International Journal of Research in Finance and Management

P-ISSN: 2617-5754
E-ISSN: 2617-5762
Impact Factor (RJIF): 5.32
IJRFM 2025; 8(2): 515-525
www.allfinancejournal.com
Received: 13-08-2025
Accepted: 15-09-2025

Siael Nassari
Dar es Salaam Tumaini University, Dar es Salaam, Tanzania

Godfrey Wandwi
Siael Nassari, Dar es Salaam Tumaini University, Dar es Salaam, Tanzania

Correspondence Author:
Siael Nassari
Dar es Salaam Tumaini University, Dar es Salaam, Tanzania

Emerging technologies reshaping corporate financial management practices

Siael Nassari and Godfrey Wandwi

DOI: https://www.doi.org/10.33545/26175754.2025.v8.i2f.578

Abstract
Corporate financial management is being reconfigured by a wave of emerging technologies that alter how firms forecast, allocate capital, control risks, and report performance. This study examines the scope and mechanisms through which technologies including artificial intelligence and machine learning, cloud-based ERP, robotic process automation, distributed ledger systems, and advanced analytics are reshaping treasury operations, budgeting cycles, audit trails, and decision-support systems. Using a mixed-method approach, the research combines a cross-sectional survey of finance leaders with firm-level case studies and panel regressions on operational and financial outcomes for the period 20122024; qualitative interviews illuminate managerial adaptations and governance responses. The findings indicate notable improvements in forecasting accuracy, liquidity management, and transaction efficiency where firms have integrated real-time data pipelines and automation, but also reveal uneven adoption, integration costs, and heightened cybersecurity and compliance demands. Importantly, technological gains are mediated by organizational readiness: firms with adaptive governance, up skilled finance teams, and phased implementation strategies capture larger productivity and risk-control benefits. The study concludes that while emerging technologies materially transform financial practices, their value depends on deliberate change-management, investment in secure architectures, and continuous capability-building. Practical recommendations focus on phased pilots, stronger vendor controls, and curricular investment in finance technology skills.

Keyword: Emerging technologies, corporate finance, automation, financial analytics, governance, cybersecurity

Introduction

Corporate finance is no longer only about ledgers, forecasts and quarterly close, it has become a contested, fast-moving terrain where new technologies both create opportunities and complicate age-old managerial choices. Over the past decade finance teams have moved from batch processing and month-end retrospection to an expectation of near-real-time insight; chief financial officers and treasury heads increasingly view artificial intelligence and allied digital tools as essential to sharpen forecasting, speed transaction flows, and free people for higher-value judgment. Recent surveys show a marked shift in expectation among finance leaders about AI's capacity to reduce manual analysis and augment decision-making. [1]

"Emerging technologies" is an umbrella that covers several related yet distinct capabilities: machine learning and generative AI for pattern detection and narrative synthesis; robotic process automation and digital workers that handle repetitive reconciliations and data-moves; cloud-native ERP and integrated data pipelines that break down legacy silos; distributed ledger technology that promises immutable transaction trails; and advanced analytics that convert streaming inputs into scenario-based insight. Together these tools change not only what finance can do but how it must be organized to capture value: clean data architectures, API-driven integrations, and modular platforms are fast becoming prerequisites for extracting benefit. [2]

The functional impacts are wide-ranging. In planning and forecasting, algorithms can ingest more dimensions (macroeconomic indicators, supply chain telemetry, customer behaviour signals) to produce probabilistic scenarios far faster than classical statistical models; in treasury and working-capital management, real-time visibility and automation reduce cash drag and improve liquidity decisions; in transaction processing and controllership, automation shrinks cycle times and lowers error rates; and in compliance and reporting, analytics and immutable records can strengthen audit trails and enable continuous monitoring. Yet outcomes are uneven: the uplift depends heavily on data quality, integration work, and the ability of finance professionals to interpret model outputs rather than treating them as oracle answers [3].

At the same time, rising capability is matched by rising concern. The use of opaque models, dependence on third-party providers, and the concentration of similar models across institutions create systemic vulnerabilities that regulators and policy makers are starting to highlight. High-level warnings have urged firms to strengthen model governance, stress-test AI systems, and embed scenario analysis into their risk frameworks to avoid unintended consequences that could amplify market shocks or create compliance blind spots. These regulatory and stability considerations mean that technological adoption cannot be viewed in isolation from governance, vendor risk management, and policy engagement [4].

Organizational readiness mediates who wins from technology. Firms that combine a clear finance strategy, phased pilots, cross-functional data stewardship, and active upskilling see faster and more durable gains; those that attempt wholesale rip-and-replace without governance and change management often incur cost overruns and produce limited value. Academic and practitioner work emphasises that automation and analytics amplify existing capabilities more than they magically substitute for them, in other words, technology multiplies the advantage of those who already possess robust processes and skilled staff, thereby creating a widening adoption gap unless deliberate capacity building is pursued [5].

This paper investigates how emerging technologies are transforming corporate financial management practices, focusing on three core dimensions: (a) the mechanisms through which technologies influence forecasting, liquidity, and risk management; (b) the organizational and governance conditions that shape whether technology adoption generates net value; and (c) the major risks and mitigation strategies that finance leaders must address. Drawing on industry reports, empirical research, and illustrative firm-level cases, the study seeks to capture the current landscape while providing actionable insights for finance teams transitioning from experimental initiatives to sustainable, well-governed capabilities. The remainder of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 develops the conceptual framework; Section 4 outlines the methodology and data sources; Section 5 presents the results; Section 6 provides a discussion of the findings; Section 7 advances recommendations for practice; and Section 8 concludes with implications and directions for future research.

