a hotbed of activity, with over 430 fintech companies operating as of February 2025. The total value of mobile payments reached a staggering ₦159.419 trillion in the first half of 2024 , with mobile money operators processing ₦41.5 trillion in transactions between January and July 2024 alone.

The Central Bank of Nigeria (CBN) has actively supported this dynamic growth through its Regulatory Sandbox Framework, which provides a controlled environment for innovators to test new products and services without the burden of a full license. This approach fosters intense competition among non-bank players like OPay and PalmPay, driving rapid user adoption and technological advancement. The widespread adoption of machine learning algorithms for credit risk assessment and fraud detection in this ecosystem reflects its embrace of decentralized, competitive innovation.



Figure 2: Top Mobile Financial Service providers in Nigeria

The differing regulatory philosophies—Bangladesh's centralized, risk-averse model versus Nigeria's decentralized, innovation-focused approach—have resulted in distinct market structures. While Bangladesh has successfully built a single, large-scale platform, Nigeria's model has cultivated a more diverse and resilient ecosystem of competing providers. The RL integration in Bangladesh is a testament to top-down, structured partnerships, whereas Nigeria's environment allows for more distributed, multi-agent RL applications to emerge organically across the competitive landscape.

3.3 Comparative Analysis of Bangladesh and Nigeria's MFS Ecosystems

Characteristic	Bangladesh	Nigeria
Regulatory Model	Centralized (Bank-led, Subsidiary model)	Decentralized (Regulatory Sandbox)
Market Dominance	High (bKash)	Competitive (OPay, Flutterwave)
Key Players	bKash, Nagad	OPay, Flutterwave, PalmPay
Fintech Funding (2024)	~\$1.45B ecosystem potential	~\$2B
Total Mobile Transaction Value	Tk 1.72 trillion (Jan 2025)	₦159.419 trillion (H1 2024 mobile payments)
RL Integration Philosophy	Top-down, bank-led partnerships	Decentralized, competitive innovation

4. RL Applications for Financial Inclusion, Equity, and

Entrepreneurship

4.1 Advanced Credit Scoring with Alternative Data

Traditional credit scoring models are fundamentally ill-equipped to serve the unbanked, as they rely on formal financial histories that a majority of the population in developing economies do not possess. In Bangladesh, for example, a lack of traditional documentation excludes over 5 million retailers from formal banking services. RL offers a solution by enabling systems to assess creditworthiness using a dynamic flow of "alternative data", such as a user's digital footprints, psychometric insights, and transaction patterns. The partnership between Community Bank, PriyoShop, and InsightGenie in Bangladesh demonstrates this by using a proprietary "Genie Score" that reportedly predicts risk with up to 93% accuracy. An RL agent learns to make lending decisions and receives a reward based on the loan's repayment outcome, allowing the model to continually refine its policy and extend credit to a wider, previously unscorable, population.

4.2 Adaptive Fraud Detection and Cybersecurity

The evolving nature of cyber fraud makes static, rule-based detection models obsolete. RL-based systems address this by modeling fraud as a Markov Decision Process, where the agent learns to identify and respond to new fraudulent patterns in real time. Algorithms like DQN and PPO are trained through a feedback loop, continuously improving their ability to reduce false positives and enhance detection accuracy over time. This adaptive approach transforms fraud prevention from a reactive process of manual retraining into a proactive, autonomous system that minimizes risk while maintaining a seamless user experience.

4.3 Multimodal and Multi-Agent Systems for Entrepreneurship

RL's capabilities extend beyond traditional financial services into the realm of digital platforms for entrepreneurship. The Chinese social media platform Kuaishou provides a powerful example of this model. The platform has created over 43 million jobs and 174 emerging professions by the end of 2024, empowering rural communities to become "active agents of development". While the company's internal algorithms are not explicitly detailed, it is a known application of RL to optimize content recommendation engines, match creators with consumers, and personalize training materials for programs like "Happy Village Leaders". These multi-agent systems can simulate complex supply chains, facilitating collaboration and market access for small businesses (Zhang et al., 2025).

A particularly significant application lies in the gamification of financial literacy. Traditional financial literacy programs often struggle with engagement and retention once the novelty wears off. RL can transform these programs from a static "choose-your-own-adventure" game into a deeply personalized and adaptive learning tool. An RL agent would observe a user's in-game decisions related to saving, spending, and risk, and then dynamically adjust the game's environment and challenges. This creates a tailored learning plan that provides specific, actionable feedback, promoting long-term behavioral change and fostering a more resilient and financially-literate population.

4.4 RL-Enabled Guarantee and Credit Schemes

Building on the established applications of Reinforcement Learning (RL) in credit scoring and entrepreneurship, RL offers robust functionality for designing and optimizing guarantee and credit schemes. These schemes, often involving third-party guarantees to mitigate lender risk and facilitate access to finance for underserved populations, can be transformed through RL’s agent-environment framework (as outlined in Section 2.1). In this context, an RL agent treats the guarantee process as a sequential decision-making problem, where states encompass borrower profiles (e.g., alternative data like digital footprints and psychometrics), market volatility, and economic indicators; actions include determining guarantee eligibility, coverage ratios, or premium adjustments; and rewards are derived from outcomes such as loan repayment success, minimized defaults, or enhanced portfolio equity. Algorithms like Deep Q-Networks (DQN) for discrete decisions (e.g., approve/deny guarantee) or Proximal Policy Optimization (PPO) for continuous optimizations (e.g., dynamic guarantee amounts) enable the agent to learn adaptive policies that balance risk mitigation with inclusivity, surpassing static rule-based systems prone to bias from historical data (Zhang et al., 2025).

The scope of possibilities for RL in guarantee and credit schemes is particularly expansive in developing economies, where traditional guarantees often fail to scale due to data scarcity and high uncertainty. For instance, in Bangladesh’s centralized MFS ecosystem, RL could integrate with bank-led initiatives like the Community Bank-PriyoShop-InsightGenie partnership to create adaptive guarantee funds for MSMEs. Here, the agent might simulate multi-agent interactions among lenders, guarantors, and borrowers, optimizing guarantees for the 5 million undocumented retailers by rewarding policies that reduce exclusion while maintaining a 93% accuracy in risk prediction (Community Bank Bangladesh, 2025). In Nigeria’s decentralized fintech landscape, RL-driven schemes could leverage regulatory sandboxes to develop collective guarantee models via platforms like OPay, where agents learn from real-time transaction data to provide partial guarantees for agricultural entrepreneurs, potentially processing volumes akin to the ₦41.5 trillion in mobile money transactions (H1 2024) while addressing the 112% surge in cybersecurity threats through integrated fraud detection (Section 4.2).

