



An Explainable Predictive Risk Intelligence Framework for Strengthening Governance Effectiveness and Project Success

Abstract

Artificial intelligence has become central to how African FinTech firms detect fraud, assess credit risk, and extend financial services to previously underserved populations. However, its rapid deployment has outpaced the governance structures meant to keep it accountable. This study set out to understand how explainable predictive risk intelligence relates to AI governance effectiveness in African FinTech organisations, and, in turn, how that governance effectiveness shapes the success of AI-enabled digital transformation projects. The inquiry drew on the Technology-Organization-Environment framework and Dynamic Capabilities Theory to make sense of how firms convert technological capability and regulatory pressure into workable governance practice. Because the aim was conceptual rather than statistical, the study proceeded through a qualitative systematic literature review, synthesised Seventeen evidence sources published between 2019 and 2025, supplemented by foundational theoretical and methodological works from Scopus, Web of Science, Google Scholar, and relevant regulatory and industry publications. The literature was analysed using Jabareen's (2009) conceptual framework analysis method. The review's central finding was that, while explainability is widely treated in the literature as a mechanism that strengthens governance, and governance is in turn widely linked to project success, no source retrieved through the search integrated all three constructs such as; explainability, governance, and project success, within an African institutional setting. Existing African-focused scholarship addresses AI regulation or financial inclusion in isolation, leaving governance frameworks that combine predictive risk intelligence with explainability largely theorised outside the continent. The study concluded that sustainable AI-enabled transformation in African FinTech rests less on predictive sophistication than on the institutional capacity to govern that intelligence transparently. It recommended that African FinTech regulators and industry bodies establish mandatory explainability standards, requiring that predictive risk systems used in credit, fraud, and compliance decisions be auditable and interpretable by both supervisors and the institutions that deploy them.

Keywords: Explainable Artificial Intelligence; Predictive Risk Intelligence; AI Governance; African FinTech; Project Success; Digital Transformation.

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Introduction

Artificial intelligence is arguably a defining technology of the current wave of industrial change, increasingly

influencing how organisations create value, manage risk, and respond to rapidly changing business environments. AI has evolved from experimental

applications into an important organisational capability supporting decision-making, risk management, fraud detection, and customer-service processes. This transition reflects a broader shift in which organisations are integrating AI into core workflows and strategic activities. Recent survey evidence indicates that more than three-quarters of organisations report active AI use in at least one business function, with many redesigning workflows around AI-enabled capabilities (McKinsey & Company, 2025). Consistent with earlier theorising on how firms develop and renew capabilities in response to changing environments (Teece, Pisano, & Shuen, 1997), this development extends beyond technological adoption to the reorganisation of organisational processes around data, analytics, and predictive capabilities.

That reorganisation is what most people mean by digital transformation, not simply automating an existing process, but rebuilding structures, business models, and decision systems around what digital tools now make possible. AI sits at the centre of this because of a fairly narrow but consequential ability, to process large volumes of data, surface patterns a human analyst would miss, and generate predictions that inform decisions in real time (Teece *et al.*, 1997; McKinsey & Company, 2025). Financial services have absorbed more of this than almost any other sector, and the reason is structural rather than incidental. Banks and financial institutions already operate

in data-dense, transaction-heavy, tightly regulated environments, which makes them a natural fit for AI-driven credit assessment, fraud detection, anti-money-laundering monitoring, and algorithmic forecasting (Vuković, Dekpo-Adza, & Matović, 2025). The gains are real, faster decisions, tighter risk controls, better-tailored products, but they come bundled with a governance problem that is easy to underestimate: as these systems grow more sophisticated, it becomes correspondingly harder to say with confidence why a given system reached a given decision, and that opacity has direct implications for oversight and trust (Černevičienė & Kabašinskas, 2024).

Within financial services, FinTech is where this tension shows up most visibly. FinTech, broadly, is the use of digital technology to make financial products and services more accessible, cheaper to deliver, and easier to use, and AI has become one of its principal engines, powering digital payments, mobile banking, alternative credit scoring, robo-advisory, identity verification, and fraud prevention (Vuković *et al.*, 2025). Nowhere is this more visible than in Africa, where mobile money and digital payment platforms have driven a decade of rapid growth in financial inclusion, reaching populations that conventional banking had largely bypassed (Oriji, Shonibare, Daraojimba, Abitoye, & Daraojimba, 2023). African FinTech firms now lean on AI to assess creditworthiness in markets with thin credit histories, to flag fraudulent transactions, and to

personalise services for highly diverse customer bases, all tasks well suited to AI's pattern-finding strength, and all tasks that matter more, not less, in environments where the margin for error is thinner (Mota Makore, 2024).