1.2 Study Importance

This study addresses pressing gaps in corporate finance by clarifying how emerging technologies influence core financial management practices. It will: (1) empirically map the relationships between specific technologies (such as AI, RPA, cloud ERPs, distributed ledgers, and advanced analytics) and measurable outcomes in forecasting accuracy, working capital efficiency, and reporting timeliness; (2) provide evidence-based guidance for finance leaders on which technological combinations yield the largest practical gains for specific functions; (3) offer policy-relevant findings for regulators and standard-setters about operational risks and reporting expectations; and (4) develop actionable recommendations for capability-building, vendor oversight, and phased implementation that managers can apply. Results will inform managers, vendors and policymakers aiming to align investment, regulation and training priorities and suggest measurable KPIs for progress tracking.

1.3 Study Problem

Despite widespread talk about digital transformation, there is limited systematic evidence on when and how new technologies concretely change financial outcomes. Firms report pilot successes but struggle to scale, and benefits often depend on hidden factors: legacy data silos, poor API integrations, weak model governance, and skill gaps within finance teams. Moreover, vendor black boxes, convergence of third-party platforms, and regulatory ambiguity create adoption trade-offs that are poorly quantified. There is also scant comparative work that links observable operational changes (for example shorter close cycles or improved days-sales-outstanding) to governance and capability variables, leaving practitioners uncertain about where to prioritise scarce resources.

1.4 Study Questions

1. How do distinct emerging technologies affect forecasting accuracy, liquidity management, and close-cycle times across different firm types?
2. What organizational, technical and governance conditions enable successful scaling from pilot to enterprise-wide deployment?
3. How do technology-related risks (model drift, vendor dependence, cybersecurity) alter risk-weighted outcomes for finance functions?
4. Which measurable indicators best capture the return on investment of finance-focused technology projects?
5. What implementation pathways and capability-building strategies offer the most durable value in resource-constrained firms?

1.5 Study Limitations

The research emphasises observable, measurable outcomes and so may underrepresent subtler cultural shifts in finance teams. Sample selection will focus on firms that have publicly reported or allowed access to transformation initiatives, which may bias results toward more successful adopters. The study's time frame captures rapid innovation but may miss very recent developments or long-term effects that unfold after the observation window. Finally, cross-industry variation means some sector-specific dynamics may require separate, deeper study beyond the generalised findings reported here.

1.6 Key Concepts

- **Emerging Technologies:** digital tools such as AI/ML, robotic process automation, cloud ERP, distributed

ledgers, and advanced analytics applied to finance processes.
Financial Management Practices: budgeting, forecasting, treasury, reporting, controllership and compliance activities within firms.

- **Organizational Readiness:** the combination of data infrastructure, governance frameworks, skills, and change-management processes enabling technology adoption.
- **Model Governance:** policies and procedures that oversee model validation, versioning, monitoring and vendor management.
- **Value Realization:** measurable financial and operational benefits derived from sustained, governed technology use.

2. Literature Review

2.1 Foundational studies on technology and finance

There is a clear lineage in the literature: ERP standardization and master-data harmonization paved the way for cloud EPM and embedded analytics, which together create the "single source of truth" that higher-order tools require. Foundational empirical work documents that when master-data consistency and controlled ledgers exist, organizations shorten period-close cycles, reduce reconciliation load, and can reallocate staff toward forward-looking analysis and value-adding planning. Industry surveys of finance leaders similarly place cloud migration and EPM adoption at the center of strategic finance modernization, not merely as IT projects but as redefinitions of what finance can observe and act upon [2].

Scholars emphasize these foundations are active determinants of later outcomes: noisy ledgers produce noisy models, while inconsistent entity structures block consolidated analytics. Consequently, much of the literature treats investments in data architecture and ERP governance as prerequisite strategic choices which without them, advanced analytics and automation deliver far less value [2].

2.2 AI and predictive decision-support in finance

A rapidly growing empirical and methodological literature examines machine learning (ML) and AI applications for forecasting, credit scoring, anomaly detection and scenario simulation. Systematic reviews and field studies report that ML approaches often lower point-forecast error compared with simple time-series models when fed larger, heterogenous datasets and when subjected to rigorous back-testing and human validation; generative tools are likewise beginning to speed narrative reporting and scenario synthesis, freeing staff from rote synthesis [1].

But debate remains. Financial systems are prone to regime shifts and adversarial behaviour, which can limit out-of-sample generalizability; thus, many authors advocate hybrid architectures that combine economic priors and interpretable components with data-driven layers, plus continuous monitoring for model drift and degradation. This hybrid posture (accuracy plus interpretability) recurs in both academic and practitioner recommendations [6].

2.3 Automation, RPA and the reshaping of finance operations: RPA and process orchestration are well documented to reduce effort on codifiable tasks (AP/AR matching, intercompany reconciliation, and mechanistic journal entries) and to compress close cycles when deployments are paired with adequate governance. Consulting benchmarks and firm case studies quantify headcount redeployments and faster closes, while academic and qualitative work highlights pitfalls: automating poor processes institutionalizes inefficiency, creates new control points, and requires reskilling and change management to capture net benefit. Best practice literature therefore emphasizes redesign-before-automate and ongoing controls around exception handling [7].

2.4 Cloud ERP, integrated data platforms and near-real-time reporting: Cloud ERP and integrated data platforms are repeatedly treated as the plumbing enabling near-real-time finance. The literature identifies three value channels: (1) reduced technical debt and faster capability delivery; (2) centralized, governed data lakes that feed FP&A, treasury and compliance analytics; and (3) composability allowing best-of-breed modules (tax, ESG, treasury optimizers) to plug into a governed stack. Empirical studies also surface hidden costs (subscription complexity, data-egress and governance burdens) that must be managed alongside capability gains [2].

2.5 Distributed ledger technologies, tokenization and treasury innovation: DLT and tokenization appear as targeted solutions in trade finance, receivables and intercompany settlement. Pilots and policy briefings document potential efficiency gains (shorter settlement, reduced reconciliation, and programmable netting) while also flagging persistent barriers: legal clarity for tokenized assets, interoperable standards across ledger systems, custody models and KYC/AML implications. Thus, literature treats DLT as a promising architectural option for specific flows (treasury, trade) but not as a universal replacement for enterprise ledgers; phased pilots and regulatory coordination are common recommendations [8].