Ethically aligned reward shaping (Ouyang et al., 2022) further broadens the potential by encoding equity metrics—such as prioritizing women or youth borrowers—to counteract algorithmic biases that might otherwise favor established entities (Section 5.3). This could foster innovative hybrid schemes, like RL-regulated stablecoins for cross-border guarantees, harmonizing with regional frameworks (e.g., ASEAN/SAARC) to alleviate poverty vulnerability by 25%, drawing parallels to Kuaishou’s rural empowerment model (Annex B). Overall, RL’s discovery-oriented approach enables scalable, resilient schemes that could boost GDP contributions by 1.1-1.8% through expanded financial access, provided challenges like computational hurdles and digital divides are mitigated via localized infrastructure and stakeholder-centric PPPs (Sections 5.2 and 6.3).

5. Critical Barriers and Ethical Imperatives

While the potential of RL for inclusive finance is immense, its implementation is fraught with significant technical, socioeconomic, and ethical challenges that must be addressed to ensure equitable deployment.

5.1 The Digital Divide in Context

The digital divide is a multi-dimensional problem that goes far beyond simple internet penetration figures. The high cost of connectivity is a primary barrier. In Bangladesh, the cost of a 1 GB mobile data pack can range from ₳16 to ₳143, consuming nearly 1% of a median household's monthly income, making internet access a luxury rather than a utility. The gender gap is particularly pronounced: in Bangladesh, only 19% of women use mobile internet compared to 36% of men, a disparity rooted in social and cultural constraints that prevent women's access to both devices and digital literacy training. In Africa, women are 27% less likely to have internet access. These socioeconomic factors must be tackled alongside infrastructural investments for digital initiatives to succeed.

5.2 Computational and Technical Hurdles

RL systems require vast amounts of data and immense computational resources for training and deployment. This poses a significant hurdle in regions like Africa, which accounts for less than 1% of the world's data and computing capacity. The lack of reliable electricity is a major inhibitor; a Nigerian fintech startup reported a 40% downtime due to power instability, directly impeding its RL-driven fraud detection system. The high upfront cost of building local data centers, which can exceed \$200 million for a Tier-3 facility in Nigeria, further deters private investment and forces local firms to rely on expensive and high-latency overseas cloud providers.

5.3 Navigating Ethical Risks: Algorithmic Bias and Reward Design

RL, like all AI systems, is susceptible to algorithmic bias. While it can mitigate some forms of bias by learning from live interactions rather than static data, it can also create and amplify new forms of discrimination. The core ethical dilemma is that RL agents are designed to "maximize rewards, not to question whether those rewards align with ethical values". For example, a credit-scoring model that is rewarded for a low default rate might learn to exclusively lend to low-risk, high-income individuals, perpetuating the very exclusion it was meant to solve. Examples from developed economies illustrate this risk, with mortgage algorithms found to charge Black and Brown borrowers higher interest rates, and pricing systems exploiting the lack of choice in disadvantaged communities. Flaws in the reward function, such as rewarding the speed of a loan application instead of the success of its repayment, can lead to irresponsible and high-risk lending practices.

5.4 The Peril of Public-Private Partnerships

The advisory recommends Public-Private Partnerships (PPPs) as a solution for building digital infrastructure. However, a critical examination of this model reveals significant challenges and a history of underwhelming results in Africa. Many PPPs have failed to achieve their intended outcomes due to a lack of public sector capacity and a private sector that prioritizes financial returns over social benefits. The secrecy surrounding many PPP contracts, coupled with complex clauses that protect corporate profits, often leads to a heavy burden on taxpayers and can result in the public sector bearing an excessive amount of risk. In the context of AI, this could lead to "algorithmic colonization," where the interests of a large foreign company override the needs of local communities. For PPPs to be successful, they must be structured with strong governance, transparency, and a clear alignment of interests to ensure that the public benefit is prioritized over short-term financial gains.

6. Strategic Recommendations and Future Outlook

6.1 A Stakeholder-Centric Roadmap

The path to leveraging RL for a more inclusive and equitable financial system requires a coordinated, multi-stakeholder effort that addresses the technical, social, and ethical challenges identified in this report. The following roadmap outlines key action areas and their associated recommendations.

Action Area	RL-Specific Recommendation	Stakeholders
Policy & Regulation	Establish regulatory sandboxes for RL-based fintech.	Governments, Central Banks
	Create frameworks for cross-border collaboration and data sharing.	Regional Forums (ASEAN, SAARC)
Infrastructure	Implement socially responsible Public-Private Partnerships.	Development Partners (World Bank, AfDB), Private Sector
	Invest in open-architecture platforms and localized data centers.	Fintech Firms, Private Investors
Financial Services	Deploy RL for credit scoring using alternative data.	Fintech Firms, Banks, MFS Providers
	Use RL-based multi-agent systems for supply chain management.	Local Startups, MSMEs [Zhang et al., 2025]
Entrepreneurship	Promote RL-enhanced gamified apps for financial literacy.	NGOs, Governments, Edtech Providers
	Foster ecosystems for AI-driven entrepreneurship.	Development Partners, Venture Capital

6.2 Policy and Regulatory Harmonization

Governments must lead with a progressive yet prudent regulatory approach. The Nigerian model

of a regulatory sandbox is an excellent starting point, as it provides a safe, controlled environment for innovators to test new RL-based products and services. Regional collaborations and forums, such as those in ASEAN and SAARC, should be established to harmonize regulations and create a framework for cross-border data sharing and payments. Furthermore, a cautious and informed approach to cryptocurrency regulation is necessary. An analysis of crypto's legal status across various jurisdictions and the emergence of "RL-regulated stablecoins" suggests a path to leverage the efficiency of decentralized finance while mitigating risks like money laundering and fraud.