The trouble is that governance has not kept pace with adoption across much of the continent, the legal and regulatory instruments meant to oversee financial technology predate widespread AI use, and consequently say little about explainability, algorithmic bias, or automated decision-making (Mota Makore, 2024). Internally, many organisations show the same lag, they roll out AI systems faster than they build the policies, oversight mechanisms, and risk structures needed to manage them responsibly, leaving gaps in model monitoring, transparency, and accountability that raise the odds of operational, ethical, and reputational harm (Kuiper, van den Berg, van der Burgt, & Leijnen, 2022). Much of this stems from a structural feature of modern AI itself, many of the models in use function as black boxes, producing accurate outputs through processes that are difficult for developers, let alone regulators or customers, to trace or explain (Sokol & Flach, 2020; Fritz-Morgenthal, Hein, & Papenbrock, 2022). When those outputs determine who gets credit, whose transaction gets flagged, or how a customer is classified, that opacity stops being a technical footnote and becomes a governance liability.

This matters beyond compliance, because governance effectiveness has a direct bearing on whether digital transformation initiatives succeed at all. These projects already carry substantial risk on their own, heavy investment, organisational disruption, and the ordinary difficulty of getting people to change how they work, and research on transformation failure consistently points to weak governance and poor risk management as recurring culprits. Layering AI onto that picture adds further complexity around data quality, model drift, and regulatory exposure. What follows from this is the concern this study takes up, how African FinTech organisations can govern increasingly autonomous AI systems in ways that build rather than erode trust, and what role explainable predictive risk intelligence might play in making that possible.

Problem Statement

AI has undeniably expanded what African FinTech firms can do, automate decisions, catch fraud earlier, assess credit more precisely, and reach customers that traditional banking structures were never built to serve (Vuković *et al.*, 2025; Oriji *et al.*, 2023). But that expansion has occurred largely without a matching expansion in the ability to govern it. The core difficulty is one of interpretability, as AI models used for credit approval, fraud investigation, and risk scoring become more complex, they also become harder to audit, and this opacity strains the trust of regulators,

customers, and the institutions themselves (Černevičienė & Kabašinskas, 2024; Kuiper *et al.*, 2022).

The problem is sharper in African markets specifically, because the regulatory scaffolding that might otherwise compensate for this opacity is itself still forming. Legal frameworks in many jurisdictions were not designed with AI in mind and offer little explicit guidance on algorithmic accountability or automated decision-making (Mota Makore, 2024), and evidence suggests organisations are adopting AI faster than they are building the governance capacity to manage it (Centre for Economic Policy Research, 2025). The result is an environment where regulatory uncertainty, fragmented compliance expectations, and limited institutional capacity intersect at exactly the point where the stakes are highest.

In this study, project success extends beyond traditional measures of time, cost, scope, and quality to include stakeholder acceptance, effective adoption, regulatory compliance, risk reduction, and the achievement of intended digital transformation outcomes. Such projects already fail at high rates because of inadequate governance and weak risk management even before AI is introduced (Boston Consulting Group, 2020), and AI adds its own layer of difficulty through model drift, data quality problems, and algorithmic bias. Existing governance approaches tend to emphasise compliance and oversight after the fact, rather than building predictive

risk intelligence and explainability into decision-making as it happens. The problem this study addresses, then, is a practical one: African FinTech organisations need a way to govern AI that is transparent and accountable enough to sustain trust, and predictive enough to catch risk before it compounds, and at present, no coherent approach combines both.

Aim and Objectives of the Study

The primary aim of this study is to develop an explainable predictive risk intelligence framework for strengthening AI governance effectiveness and enhancing project success in African FinTech digital transformation initiatives. In pursuit of this aim, the study set out to:

- i. Examine the role of explainable predictive risk intelligence in strengthening AI governance effectiveness within African FinTech organisations;
- ii. Assess the influence of AI governance effectiveness on project success in AI-enabled digital transformation initiatives within African FinTech organisations; and
- iii. Develop a conceptual framework explaining how explainable predictive risk intelligence can enhance AI governance effectiveness and contribute to project success in African FinTech digital transformation.

Research Questions

- i. How does explainable predictive risk intelligence strengthen AI

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governance effectiveness within African FinTech organisations?

ii. How does AI governance effectiveness influence project success in AI-enabled digital transformation initiatives within African FinTech organisations?

iii. How can explainable predictive risk intelligence and AI governance be integrated into a conceptual framework for enhancing project success within African FinTech digital transformation environments?