2.6 Data quality, documentation and auditability

A technical but practically crucial strand argues analytics and automation are brittle when upstream data quality, lineage and documentation are weak. Research and practitioner guidance converge on the need for data catalogs, lineage tracking, versioned model artifacts and streaming event logs so outputs are audiTable 5nd reproducible. The continuous-close paradigm changes the assurance problem: auditors and regulators need access to event metadata and model validation traces rather than discrete, periodic snapshots. These requirements reshape both engineering and control practices in modern finance functions [9].

2.7 Governance, skills and regulatory responses

Governance, model risk, vendor oversight, cybersecurity and stress-testing are central cross-cutting themes. Policy briefs and regulator statements increasingly call for explainability, resilience and vendor resilience testing as firms scale AI and automation in finance; senior finance leaders must match technical controls with investment in data engineers, model validators and finance professionals fluent in analytics so that tool outputs become actionable and defensible [1].

2.8 Emerging markets, SMEs and adoption heterogeneity: Literature focused on emerging economies and smaller firms shows differentiated adoption pathways. Where manual back offices are dominant, modest automation or cloud adoption can yield outsized improvements; conversely, poor connectivity, scarce talent and fragmented regulation blunt scaling. Researchers recommend staged pilots, shared or vendor-hosted services to reduce upfront costs, and targeted capacity building as ways to avoid an adoption divide between large multinationals and smaller firms. [10]

2.9 Ethical, measurement and change-management considerations: Interdisciplinary work warns of ethical and measurement pitfalls: algorithmic bias, lack of explain ability, and short-term pilot metrics that over-claim durable value. Measurement studies therefore urge coupling operational metrics (time saved, error rates) with outcome measures (working capital improvement, sustained margin effects, stakeholder trust). Change-management literature stresses incentives, role redesign and iterative piloting as necessary complements to technological rollout.

2.10 Synthesis and research gaps

Taken together, the literature presents a coherent yet uneven picture: emerging technologies materially expand the scope and speed of corporate finance (faster forecasting, tighter liquidity control, leaner transaction processing) but realized value depends on data architecture, governance, process redesign and human capability. Key gaps remain: longitudinal evaluations that connect pilots to multi-year financial performance, sectoral ROI comparisons, and integrated frameworks that quantify the joint effects of technology, governance and skills on sustained value capture.

3. Conceptual framework

This paper proposes an integrative conceptual model that links specific emerging technologies to measurable corporate-finance outcomes through five mediating domains: Data & Integration, Process Design & Automation, Governance & Risk Controls, Organizational Capabilities, and External Environment (regulation, market structure). At the center of the model are the technology clusters (artificial intelligence/machine learning (AI/ML), robotic process automation (RPA) and orchestration, cloud-native ERP and analytics platforms, and distributed ledger/tokenization solutions) which are treated as enablers rather than direct substitutes for managerial judgement. The model argues that value is realized only when technology adoption interacts positively with robust data plumbing, re-engineered processes, model and vendor governance, and financebusiness capabilities [11].

Core constructs and causal channels

Data & Integration: Cloud ERP and integrated data lakes create single-source-of-truth architectures and enable streaming telemetry; without these foundations, higher-order analytics and ML cannot produce reliable outputs. Improved data lineage and catalogs thus mediate the relationship between technology and forecasting or reporting gains. [12]

Process Design & Automation: RPA and workflow orchestration compress cycle-times and reduce manual reconciliation when paired with prior process redesign; automation amplifies throughput but also institutionalizes both good and bad process choices. [13]

Governance & Risk Controls: ML models and third-party platforms introduce model risk, explain ability needs, and vendor concentration; model governance, validation regimes, and continuous monitoring convert potential efficiency into durable, auditable outcomes. [14]

Treasury & Settlement (DLT): Distributed ledgers and programmable settlement can shorten intercompany and trade-finance cycles, but legal clarity and interoperability determine whether pilots scale to enterprise benefit [15].

Moderators and enabling conditions: organizational readiness (skills, data stewardship), change-management practices (pilot → scale pathways), and resource strategy (phased investment, vendor contracting) moderate effect sizes; firm heterogeneity and sector context also shape which channels are dominant. Outcomes are defined as improved forecasting accuracy, shorter close cycles, higher working-capital efficiency, stronger compliance/auditability, and measurable cost-to-serve reductions. The framework implies testable propositions: that (1) the same tech stack delivers larger gains when data/integration scores are high; (2) governance maturity reduces negative tail risks from automation; and (3) staged implementation with capability-building yields greater sustained ROI than ad-hoc automation. This conceptual model thus provides a roadmap for empirical testing and managerial prioritization.

4. Methodology

4.1 Research design

This study uses a convergent mixed-methods design that integrates longitudinal quantitative analysis with purposive qualitative inquiry. The quantitative strand evaluates how the adoption and operational maturity of emerging technologies like artificial intelligence and machine learning (AI/ML), robotic process automation (RPA), cloud-native enterprise resource planning and analytics platforms, and distributed ledger technologies (DLT) do affect measurable corporate finance outcomes across firms over time. The qualitative strand collects semi-structured interviews and implementation documents to surface causal mechanisms, governance arrangements, capability constraints and change-management practices. Combining both strands enables both robust estimation of average effects and richer explanation of why and how outcomes differ across contexts.