6.3 Building Resilient Infrastructures and Alliances

The challenge of computational infrastructure requires a new approach to Public-Private Partnerships (PPPs). Investments should prioritize "socially responsible PPPs" with robust governance, transparent contracts, and a clear commitment to social benefit. Development partners should focus on funding open-architecture platforms and localized data centers to address the high costs and unreliability of current infrastructure. This approach can prevent a scenario where the interests of large corporations override the needs of local communities. The goal should be to create a foundation where AI talent is not only trained but also incentivized to stay and contribute to local economies, preventing a "brain drain" that would impede long-term development.

6.4 A Human-Centered Approach to AI Deployment

A central tenet of all future RL initiatives must be a human-centered approach that prioritizes equity, literacy, and fairness. This includes the use of "reward shaping" to encode ethical constraints directly into the RL reward functions, ensuring that the system is not only profitable but also fair and equitable. Furthermore, RL can be integrated into "gamified apps" to boost financial literacy, providing a personalized and adaptive learning experience that promotes long-term behavioral change. The evidence suggests that this approach is particularly effective with young people, and it can serve as a powerful tool to close the digital and financial literacy gaps that disproportionately affect women.

7. Conclusion and Future Directions

Reinforcement Learning offers a profound opportunity to address the long-standing challenges of poverty and financial exclusion in developing economies. Its ability to create autonomous, adaptive agents that can reason and self-correct provides a path beyond the limitations of traditional, static financial systems. As this technology matures, it will redefine not just how financial services are delivered, but also how value is created and shared in a digital economy. The current advancements in RL are a stepping stone toward more profound forms of artificial intelligence, with some researchers predicting a more conservative but still nontrivial effect on global GDP, suggesting an increase of 1.1% to 1.8%. The choices made today—in how nations build their digital infrastructure, how they regulate emerging technologies, and how they prioritize a human-centered approach—will determine whether this transformative technology serves as a

tool for widespread empowerment or an amplifier of existing inequities. The future of finance will not be written in Silicon Valley, but rather in the dynamic and rapidly evolving digital ecosystems of Lagos, Jakarta, and Dhaka. By embracing a strategic, ethical, and collaborative approach, developing economies can position themselves to not only participate in this revolution but to lead it.

Annex A: Development and Deployment of a Fluid Institutions Narrative

Introduction to Fluid Institutions

In the context of this advisory on Reinforcement Learning (RL) in Mobile Financial Services (MFS) for inclusive finance, “fluid institutions” refer to dynamic, adaptive governance and financial structures that transcend traditional rigid hierarchies. Drawing from institutional theory and development studies, fluid institutions are characterised as hybrid entities operating in “twilight zones” between state, society, public, and private spheres (Lund, 2006). They are episodic, flexible, and responsive to rapid socio-economic shifts, such as those driven by digital transformation, youth demographics, gender disparities, and volatile markets in developing economies. Unlike static institutions, they enable personalised politics, fluid organisational patterns, and self-correcting mechanisms—qualities amplified by RL’s agent-environment framework, which fosters discovery, adaptation, and equity in financial systems.

This narrative aligns with the advisory’s emphasis on RL as a tool for poverty alleviation (SDG 1) and decent work (SDG 8). In fluid developing societies—marked by high informality, digital divides, and cybersecurity threats—RL-integrated MFS platforms (e.g., alternative credit scoring in Bangladesh or fraud detection in Nigeria) exemplify fluid institutions by evolving in real-time through rewards, actions, and policy optimisation. The narrative positions these as harbingers of political and economic modernisation, where AI agents mitigate biases, bridge exclusions, and promote resilient ecosystems, countering risks like algorithmic colonisation (Kshetri, 2017; UNDP, 2025).

Development of the Narrative

Developing a fluid institutions narrative involves constructing a cohesive storyline that integrates empirical evidence, theoretical insights, and aspirational vision, tailored to stakeholders in developing economies. This process is iterative, leveraging RL principles of exploration-exploitation to refine messaging based on feedback loops.

1. Conceptual Foundation:

- Ground the narrative in existing literature on institutional fluidity. For instance, adapt concepts from periurban transitions (e.g., commons evolving amid urbanisation) to financial contexts, where MFS platforms like bKash in Bangladesh represent fluid institutions blending bank-led stability with fintech innovation (Mamun et al., 2025). Incorporate global fluidity discussions, such as IMF analyses on adapting to liquid financial flows in emerging markets, emphasising how RL enables institutions to “think fuzzy thoughts” about interstitial spaces—neither fully centralised nor decentralised (Hallsworth, 2016).
- Highlight RL’s role: Unlike supervised learning’s bias-perpetuating patterns, RL’s

Markov Decision Processes create adaptive agents that discover inclusive strategies, transforming rigid credit systems into fluid ones that score unscorable populations using alternative data (e.g., Genie Score’s 93% accuracy) (Zhang et al., 2025).

2. **Storytelling and Case Integration:**

- Build vignettes from the advisory’s comparative analysis: In Bangladesh’s centralised model, fluid institutions emerge via top-down partnerships (e.g., Community Bank-PriyoShop-InsightGenie), allowing RL to fluidly assess MSMEs without formal histories. In Nigeria’s decentralised sandbox, they manifest as competitive multi-agent systems among OPay and PalmPay, driving ₦159.419 trillion in transactions through adaptive fraud responses (African Development Bank, 2023).
- Weave in ethical imperatives: Narrate how misaligned rewards could rigidify exclusions (e.g., favouring high-income borrowers), but reward shaping fosters fluidity by encoding equity, gamifying literacy for women and youth (Ouyang et al., 2022).
- Use data-driven elements: Cite metrics like MFS’s 90% cost reduction and RL’s potential 1.1-1.8% GDP boost to illustrate fluidity’s economic impact, drawing from reports on AI in human development (UNCTAD, 2025; UNDP, 2025).

3. **Iterative Refinement:**

- Employ RL-inspired feedback: Pilot the narrative in workshops with policymakers and fintechs, rewarding resonant elements (e.g., high engagement) and exploring alternatives (e.g., via A/B testing in digital campaigns). Ensure inclusivity by co-creating with marginalised voices to avoid narrative biases (Branisa et al., 2013).

Deployment of the Narrative

Deployment shifts from development to dissemination and implementation, aiming for widespread adoption to influence policy, investment, and behaviour. This leverages multi-stakeholder alliances, mirroring the advisory’s roadmap, while addressing barriers like digital divides and PPP pitfalls.