Theoretical Framework

This study rests on two theoretical anchors that, taken together, explain both why AI governance breaks down and how organisations might fix it. The first, the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990), holds that technology adoption decisions are shaped simultaneously by three forces; the technological attributes of the innovation itself, the internal readiness of the organisation to absorb it, and the external environmental conditions, regulation, market pressure, competitive dynamics, within which the organisation operates. Applied here, TOE gives structure to what would otherwise be a diffuse list of governance problems. Explainability and model interpretability sit on the technological dimension; internal oversight capacity, risk policies, and staff competence sit on the organisational dimension; and the immaturity of AI-specific regulation across African

jurisdictions sits on the environmental dimension. Read this way, the governance failures described in the literature can therefore be understood as consequences of misalignment across the three dimensions, particularly where technological capability outpaces organisational and environmental readiness.

The second, Dynamic Capabilities Theory (Teece *et al.*, 1997), explains how firms might close that gap over time rather than simply naming where it lies. Teece and colleagues describe three capabilities organisations need to adapt to changing conditions; sensing opportunities and threats, seizing them through timely resource allocation, and reconfiguring internal structures to sustain the advantage gained. Mapped onto AI governance, sensing corresponds to an organisation's ability to detect emerging model risk before it materialises into harm, which is precisely what predictive risk intelligence is meant to do. Seizing corresponds to the governance structures that translate a detected risk into a concrete response, such as escalation protocols or model retraining. Reconfiguring corresponds to the institutional learning that lets an organisation update its governance policies as its AI systems and regulatory environment evolve. TOE and Dynamic Capabilities Theory frame explainability not as a technical add-on but as a governance capability in its own right, one that only functions when technological, organisational, and

environmental conditions are aligned, and one that must be continuously sensed, seized, and reconfigured rather than installed once and left alone. This dual lens underpins the conceptual synthesis that this review builds toward.

Methodology

Because the aim of this study was to build conceptual understanding rather than to test a hypothesis against primary data, a qualitative systematic literature review (SLR) was the most suitable design. This approach is well suited to synthesising scattered scholarly and institutional knowledge into a coherent conceptual account, consistent with established guidance on using systematic review to generate evidence-informed conceptual and managerial insight rather than merely to catalogue prior findings (Tranfield, Denyer, & Smart, 2003).

Literature was retrieved systematically from Scopus, Web of Science, and Google Scholar, supplemented by targeted searches of institutional and regulatory sources such as McKinsey & Company and relevant financial regulatory authorities. Search strings combined the study's core constructs using Boolean operators for instance, pairing explainable artificial intelligence or XAI with financial services or FinTech; pairing AI governance or algorithmic governance with project success or digital transformation; and pairing predictive risk intelligence or risk analytics with Africa or emerging markets. Each string was run independently across databases,

with results exported to a reference manager for deduplication.

Sources qualified for inclusion if they were published between 2019 and 2025, written in English, addressed AI governance, explainability, predictive risk analytics, or project success within financial services or a comparably data-intensive sector, and were either peer-reviewed or, where grey literature was used, issued by a credible institutional or regulatory body. Purely technical papers with no organisational or governance relevance, unsupported opinion pieces, non-English sources, and duplicates were excluded. This process yielded a final synthesis sample of seventeen sources.

The retained literature was analysed using Jabareen's (2009) conceptual framework analysis method, which proceeds through mapping the literature across thematic domains, identifying recurring categories, assessing each category's theoretical role against the TOE and Dynamic Capabilities lenses, integrating categories into coherent relationships, and validating the resulting framework against the full source set, including checking for domains the search failed to surface. Because the review was conducted by a single researcher, credibility was supported through triangulation across academic, industry, and regulatory source types and through a documented, auditable search-and-selection trail, consistent with established criteria for trustworthiness in qualitative research (Lincoln & Guba, 1985). The scope of the review was

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deliberately bounded to English-language, database-indexed sources published within the 2019–2025 window, a limitation stated here explicitly rather than treated as incidental.

Finding

i. No Integrated Governance Framework Exists for African FinTech

The review surfaced several patterns, but one finding stands out as the most consequential for both scholarship and practice; despite a search deliberately designed to capture work at the intersection of explainability, AI governance, and project success, no retrieved source integrates all three constructs within an African institutional context.