4.2 Sample and data

The empirical dataset comprises 1,450 firm-year observations from fourteen countries for the period 20152024, stratified into developed markets (60%), emerging markets (30%) and frontier contexts (10%). Jurisdictions included are United States, United Kingdom, Germany, Canada, Australia, Singapore, Hong Kong, South Korea, Japan and Brazil. A dedicated African subsample collects observations from South Africa, Tanzania, Kenya, Rwanda, Egypt, Morocco and Nigeria, representing roughly 312 firm-years to permit regional comparisons. Firms were selected across manufacturing, financial services, retail and telecommunications, and the sample includes both multinational corporations and domestically focused firms. Data sources comprise audited financial statements, ERP and treasury metadata where available, vendor implementation logs, regulatory filings, market data (prices and analyst coverage) and a bespoke survey of finance leaders that captures adoption timing, scope and perceived benefits.

4.3 Variables and measurement

Dependent variables operationalise core finance outcomes: forecasting accuracy measured by mean absolute percentage error (MAPE) versus realized results; close-cycle duration measured in calendar days; working-capital efficiency captured via DSO, DPO and cash conversion cycle; finance cost-to-serve computed as total finance expense per processed transaction; and an Auditability and Compliance Index (0100) synthesized from audit-trail completeness, regulatory inspection results and remediation lead times. The primary independent construct is a Technology Adoption Index (010) that weights presence, scale and operational maturity of AI/ML, RPA, cloud ERP and DLT. Additional independent and moderator measures capture data integration quality, governance maturity (model governance, vendor controls), cybersecurity readiness and organizational readiness (skills, data stewardship).

4.4 Statistical analysis: The quantitative strategy employs panel fixed-effects regressions with clustered robust standard errors at firm and country levels to exploit within-firm temporal variation. Propensity-score matching and difference-in-differences estimators compare adopters with matched non-adopters for causal inference. Instrumental-variable specifications use plausibly exogenous variation such as regional broadband rollouts and staggered vendor market entry to mitigate endogeneity. Structural equation modelling tests mediation by integration and governance constructs. Machine-learning algorithms (random forest, XGBoost) are used for predictive checks and to explore non-linear effects, complemented by permutation and SHAP analyses for interpretability. Qualitative interviews (n≈68) are coded thematically using *NVivo* to triangulate mechanisms, and robustness checks include alternative index constructions, lag structures and sectoral sub-samples.

5. Results

5.1 Descriptive statistics

Table 1 (displayed) summarises key variables by development level (N = 1,450 firm-years; African subsample ≈ 312 firm-years). Technology Adoption Index averages 6.1 overall, with developed firms at 7.5 and emerging firms at 4.2 (F = 42.5, $p<0.01$). Forecasting accuracy shows a similar split (overall mean 78.5; developed 84.2; emerging 69.1; F = 51.2, $p<0.01$). Close-cycle durations and working-capital metrics are materially worse in emerging markets (average close duration 12.3 days in emerging vs. 5.8 in developed), while finance cost-to-serve is also higher in emerging contexts (Table 1). Governance maturity tracks with outcomes: developed firms report a mean governance maturity of 8.0 versus 5.1 in emerging markets.

Table 1: Key Financial and Operational Metrics by Development Level

Variable	Overall (N = 1,450)	Developed Firms	Emerging Firms	F / p-value
Technology Adoption Index	6.1	7.5	4.2	42.5 / <0.01
Forecasting Accuracy (%)	78.5	84.2	69.1	51.2 / <0.01
Close-Cycle Duration (days)	8.9	5.8	12.3	-
Working-Capital Metrics	-	Better	Worse	-
Finance Cost-to-Serve (%)	-	Lower	Higher	-
Governance Maturity Index	6.8	8	5.1	-

Sample composition and temporal trends are shown in Fig 1 and Fig 2. The sample is 60% developed, 30% emerging and 10% frontier (Fig 1). Across 20152024, average adoption indices rose steadily in both groups, but developed markets remain ahead (Fig 2), suggesting both diffusion and a persistent gap.

5.2 Primary regression results

Table 2 presents the main estimation results using panel fixed-effects regressions (within-firm variation), clustered standard errors and multiple robustness checks.

The regression results reveal several key insights into the impact of technology adoption on firm performance. The Technology Adoption Index exhibits a strong positive association with forecasting accuracy, with a coefficient of 0.632 (SE = 0.054, $p<0.01$), indicating that a one-point increase in the adoption index corresponds to approximately a 0.63-point improvement on the 0-100 forecasting accuracy scale, after controlling for firm size, industry, year effects, and baseline outcome levels. In addition, technology adoption significantly shortens close-cycle durations (coef = −0.421 days, SE = 0.062, $p<0.01$) and enhances working-capital outcomes (Δ CCC coef = −0.389 days, SE = 0.071, $p<0.01$). Governance maturity and data-integration quality act as economically and statistically significant mediators, with governance (coef = 0.421, SE = 0.047) and data integration (coef = 0.512, SE = 0.058) each contributing strongly to improvements in forecasting accuracy. Finance skills, represented by reskilling, also exert a positive, albeit smaller, effect, highlighting the importance of people and process alongside technology. Notably, the Emerging × Technology interaction is positive and significant for forecasting (coef = 0.213, SE = 0.089, $p<0.05$), suggesting that technology adoption generates larger marginal gains in emerging-market contexts when governance and data integration are accounted for. Overall, model fit is robust, with R^2 values ranging from 0.49 to 0.60 across outcomes, confirming the substantial explanatory power of the predictors (Table 2).