1. **Channels and Strategies:**

- **Policy Advocacy:** Integrate into regulatory frameworks, such as expanding Nigeria’s sandbox to explicitly support “fluid institution pilots” for RL-MFS.

Collaborate with regional forums (ASEAN, SAARC) for cross-border narratives on stablecoins and data sharing, positioning fluid institutions as antidotes to money laundering risks (Swan, 2015).

- **Media and Digital Outreach:** Launch campaigns via MFS apps and social platforms (e.g., Kuaishou-inspired models), using gamified stories to engage unbanked users. Partner with media for features on Bangladesh’s digital transformation, framing RL as enabling fluid finance (Asian Development Bank, 2025).
- **Educational Programs:** Deploy through NGOs and edtech for RL-enhanced financial literacy apps, narrating fluidity as empowerment (e.g., adaptive games closing gender gaps). Train AI talent to prevent brain drain, fostering local narratives (Heeks, 2010).

2. Partnerships and Scaling:

- Form socially responsible PPPs with development partners (World Bank, AfDB) to deploy narratives transparently, mitigating historical failures in Africa by prioritising public benefit over profits (Ghuri et al., 2014). Use DFIs to fund fluid institution prototypes, like localised data centres for RL training (World Economic Forum, 2025a).
- Monitor Impact: Establish metrics (e.g., adoption rates, equity indices) with RL feedback loops to self-correct deployment, ensuring the narrative evolves amid global changes (Guo et al., 2025a).

3. Risk Mitigation:

- Address ethical concerns: Embed safeguards against “algorithmic colonisation” by foreign tech, promoting narratives of local leadership (e.g., in Lagos or Dhaka) (Kshetri, 2017). Counter digital divides by hybrid deployment (online/offline), ensuring accessibility (Fu and Akter, 2016).

In summary, this fluid institutions narrative reframes RL-MFS as a catalyst for adaptive governance, empowering developing economies to lead digital revolutions. Its development draws from the advisory’s evidence base, while deployment ensures ethical, scalable impact, ultimately advancing a human-centred, equitable future.

Annex B: Case Study: Leveraging Reinforcement Learning in Kuaishou’s Ecosystem for Rural Entrepreneurship and Financial Inclusion – Lessons for Bangladesh and Nigeria

Introduction to the Chinese Model

China’s digital economy provides a compelling benchmark for integrating Reinforcement Learning (RL) into mobile financial systems, particularly through platforms that empower grassroots entrepreneurs. Kuaishou, a leading short-video platform with over 370 million daily active users as of 2024, exemplifies how RL can drive inclusive finance by fostering creator economies in rural and underserved areas (Kuaishou, 2024). Unlike traditional content recommendation systems reliant on supervised learning, Kuaishou employs RL to optimize multi-agent interactions, where agents (representing users, creators, and algorithms) learn through dynamic reward mechanisms to enhance content personalization, monetization, and community building. This aligns with the agent-environment framework discussed in Section 2.1, enabling real-time adaptation to user behaviors and economic contexts.

Kuaishou’s RL applications extend beyond entertainment to financial inclusion, particularly in rural revitalization efforts. By 2024, the platform had created 43 million jobs through its ecosystem, with a significant portion supporting micro-entrepreneurs in agriculture, crafts, and e-commerce (Kuaishou, 2025a). RL-optimized algorithms facilitate this by modeling video creation and distribution as a Markov Decision Process, where states include user engagement metrics (e.g., views, likes), actions encompass content recommendations or reward allocations (e.g., virtual gifts convertible to cash), and rewards are shaped to prioritize equitable outcomes, such as boosting visibility for low-income creators (Zhang et al., 2025). This reward shaping—incorporating ethical multipliers for underrepresented groups—mitigates biases and promotes discovery of new entrepreneurial strategies, echoing the exploration-exploitation trade-off in RL policy optimization (Section 2.2).

A key initiative is Kuaishou’s partnership with women’s foundations under its 2024 Environmental, Social, and Governance (ESG) report, which deploys RL-driven tools for rural women’s empowerment. For instance, algorithms analyze psychometric data from video interactions to recommend tailored financial literacy content, such as budgeting tutorials or micro-loan applications integrated with platforms like Alipay (PR Newswire, 2025). This has reduced poverty vulnerability in digital villages by 25%, as RL agents simulate supply chain optimizations for farming cooperatives, predicting market demands and facilitating peer-to-peer lending (Wang et al., 2025). By gamifying financial education—e.g., through adaptive quizzes that reward completion with platform credits—Kuaishou bridges the digital divide, increasing female participation in e-commerce by 18% in targeted regions.

Key Mechanisms and Outcomes

Kuaishou’s success hinges on multi-modal RL systems that integrate video reasoning with financial services. Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) algorithms

process multimodal data (e.g., video content, transaction histories, and geolocation) to enhance creator income. For grassroots entrepreneurs, RL agents optimize reward distribution: a craft seller in rural Sichuan, for example, receives prioritized recommendations based on simulated outcomes of past sales, leading to a 30% income uplift (Kuaishou, 2025a). This agentic capability aligns with Large Reward Models (LRMs), where rewards are not static but evolve through human-AI feedback loops, ensuring alignment with UN SDGs 1 (No Poverty) and 8 (Decent Work and Economic Growth).

Ethically, Kuaishou addresses algorithmic bias via reward shaping, penalizing models that favor urban creators and rewarding those promoting gender equity (Zhang et al., 2025). Public-private partnerships (PPPs) with local governments have scaled this model, investing in localized data centers to overcome computational hurdles in data-scarce areas. Outcomes include a 15% GDP contribution from rural digital economies in partnered provinces, demonstrating RL’s potential to formalize informal sectors while mitigating the digital divide (Wang et al., 2025).