This gap is worth dwelling on because it is not for lack of relevant surrounding scholarship. The literature is, if anything, fairly confident that explainability strengthens governance. Černevičienė and Kabašinskas (2024), synthesising 138 studies, argue that interpretability is necessary to improve risk assessment and to sustain a resilient, trustworthy financial ecosystem, a position echoed by Kuiper *et al.* (2022) in their study of how banks and supervisory authorities treat explainability as a precondition for trusting AI-driven financial decisions, and by Sokol and Flach (2020), who propose standardised fact sheets as a way of making explainability auditable within governance processes. The literature is

similarly confident, if less precise, that governance effectiveness relates to project success. Vuković *et al.* (2025) treat governance and explainability as central to successful AI-enabled financial transformation, while noting the absence of standardised implementation frameworks; Chang and Chen (2025) identify leadership commitment and organisational readiness as success drivers in digital transformation more broadly; Barba-Sánchez, Meseguer-Martínez, Gouveia-Rodrigues, and Raposo (2024) similarly link firm-level IT capability and digital orientation to transformation performance, again without reference to AI governance specifically; and the Boston Consulting Group (2020) frames transformation success in largely financial-outcome terms that do not explicitly account for AI governance maturity at all. Taken together, these strands support a directional relationship rather than a precise one, governance and success are measured through non-comparable proxies across studies, a limitation the field has inherited rather than resolved.

What is missing is the connective tissue between these strands, and specifically, the African institutional context in which that connective tissue would need to hold. The African-focused sources the search did retrieve, Mota Makore (2024) on AI regulation and financial inclusion in South Africa, Oriji *et al.* (2023) on FinTech legal frameworks across the continent, and the Centre for Economic Policy Research (2025) on AI in emerging-

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market financial supervision, each treats governance or financial inclusion as a subject in its own right, without connecting either to explainability or to project-level outcomes. This should be read as a bounded finding rather than a sweeping one: African-specific AI governance scholarship clearly exists and is growing, which tempers any claim that the continent is simply absent from the literature. But within the parameters of this review's English-language, database-indexed search, the pattern held consistently enough across all three African-focused sources to support a fairly direct conclusion, that an integrated, Africa-contextualised framework linking explainability, governance, and project success is not merely a nice addition to the literature but a genuine and currently unmet need.

Conclusion

The single point worth holding onto from this review is a reframing rather than a summary: explainability in African FinTech should not be treated as a technical feature bolted onto an AI system after the fact, but as a governance capability in its own right, on the same footing as risk policy or regulatory compliance. The literature already accepts, fairly comfortably, that explainability helps governance and that governance helps project success. What it has not yet done, and what this review makes newly visible by its absence, is treat those two relationships as parts of a single institutional capability that African FinTech organisations need to build

deliberately, rather than acquire as a side effect of adopting better models. That distinction matters because it changes where the responsibility sits; not with the sophistication of the AI system a firm buys or builds, but with whether the institution has the structures in place to sense, interpret, and act on what that system is doing. Until governance is understood in those terms, predictive capability alone will keep outrunning the institutional capacity meant to keep it accountable.

Recommendations

Based on the findings of the study, the following actionable recommendations are proposed:

- i. Institutionalise mandatory explainability requirements for AI deployment - African FinTech regulators, central banks, and financial-sector governance bodies should establish mandatory explainability requirements as a formal condition for deploying AI systems in high-impact financial decision-making. The requirements should initially prioritise AI applications used for credit assessment, fraud detection, customer-risk classification, and regulatory compliance, where algorithmic decisions can have significant consequences for customers and financial institutions.
- ii. Integrate explainability requirements into existing

supervisory and licensing processes -

National financial regulatory authorities should incorporate explainability assessments into existing licensing, authorisation, model-validation, and supervisory-review procedures rather than waiting for comprehensive AI-specific legislation. This would enable regulators to use existing institutional mechanisms to require FinTech organisations to demonstrate that their AI systems can produce understandable and reviewable outputs.

- iii. Adopt standardised AI explainability documentation - Regulators and industry governance bodies should develop a standardised documentation template for AI systems, drawing on the explainability fact-sheet approach proposed by Sokol and Flach (2020). At a minimum, the documentation should identify the model's purpose, data sources, key variables, decision logic, limitations, known risks, validation procedures, and the basis for individual or aggregate AI-generated decisions. This documentation should be accessible to authorised internal auditors, risk managers, and regulatory supervisors.
- iv. Require continuous explainability and risk monitoring throughout

the AI lifecycle -

FinTech organisations should not treat explainability as a one-time requirement completed during system development. Regulators should require organisations to establish continuous monitoring mechanisms that assess model performance, data changes, model drift, emerging risks, and the consistency of explanations throughout the AI system's operational lifecycle. Significant changes in model behaviour or risk exposure should trigger documented review and, where necessary, model recalibration or suspension.

- v. Establish clear accountability for AI-generated decisions - FinTech organisations should assign clearly defined responsibilities to senior management, AI developers, data scientists, risk managers, compliance officers, and internal auditors for overseeing AI systems. Explainability documentation should therefore be incorporated into existing AI governance, risk management, audit, and compliance structures, ensuring that responsibility for AI-supported decisions does not become diffused across technological systems.

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