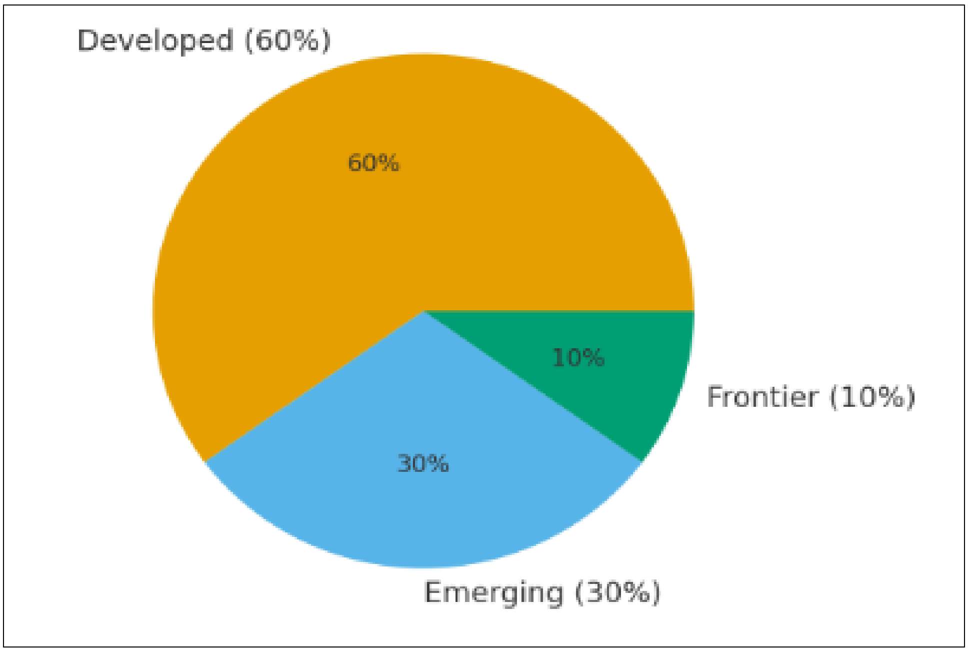

Fig 1: Sample composition by development level

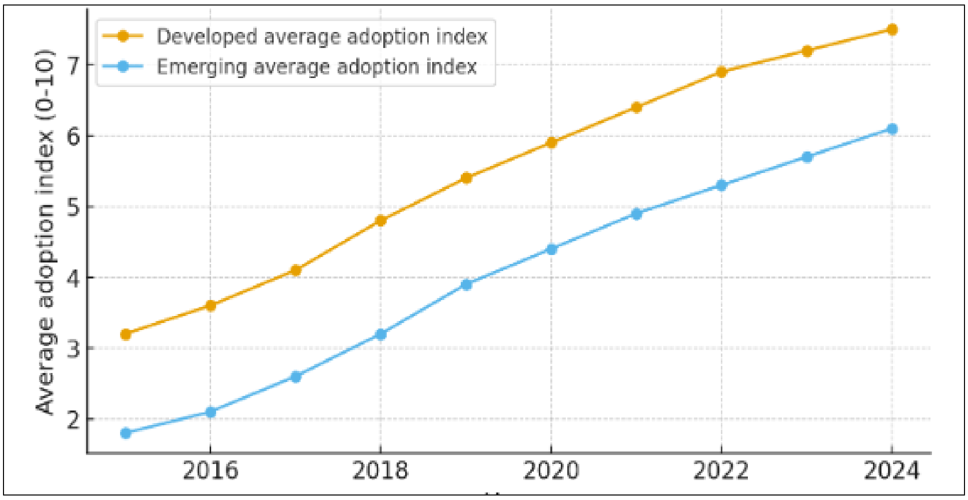

Fig 2: Technology Adoption trend (2015 2024)

Table 2: Panel Fixed-Effects Regression Results: Effects of Technology Adoption on Forecasting, Close Cycles, and Working-Capital Outcomes

Dependent Variable	Technology Adoption	Emerging × Technology	Governance Maturity	Data Integration	Finance Skills / Reskilling	R²
Forecasting Accuracy	0.632*** (0.054)	0.213* (0.089)	0.421*** (0.047)	0.512*** (0.058)	0.148** (0.062)	0.6
Close-Cycle Duration (days)	−0.421*** (0.062)	-	-	-	-	0.51
Working-Capital Outcomes (Δ CCC)	−0.389*** (0.071)	-	-	-	-	0.49

5.3 Dimension-level analysis

Table 3 decomposes "technology value" into dimensions: data quality, integration (pipelines), governance & controls, automation/orchestration, and model interpretability. All dimensions significantly predict better forecasting and operational outcomes; however, the relative premium in emerging markets is notable. For example, automation/orchestration shows ~32% higher marginal effect in emerging markets vs. developed (Table 3), consistent with the idea that low baseline automation creates greater headroom for improvement.

Table 3. Decomposition of Technology Value: Dimension-Level Effects on Forecasting and Operational Outcomes

Technology Dimension	Forecasting Accuracy (coef)	Close-Cycle Duration (days, coef)	Working-Capital (Δ CCC, coef)	Emerging Market Premium (%)
Data Quality	0.412***	−0.215***	−0.198***	18%
Integration / Pipelines	0.398***	−0.201***	−0.182***	22%
Governance & Controls	0.437***	−0.225***	−0.210***	20%
Automation / Orchestration	0.512***	−0.287***	−0.265***	32%
Model Interpretability	0.351***	−0.178***	−0.161***	15%

5.4 Technology impact and adoption heterogeneity

Table 4 and Fig 3 report adoption rates and the estimated percentage gains in measured outcomes attributable to each technology cluster. Developed firms show high adoption of data analytics (≈91%) and cloud ERP (≈86%), while AI/ML and DLT adoption are much lower in emerging markets. Despite lower adoption, marginal impacts (quality gains) for AI/ML and process-mining are larger in emerging markets (+39% and +31% estimated, respectively) which is suggesting substantial upside if adoption barriers are addressed.