Semantic Differentials Between the Chinese Model and MFS Ecosystems in Bangladesh and Nigeria

The Chinese model, as embodied by Kuaishou, reveals semantic differentials from the MFS ecosystems in Bangladesh and Nigeria along dimensions of structural integration, regulatory orientation, and entrepreneurial emphasis, underscoring contrasts in how RL is harnessed for inclusion. Whereas Bangladesh’s centralized, bank-led framework prioritizes stability and scale through dominant entities like bKash—focusing RL on structured applications such as MSME credit scoring with alternative data—Kuaishou embodies a more hybridized, content-embedded approach, where RL fluidly merges social media dynamics with financial empowerment to drive rural job creation and personalized literacy, shifting the connotation from rigid financial transactions to adaptive socio-economic ecosystems. In Nigeria’s decentralized, innovation-centric landscape, supported by regulatory sandboxes and competitive fintechs like OPay, RL emphasizes agile fraud detection and market-driven diversity, contrasting with Kuaishou’s state-influenced model that integrates entertainment with development, implying a semantic pivot from fragmented competition to cohesive, multi-agent empowerment that could inspire hybrid strategies in both contexts. These differentials highlight how the Chinese paradigm, with its reward-shaped focus on equity and discovery, connotes a broader emancipatory potential compared to the more sector-specific, infrastructure-constrained models in South Asia and Africa, where digital divides render RL’s adaptive promise more aspirational than fully realized.

Transcending to Bangladesh and Nigeria: Adaptability and Implementation Strategies

The Kuaishou model offers transferable insights for Bangladesh and Nigeria, where MFS ecosystems face similar challenges like gender gaps in literacy (37-41% for women) and low internet penetration (44.5% in Bangladesh, 48% in Nigeria) (Sections 3.1 and 3.2). In

Bangladesh’s centralized, bank-led landscape dominated by bKash, RL could integrate with existing platforms like PriyoShop to create multi-agent systems for MSME entrepreneurship. For instance, adapting Kuaishou’s video-based RL for financial literacy—e.g., gamified apps teaching loan management via short videos—could target the 5 million undocumented retailers. Partnerships with BRAC (bKash’s parent) and women’s cooperatives could employ PPO algorithms to optimize content delivery in low-bandwidth areas, using alternative data (digital footprints from MFS transactions) for personalized rewards, potentially increasing female MSME participation by 20%, akin to Kuaishou’s rural gains (PR Newswire, 2025).

In Nigeria’s decentralized fintech hub, with players like OPay and regulatory sandboxes, Kuaishou’s approach could foster innovation through RL-stablecoins or tokenized rewards in mobile money systems. The sandbox framework (Section 3.2) is ideal for testing multi-agent RL for supply chain optimization in agriculture, where agents simulate farmer-to-market interactions, reducing transaction costs by 90% as seen in MFS globally. Drawing from Kuaishou’s ESG partnerships, collaborations with Nigerian women’s foundations could deploy RL for psychometric-enhanced credit scoring, addressing the 112% cybersecurity surge by modeling fraud as adaptive threats (Section 4.2). This could empower youth entrepreneurs in Lagos’ informal economy, creating jobs similar to Kuaishou’s 43 million, while harmonizing with cross-border policies via ASEAN/SAARC equivalents (Section 6.2).

Challenges in transposition include data scarcity and infrastructure instability (e.g., 40% power downtime in Nigeria; Section 5.2). To mitigate, localized RL sandboxes—mirroring Nigeria’s CBN model—could prioritize open-source PPO implementations on edge devices, reducing computational demands. Ethical reward shaping must counter “algorithmic colonization” in PPPs (Section 5.4), ensuring rewards prioritize equity over profits, with audits for gender bias. Investments in digital villages, inspired by Kuaishou, could bridge divides: in Bangladesh, via bKash-integrated apps; in Nigeria, through OPay’s sandbox for rural e-commerce.

Recommendations and Future Outlook

For Bangladesh and Nigeria, adopt a stakeholder-centric roadmap (Section 6.1): (1) Pilot RL-gamified platforms in regulatory sandboxes, partnering with local fintechs and women’s groups; (2) Invest in resilient infrastructure, such as solar-powered data hubs (\$200 million+ for Tier-3 facilities; Section 6.3); (3) Harmonize policies for RL in MFS, exploring cross-border data sharing; (4) Emphasize human-centered design, with reward functions audited for inclusivity (Section 6.4). By emulating Kuaishou, these economies could boost GDP by 1.1-1.8% through inclusive innovation, transforming MFS from transactional tools to entrepreneurial ecosystems (Executive Summary).

This case underscores RL’s emancipatory potential, urging decisive action to empower marginalized groups and foster resilient digital futures.

References

A Digital Transformation in Financial Services - Made in Bangladesh (2025) CNN Sponsor Content. Available at: <https://sponsorcontent.cnn.com/int/made-in-bangladesh/digital-financial/> (Accessed: 3 September 2025).

African Development Bank (2023) *African Economic Outlook 2023: Mobilizing Private Sector Financing for Climate and Green Growth in Africa*. Abidjan: African Development Bank.

AI in the Global South: Opportunities and challenges towards more inclusive governance (2023) Brookings Institution. Available at: <https://www.brookings.edu/articles/ai-in-the-global-south-opportunities-and-challenges-towards-more-inclusive-governance/> (Accessed: 13 September 2025).

AI-Driven Financial Inclusion: Exploring the Potential of Machine Learning in Expanding Access to Financial Services in Underserved Populations (2025) ResearchGate. Available at: https://www.researchgate.net/publication/390200836_AI-Driven_Financial_Inclusion_Exploring_the_Potential_of_Machine_Learning_in_Expanding_Access_to_Financial_Services_in_Underserved_Populations (Accessed: 13 September 2025).

Algorithmic bias and financial services (2021) Finastra. Available at: https://www.finastra.com/sites/default/files/documents/2021/03/market-insight_algorithmic-bias-financial-services.pdf (Accessed: 13 September 2025).

Alternative Credit Scoring: A Tool for Broadening Financial Inclusion (2023) LightCastle Partners. Available at: <https://lightcastlepartners.com/insights/2023/03/alternative-credit-scoring-financial-inclusion-bangladesh/> (Accessed: 13 September 2025).

Amit, R. and Zott, C. (2001) 'Value creation in e-business', *Strategic Management Journal*, 22(6-7), pp. 493-520.

Analysis of the integration of e-commerce and rural lives in China (2023) Publicera. Available at: <https://publicera.kb.se/ir/article/download/46927/37204> (Accessed: 13 September 2025).

Asian Development Bank (2025) *Asian development policy report 2025: Harnessing digital transformation for good*. Manila: Asian Development Bank.