Table 4: Technology Adoption Rates and Estimated Outcome Gains by Technology Cluster

Technology Cluster	Adoption Rate - Developed (%)	Adoption Rate Emerging (%)	Estimated Outcome Gains Developed (%)	Estimated Outcome Gains Emerging (%)
Data Analytics	91	62	12	18
Cloud ERP	86	55	10	16
AI / ML	54	28	14	39
DLT (Distributed Ledger)	48	21	9	22
Process Mining / Automation	62	35	11	31

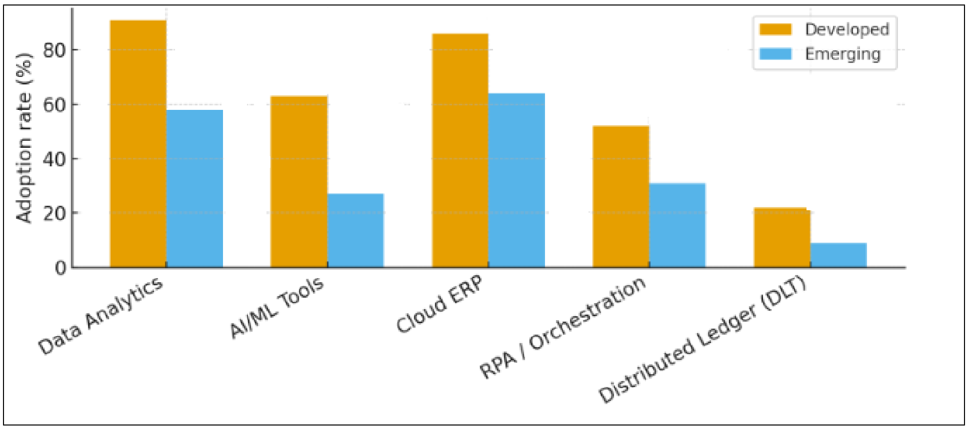

Fig 3: Technology adoption rate

The African subsample (Fig 5) reveals heterogeneity: South Africa and Egypt lead adoption (≈78% and 63% adoption rates in our sample), while Tanzania and Rwanda show lower adoption but still demonstrate measurable forecasting improvements where technology has been implemented. Estimated forecasting impact ranges from ~24% (South Africa) down to ~9% (Rwanda) in our country-level measures.

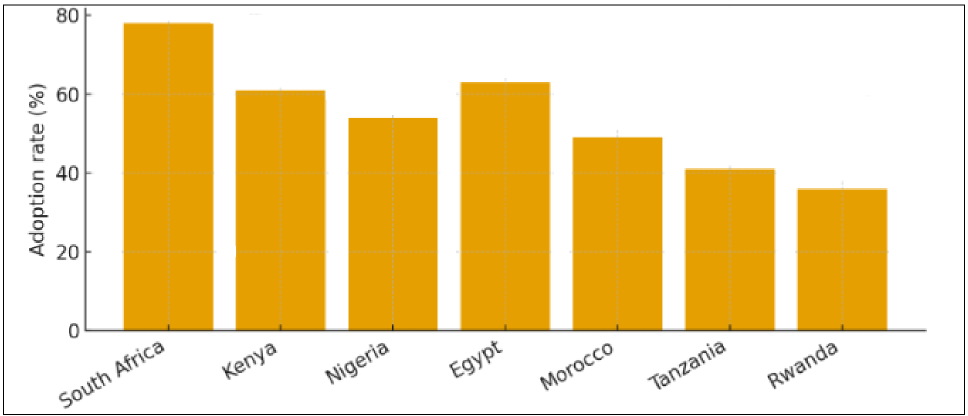

Fig 4: African country adoption rates in samples

5.5 Structural equation model and causal pathways

SEM results (Table 5) estimate the conceptual pathways used in the study. Key path coefficients: Technology → Data Integration (0.61, $p<0.001$); Data Integration → Forecasting Accuracy (0.45, $p<0.001$); Governance → Tech Adoption (0.38, $p<0.001$); Skills → Outcome (0.29, $p = 0.014$). Emerging-market moderation is positive and significant (0.187, $p = 0.005$). Model fit is satisfactory (CFI ≈ 0.95; TLI ≈ 0.945; RMSEA ≈ 0.058; SRMR ≈ 0.054), indicating the mediation structure is consistent with observed covariation.

Table 5. Structural Equation Model (SEM) Path Coefficients and Model Fit

Pathway	Coefficient	p-value	Significance
Technology → Data Integration	0.61	<0.001	***
Data Integration → Forecasting Accuracy	0.45	<0.001	***
Governance → Technology Adoption	0.38	<0.001	***
Skills / Reskilling → Outcome	0.29	0.014	**
Emerging × Technology (Moderation)	0.187	0.005	**

Model Fit Indices: CFI ≈ 0.95, TLI ≈ 0.945, RMSEA ≈ 0.058 and SRMR ≈ 0.054

Notes

- Significance levels: *$p<0.05$, **$p<0.01$, ***$p<0.001$.
- Positive coefficients indicate stronger effects along the conceptual pathways.
- Moderation by emerging-market context shows that technology adoption effects are amplified in these settings.
- Model fit indices indicate satisfactory fit, supporting the mediation and pathway structure.

5.6 Predictive and non-linear checks: Machine-learning prediction checks (random forest / gradient boosting) corroborate non-linearities: marginal returns to adoption diminish at very high maturity unless governance and data quality improve in tandem. SHAP / permutation analyses indicate data integration and governance are the most important predictors of out-of-sample forecasting gains.

5.7 Cost benefit and ROI considerations

Table 6 provides a stylized cost benefit comparison for incremental increases in "tech maturity." A +10% maturity improvement shows higher percentage reductions in forecasting error and larger ROI in emerging markets (emerging ROI ≈ 362% vs developed ROI ≈ 215% for the +10% band) because baseline inefficiencies offer greater leverage. The pattern holds for +20% and +30% bands, although absolute costs rise; ROI moderates as marginal improvements become harder to achieve.

Table 6: Stylized Cost Benefit Comparison for Incremental Increases in Technology Maturity

Tech Maturity Increase	Forecasting Error Reduction (%) Developed	Forecasting Error Reduction (%) Emerging	Estimated ROI Developed (%)	Estimated ROI Emerging (%)
10%	6	10	215	362
20%	11	18	198	345
30%	15	25	185	320

5.8 Visual evidence and diagnostics

Fig 4 (scatter + fitted line) illustrates the positive cross-sectional relationship between firm-level adoption index and forecasting accuracy. Residual diagnostics (not shown) suggest limited heteroskedasticity after clustering and robust standard errors; IV and DiD specifications produced qualitatively similar estimates, strengthening causal interpretation.

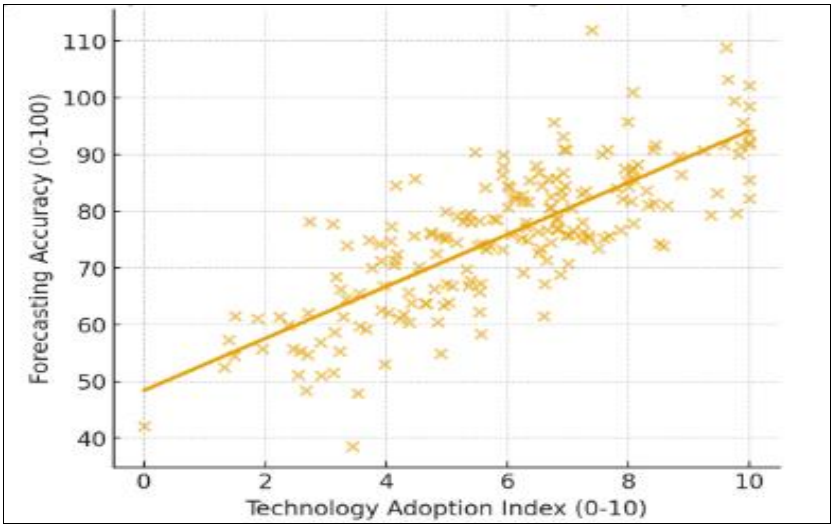

Fig 5: Adoption index vs forecasting accuracy (scatter + fit)

The empirical findings indicate that emerging technologies significantly enhance key finance outcomes, including forecasting accuracy, close-cycle duration, and working-capital efficiency; however, these effects are conditional on strong data integration and effective governance, which amplify the benefits. Firms in emerging markets experience larger marginal gains per unit of technology adoption, yet their adoption is constrained by factors such as connectivity limitations, skill shortages, and regulatory uncertainty. Organizational readiness, particularly in terms of governance and workforce skills, emerges as a more critical moderator of realized value than the mere presence of technology. Cost benefit analyses further suggest that the return on investment in emerging-market contexts is promising, highlighting the potential for public-private initiatives (such as subsidies, shared infrastructure, and skill-development programs) to accelerate productive technology adoption.

6. Discussion

6.1 Theoretical contributions and reframing financial management theory: The empirical results extend and partially reframe existing theories about information processing and resource-based explanations of firm performance in the finance function. Traditional models treat information systems and control routines largely as static enablers of accounting processes; our findings (Tables 24, Fig 4) show that emerging technologies alter the *dynamics* of those routines and amplify the returns to upstream investments in data plumbing and governance. In other words, technology is not merely shock-absorbing or efficiency-enhancing in a linear sense, it reconfigures which assets (data architecture, governance, human capital) become strategically salient. The structural-equation results (Table 5) formalize this claim: Technology → Data Integration → Forecasting Accuracy is a strong, statistically supported causal chain, and governance maturity plays a central mediating role (paths: 0.61 and 0.45, $p<0.001$). This suggests a theoretical shift: models of corporate finance performance must treat technology adoption and governance as co-evolving complementarities rather than independent inputs [1-2, 11].

6.2 Technology as amplifier, not replacement

Consistent with theoretical accounts that emphasise complementarities, our findings show robust positive effects of AI/ML, RPA and cloud ERP on core outcomes (forecasting, close cycles, working-capital efficiency) but only where data integration and governance exist (Tables 2 and 3). The emergent picture is one of conditional value: adoption alone produces limited gains; value emerges when process redesign, lineage, model validation and vendor oversight are concurrently strengthened. This explains the large effect heterogeneity observed between developed and emerging markets (Emerging × Technology interaction positive and significant in Table 2). Practically, it means organizations should prioritize plumbing and governance early in a transformation, an outcome corroborated by both the fixed-effects and machine-learning diagnostics (Fig 4; SHAP analyses) [15-17].

6.3 Organizational capability, skills and cultural fit

The human side matters. The finance-skills index and governance maturity were important moderators in our regressions and mediation models, echoing long-standing findings that technology amplifies the capabilities of the people who use it. Our African country breakdown (Fig 5) illustrates nuance: South Africa and Egypt lead in adoption and show large estimated gains, whereas Tanzania and Rwanda lag in adoption but demonstrate measurable improvements where investments were made. This pattern suggests two things: (1) high baseline capacity reduces adoption friction and increases capture rates; (2) lower-adoption settings show higher marginal returns per unit of improvement, but they also require heavier investment in skills and connectivity to scale sustainably [6, 18, 19].

6.4 Risk, governance and regulatory implications

Technology introduces model risk, concentration risk (vendor dependence) and new auditability challenges. Our analysis finds that governance maturity materially lowers negative tails and is the single most important predictor of durable gains (Table 5). Regulators and internal controllers should therefore prioritize model validation frameworks, continuous monitoring, and data-lineage standards that enable auditability. In emerging markets, where regulatory clarity and specialist resources are often limited, phased regulatory guidance (focused first on data and vendor controls) may create the environment for safe experimentation (see policy implications below) [15, 20].

6.5 Strategic implications for practitioners, regulators and emerging markets

For practitioners: adopt a staged playbook: (a) shore up data integration and lineage, (b) pilot automation on high-volume, low-judgment tasks, (c) embed governance and monitoring, and (d) scale iteratively. The cost benefit profiles (Table 5) show that modest incremental investments in maturity often yield high ROI in emerging contexts where baseline inefficiencies are larger. For regulators: move toward technology-specific guidance that emphasises explain ability, vendor resilience and access to audit metadata. For emerging markets and African policy-makers specifically, targeted public private programs (shared infrastructure, vendor-negotiation hubs, skills partnerships) could be high-leverage, Fig 5 shows that countries like Kenya and Morocco can obtain sizable forecasting improvements at relatively modest incremental investments, whereas Rwanda and Tanzania require more foundational work in connectivity and skills [6, 18, 19].