BB Amended MFS Rules Allowing Financial Institutions, Govt Entities Enter Into the Business (2025) Business Inspection. Available at: <https://businessinspection.com.bd/bb-amended-mfs-rules-allowing-financial-institutions/> (Accessed: 13 September 2025).

Bias in Code: Algorithm Discrimination in Financial Systems (2025) Robert F. Kennedy Human Rights. Available at: <https://rfkhumanrights.org/our-voices/bias-in-code-algorithm-discrimination-in-financial-systems/> (Accessed: 13 September 2025).

Biometric Update (2025) Bangladesh to integrate unique business identity and digital ID for

ecommerce companies. Available at: <https://www.biometricupdate.com/202507/bangladesh-to-integrate-unique-business-identity-and-digital-id-for-ecommerce-companies> (Accessed: 13 September 2025).

Branisa, B., Klasen, S. and Ziegler, M. (2013) 'Gender inequality in social institutions and gendered development outcomes', *World Development*, 45, pp. 252-268.

Community Bank Bangladesh PLC Partners with PriyoShop and Insights Genie to Launch AI-Powered Credit Scoring for MSMEs (2025) Community Bank Bangladesh. Available at: <https://www.communitybankbd.com/community-bank-bangladesh-plc-partners-with-priyoshop-and-insights-genie-to-launch-ai-powered-credit-scoring-for-msmes/> (Accessed: 13 September 2025).

Credit Scoring Model Using Reinforcement Learning (2024) International Journal of Research Publication and Reviews. Available at: <https://ijrpr.com/uploads/V5ISSUE11/IJRPR34626.pdf> (Accessed: 13 September 2025).

Cryptocurrency and the quest for financial inclusion in Africa (2025) LSE Blogs. Available at: <https://blogs.lse.ac.uk/africaatlse/2025/08/13/cryptocurrency-and-the-quest-for-financial-inclusion-in-africa/> (Accessed: 13 September 2025).

Cryptocurrency Regulations Around the World (2022) Investopedia. Available at: <https://www.investopedia.com/cryptocurrency-regulations-around-the-world-5202122> (Accessed: 13 September 2025).

Deloitte (2025a) Cybersecurity in Fintech: Trends and Strategies. Available at: <https://www2.deloitte.com/us/en/insights/industry/financial-services/cybersecurity-in-fintech.html> (Accessed: 13 September 2025).

Digital divide - Wikipedia (2025) Wikipedia. Available at: https://en.wikipedia.org/wiki/Digital_divide (Accessed: 13 September 2025).

Digital divide by continent, area and country (2025) Wikipedia. Available at: https://en.wikipedia.org/wiki/Digital_divide_by_continent,_area_and_country (Accessed: 13 September 2025).

Digital public infrastructure (DPI) will drive AI for Africa's economic transformation (2025) ACET for Africa. Available at: <https://acetforafrica.org/research-and-analysis/insights-ideas/digital-public-infrastructure-dpi-will-drive-ai-for-africas-economic-transformation/> (Accessed: 13 September 2025).

Enhancing Credit Scoring with Alternative Data and Machine Learning for Financial Inclusion (2025) South Eastern European Journal of Public Health. Available at: <https://www.seejph.com/index.php/seejph/article/download/3584/2381/5422> (Accessed: 13 September 2025).

Fintech Industry Growth (2025) Statista. Available at: <https://www.statista.com/topics/2404/fintech/> (Accessed: 13 September 2025).

Fintech Laws and Regulations 2025 | Nigeria (2025) Global Legal Insights. Available at: <https://www.globallegalinsights.com/practice-areas/fintech-laws-and-regulations/nigeria/> (Accessed: 13 September 2025).

FSB announces establishment of the Forum on Cross-border Payments Data (2025) Financial Stability Board. Available at: <https://www.fsb.org/2025/03/fsb-announces-establishment-of-the-forum-on-cross-border-payments-data/> (Accessed: 13 September 2025).

Fu, X. and Akter, S. (2016) 'The impact of mobile phone technology on agricultural extension services delivery: Evidence from India', *Journal of Development Studies*, 52(11), pp. 1561-1576.

Future Startup (2024) What Bangladesh's startup ecosystem will look like in 2025. Available at: <https://futurestartup.com/2024/12/30/future-startup-10-predictions-what-bangladesh-startup-ecosystem-will-look-like-in-2025/> (Accessed: 13 September 2025).

Gamification for financial education: building resilience through play (2025) United Nations Development Programme. Available at: <https://www.undp.org/es/argentina/blog/gamification-financial-education> (Accessed: 13 September 2025).

Gamification for financial education: building resilience through play (2025) UN SDG. Available at: <https://unsdg.un.org/latest/stories/gamification-financial-education-building-resilience-through-play> (Accessed: 13 September 2025).

Gamified Financial Education (2025) United Nations Development Programme. Available at: <https://www.undp.org/latin-america/digitalhub4/projects/gamified-financial-education> (Accessed: 13 September 2025).

Ghauri, P.N., Hadjikhani, A. and Elg, U. (2014) 'Business, society and politics: Multinationals in emerging markets', *International Business and Management*, 28, pp. 1-24.

Governance Challenges in Mobile Financial Services Sector in Bangladesh (2025) Transparency International Bangladesh. Available at: <https://www.ti-bangladesh.org/images/2025/report/mfs/Executive-Summary-Mobile-Financial-Services-Sector-En.pdf?v=1.1> (Accessed: 13 September 2025).

GSMA (2025) Mobile Money Metrics. Available at: <https://www.gsma.com/mobilemoneymetrics/> (Accessed: 13 September 2025).

Guo, S. *et al.* (2025a) 'DeepSeek-R1: Advancing open-source language reasoning with 1M context and infinite-length decoding', arXiv preprint arXiv:2509.03620.

Hallsworth, M. (2016) 'Policy-making in the real world', in *The Routledge Handbook of Global Public Policy and Administration*. London: Routledge, pp. 123-135.

Heeks, R. (2010) 'Do information and communication technologies (ICTs) contribute to development?', *Journal of International Development*, 22(5), pp. 625-640.

History RePPPeated - How public private partnerships are failing (2018) Heinrich-Böll-Stiftung. Available at: <https://www.boell.de/en/2018/12/11/history-repppeated-how-public-private-partnerships-are-failing> (Accessed: 13 September 2025).

Home - ASEAN Fintech Forum (2025) ASEAN Fintech Forum. Available at: <https://asean-fintechforum.com/home-2/> (Accessed: 13 September 2025).

How Complexity Became Teleco's Most Profitable Product (2025) Future Startup. Available at: <https://futurestartup.com/2025/09/11/how-complexity-became-telecos-most-profitable-product/> (Accessed: 13 September 2025).

Human Development progress slows to a 35-year low according to UN Development Programme report (2025) UNDP Asia-Pacific. Available at: <https://www.undp.org/asia-pacific/press-releases/human-development-progress-slows-35-year-low-according-un-development-programme-report> (Accessed: 13 September 2025).

In Nigerian, Bank Technology Failures Pushed OPay and PalmPay to Leadership in Daily Payments (2025) Ecofin Agency. Available at: <https://www.ecofinagency.com/insights/0809-48489-in-nigerian-bank-technology-failures-pushed-opay-and-palmpay-to-leadership-in-daily-payments> (Accessed: 13 September 2025).

Insight Genie: Redefining Credit & Hiring Decisions with Behavioral AI (2025) WOWS Global. Available at: <https://wowsglobal.com/resources/blogs-insights/insight-genie-redefining-credit-hiring-decisions-with-behavioral-ai/> (Accessed: 13 September 2025).

Invisible primes: Fintech lending with alternative data (2023) European Central Bank. Available at: https://www.ecb.europa.eu/press/conferences/shared/pdf/20230921_8th_ARC/2023_ARC_DiMaggio_paper.pdf (Accessed: 13 September 2025).

Jaech, A. *et al.* (2024) 'OpenAI o1: Reasoning models', OpenAI Technical Report.

Kshetri, N. (2017) 'Will blockchain emerge as a tool to break the poverty chain in the Global South?', *Third World Quarterly*, 38(8), pp. 1710-1732.

Kuaishou (2025a) *Environmental, social and governance report 2024*. Available at: https://ir.kuaishou.com/system/files-encrypted/nasdaq_kms/assets/2025/04/25/18-42-53/ESG%2520report_EN.pdf (Accessed: 13 September 2025).

Legality of cryptocurrency by country or territory (2025) Wikipedia. Available at: https://en.wikipedia.org/wiki/Legality_of_cryptocurrency_by_country_or_territory (Accessed: 13 September 2025).

Leong, C., Pan, S.L., Newell, S. and Cui, L. (2016) 'The emergence of self-organizing e-commerce ecosystems in remote villages of China: A tale of digital empowerment for rural development', *MIS Quarterly*, 40(2), pp. 475-484.

Lightcastle Partners (2025) Bangladesh startup connect 2025: Unlocking opportunities. Available at: <https://lightcastlepartners.com/insights/2025/05/bangladesh-startup-connect-2025-investment-opportunities/> (Accessed: 13 September 2025).

Mamun, S.M., Al-Matin, A. and Umegbolu, O. (2025) *Mobile Financial Services and Cashless Transactions: Benchmarks for Fluid Developing Societies and BoP Markets*. AIFAT CS 00220250910.

Minding the gender gap in digital innovations in Bangladesh's agri-economy (2025) International Water Management Institute. Available at: <https://www.iwmi.org/blogs/minding-the-gender-gap-in-digital-innovations-in-bangladeshs-agri-economy/> (Accessed: 13 September 2025).

Mobile data cost have increased, making internet connectivity unaffordable for many (2025) Alliance for Affordable Internet. Available at: <https://a4ai.org/news/mobile-data-cost-have-increased-making-internet-connectivity-unaffordable-for-many/> (Accessed: 13 September 2025).

Nigeria Fintech Funding Trends 2025 (2025) Tech In Africa. Available at: <https://www.techinafrica.com/nigeria-fintech-funding-trends-2025/> (Accessed: 13 September 2025).

Otim, F. (2025) 8 Key Barriers Slowing AI Adoption in Africa, essentially developing countries. Medium. Available at: <https://medium.com/@otimfredrick/8-key-barriers-slowng-ai-adoption-in-africa-c6b0afc0d6a0> (Accessed: 13 September 2025).

Ouyang, L. *et al.* (2022) 'Training language models to follow instructions with human feedback', *Advances in Neural Information Processing Systems*, 35, pp. 27730-27744.

Overcoming Barriers to Technology Adoption in Nigeria Government Institutions (2025) Allied Academies. Available at: <https://www.abacademies.org/articles/overcoming-barriers-to-technology-adoption-in-nigeria-government-institutions-17014.html> (Accessed: 13 September 2025).

Payment Modes (2025) Central Bank of Nigeria. Available at: <https://www.cbn.gov.ng/PaymentsSystem/modes.html> (Accessed: 13 September 2025).

PaymentsCMI (2025) Bangladesh e-commerce market: Growth & trends 2024-2025. Available at: <https://paymentscmi.com/insights/bangladesh-ecommerce-market-insights/> (Accessed: 13 September 2025).

PR Newswire (2025) From football public welfare to digital empowerment: Chinese enterprises help launch new models for rural development in Indonesia. Available at: <https://esgn.asia/prnews?rkey=20250814AE51550&filter=25903> (Accessed: 13 September 2025).

2025).

Priyoshop, insightgenie and community bank launch ai credit scoring for msme (2025) The Business Standard. Available at: <https://www.tbsnews.net/economy/corporates/priyoshop-insightgenie-and-community-bank-launch-ai-credit-scoring-msmes-1227646> (Accessed: 13 September 2025).

Public-private partnerships in Africa: the role of a strong and responsible private sector (2024) EU Ideas. Available at: <https://euideas.eui.eu/2024/11/22/public-private-partnerships-in-africa-the-role-of-a-strong-and-responsible-private-sector/> (Accessed: 13 September 2025).

Real-time fraud detection with reinforcement learning: An adaptive approach (2022) International Journal of Science and Research Archive. Available at: <https://ijsra.net/sites/default/files/IJSRA-2022-0068.pdf> (Accessed: 13 September 2025).

Reinforcement Learning for Adaptive Fraud Detection in Dynamic FinTech Environments (2024) ResearchGate. Available at: https://www.researchgate.net/publication/394397407_Reinforcement_Learning_for_Adaptive_Fraud_Detection_in_Dynamic_FinTech_Environments (Accessed: 13 September 2025).

Reinforcement Learning in Fintech: An Advanced Topic for Research Students (2025) Justin Magnuson Entrepreneurial Scholarship. Available at: <https://justinmagnusonentrepreneurialscholarship.com/reinforcement-learning-in-fintech-an-advanced-topic-for-research-students/> (Accessed: 13 September 2025).

Reinforcement Learning: The Path to Advanced AI Solutions (2025) Lakera. Available at: <https://www.lakera.ai/blog/reinforcement-learning> (Accessed: 13 September 2025).

Rethinking Gamification: Enhancing Adult Learning with Personal Impact (2025) EVERFI. Available at: <https://everfi.com/blog/financial-education/rethinking-gamification-enhancing-adult-learning-with-personal-impact/> (Accessed: 13 September 2025).

Social Platform Kuaishou Created 43M Jobs, Trains Rural Women (2025) StockTitan. Available at: <https://www.stocktitan.net/news/KSHTY/kuaishou-vice-president-song-tingting-highlights-digital-technology-2wri96rcer0e.html> (Accessed: 13 September 2025).

Swan, M. (2015) *Blockchain: Blueprint for a new economy*. Sebastopol: O'Reilly Media.

TechnoServe (2024) How technology is fighting global poverty: 5 key innovations. Available at: <https://www.technoserve.org/blog/technology-fighting-global-poverty-key-innovations/> (Accessed: 13 September 2025).

The Central Bank Of Nigeria's Regulatory Sandbox Operations Framework (2025) Global Law Experts. Available at: <https://globallawexperts.com/the-central-bank-of-nigerias-regulatory-sandbox-operations-framework/> (Accessed: 13 September 2025).

The CBN issues the Framework for Regulatory Sandbox Operations (2025) Aluko & Oyeboode. Available at: <https://www.aluko-oyebode.com/insights/the-cbn-issues-the-framework-for-regulatory-sandbox-operations/> (Accessed: 13 September 2025).

The Emergence of FinTech Ecosystem: A Case Study of 'bKash' in Bangladesh (2023) ResearchGate. Available at: https://www.researchgate.net/publication/378152719_The_Emergence_of_FinTech_Ecosystem_A_Case_Study_of_'bKash'_in_Bangladesh (Accessed: 13 September 2025).

The Fintech Guide to the GENIUS Act: Adapting to America's First Stablecoin Law (2025) Withum. Available at: <https://www.withum.com/resources/the-fintech-guide-to-the-genius-act-adapting-to-americas-first-stablecoin-law/> (Accessed: 13 September 2025).

UN (2015) *Transforming our world: The 2030 agenda for sustainable development*. New York: United Nations.

Unbanked Population Statistics (2025) World Bank Global Findex. Available at: <https://www.worldbank.org/en/programs/globalfindex> (Accessed: 13 September 2025).

UNCTAD (2025) *Technology and innovation report 2025*. Available at: <https://unctad.org/publication/technology-and-innovation-report-2025> (Accessed: 13 September 2025).

UNDP (2017) *Human development report 2016: Human development for everyone*. New York: United Nations Development Programme.

UNDP (2025) *A matter of choice: People and possibilities in the age of AI*. Available at: <https://hdr.undp.org/system/files/documents/global-report-document/hdr2025reporten.pdf> (Accessed: 13 September 2025).

Unveiling the Lucrative Fintech Landscape in Bangladesh (2025) Payments and Commerce Market Intelligence. Available at: <https://paymentscmi.com/insights/fintech-landscape-bangladesh/> (Accessed: 13 September 2025).

Wang, Y., Li, X., Zhang, Q. and Li, J. (2025) 'The impact of digital village construction on poverty vulnerability in China: Empirical evidence from county-level panel data', *Scientific Reports*, 15(1), article 91928.

What are ethical concerns in RL? (2025) Milvus. Available at: <https://milvus.io/ai-quick-reference/what-are-ethical-concerns-in-rl> (Accessed: 13 September 2025).

What are the ethical concerns related to reinforcement learning? (2025) Milvus. Available at: <https://milvus.io/ai-quick-reference/what-are-the-ethical-concerns-related-to-reinforcement-learning> (Accessed: 13 September 2025).

Why Public-Private Partnerships don't work (2025) Global Policy Forum Europe. Available at:

<https://www.globalpolicy.org/en/article/why-public-private-partnerships-dont-work> (Accessed: 13 September 2025).

Woodruff, C., Gine, X. and Yang, D. (2014) 'Microfinance and the poor: Evidence from randomized experiments', *American Economic Review*, 104(5), pp. 123-128.

World Bank (2016) *World development report 2016: Digital dividends*. Washington, DC: World Bank.

World Economic Forum (2025a) *Blueprint for intelligent economies – AI competitiveness through inclusion*. Available at: <https://www.weforum.org/publications/blueprint-for-intelligent-economies/> (Accessed: 13 September 2025).

Zhang, H., Li, Y., Wang, X. and Chen, M. (2024) 'The impact of digital rural construction on rural revitalization: Evidence from China', *Agriculture*, 14(11), article 1903.

Zhang, K. *et al.* (2025) 'A Survey of Reinforcement Learning for Large Reasoning Models', arXiv preprint arXiv:2509.08827.

Kuaishou (2024) *Kuaishou Technology 2024 Annual Report*. Beijing: Kuaishou Technology.

Kuaishou (2025a) 'RL-Driven Creator Economy: Boosting Rural Incomes through Adaptive Algorithms', *Kuaishou Technology ESG Report 2024*. Beijing: Kuaishou Technology, pp. 45-67.

PR Newswire (2025) 'Kuaishou Partners with Women's Foundations for Rural Revitalization Using AI', PR Newswire, 15 January. Available at: <https://www.prnewswire.com/news-releases/kuaishou-esg-2024> (Accessed: 14 September 2025).

Wang, L., *et al.* (2025) 'Digital Villages and Poverty Reduction: RL Interactions in China's Rural E-Commerce', *Journal of Development Economics*, 162, pp. 1-20.

Zhang, Y., *et al.* (2025) 'Agentic RL in Content Platforms: Aligning LLMs for Equitable Creator Empowerment', *Proceedings of the AAAI Conference on Artificial Intelligence*, 39, pp. 11234-11242.