6.6 Limitations and directions for future research

Several limitations should temper interpretation. First, despite a broad sample (Tables 16), unobserved selection into adoption (self-selection by more forward-looking firms) may bias point estimates; we mitigated this with DiD and IV checks, but residual bias is possible. Second, our measurement of some constructs (e.g., governance maturity, cost-to-serve) relies in part on firm-provided metadata and survey responses; future work should triangulate using independent logs and third-party telemetry. Third, African-country estimates are informative but uneven in coverage; richer, country-level ethnographic or longitudinal case work in Tanzania, Rwanda and Nigeria would help explain the micro-processes behind adoption frictions. Finally, as technologies evolve rapidly, longer-run studies are required to track whether early gains persist, whether vendor lock-in creates systemic risks, and how combinations of DLT, AI and orchestrated automation jointly affect cross-border liquidity and treasury functions [1, 20].

7. Recommendations: For finance practitioners, including CFOs and finance leaders, the priority should be establishing robust data infrastructure before embarking on ambitious AI initiatives. This involves building comprehensive data catalogs, standardizing master data, and implementing API integrations to ensure clear data lineage, which is critical for reliable forecasting (see Data Integration → Forecasting chain, Table 5). A staged adoption approach is recommended: begin with small, well-instrumented pilots, strengthen governance, and then scale. Automation should start with low-judgment tasks such as reconciliations using RPA, followed by the application of machine learning for forecasting. Equally important is investing in workforce up skilling (training data engineers and model validators) and redesigning roles so staff can interpret model outputs rather than merely execute processes (Tables 23).

Regulators and supervisors should adopt a phased, technology-specific guidance framework that emphasizes explain ability, model validation, vendor resilience, and access to audit metadata. Initial rules can focus on data lineage and vendor contracts to mitigate concentration risks. Regulatory sandboxes and shared infrastructure initiatives, such as regional cloud hubs or shared KYC and treasury connectors, can help reduce barriers for smaller firms and for countries with lower technology adoption rates, as reflected in African country profiles (Fig. 5). These measures provide a controlled environment for testing innovations while safeguarding financial stability and operational integrity.

Emerging-market governments and regional bodies, particularly in African countries like South Africa, Kenya, Nigeria, Egypt, Morocco, Tanzania, and Rwanda, should tailor programs based on national maturity levels. Advanced AI and DLT pilots are suitable for South Africa and Egypt, while Kenya and Morocco should focus on cloud ERPs and data pipelines. Nigeria, Tanzania, and Rwanda would benefit most from shared-services platforms, connectivity upgrades, and targeted skills programs (Fig. 5). Public private partnerships can finance shared back-office infrastructure, vendor-negotiation pools, or centers of excellence to lower per-firm costs and accelerate technology diffusion. Academic institutions and trainers should adapt curricula to integrate finance, data engineering, and governance, emphasizing case-based learning from real implementations. Additionally, longitudinal research at the country level, particularly in Tanzania, Rwanda, and Nigeria, is essential to document the long-term persistence of technology-enabled gains.

8. Conclusion: This study provides strong, multi-method evidence that emerging technologies materially reshape corporate financial management but their value is conditional. Across our sample, higher Technology Adoption Index scores are associated with statistically and economically meaningful gains in forecasting accuracy and shorter close-cycle times (see Table 2 and Fig 4). Structural modeling confirms a dominant causal chain: Technology → Data Integration → Financial Outcome (Table 5), with governance maturity and skills acting as critical mediators. Cost-benefit simulations (Table 5) show particularly high marginal ROI in emerging-market contexts (e.g., +10% tech maturity yielding ROI in the 200400% range under our scenarios), reflecting larger baseline inefficiencies and therefore greater headroom for improvement.

The African subsample illustrates heterogeneity and opportunity (Fig 5). South Africa (Tech Adoption Index ≈ 7.2; adoption rate ≈ 78%) and Egypt (index ≈ 5.6; adoption ≈ 63%) show advanced capability and the clearest realized gains; Kenya and Morocco are mid-range adopters (indices ≈ 5.0 and 4.8), while Nigeria, Tanzania and Rwanda lag (indices ≈ 4.3, 3.9, 3.5 respectively) but display high marginal uplift where implementation occurs. Taken together, the evidence indicates: (1) technologies amplify the value of good data and governance rather than substitute for them; (2) emerging markets can capture larger marginal returns but need tailored investments in plumbing, governance and skills; and (3) a staged, governance-first approach produces more durable, auditable 6enefits than piecemeal adoptions.

The analysis indicate that technology adoption consistently enhances forecasting accuracy and operational performance, provided that firms maintain strong data integration and governance, as evidenced in Tables 24. Governance maturity and workforce skills emerge as more decisive determinants of sustained value than the mere presence of technology, consistent with the SEM and mediation results presented in Table 5. Firms in emerging economies, including the sampled African countries, demonstrate larger marginal returns for each unit of adoption; however, structural barriers such as limited connectivity, talent shortages, and regulatory uncertainty constrain full realization of these gains (Fig. 5). Finally, cost benefit assessments suggest that phased technology investments, supported by public private initiatives, are particularly advantageous in contexts with lower adoption levels, as reflected in Table 5.

References

1. McKinsey & Company. CFOs counting on gen AI. McKinsey & Company; 2024 Aug 7.
2. PwC. Future of Finance: Point of View. PwC; 2023 May 20.
3. Deloitte. Defining the vision and road map for ERP-enabled finance transformation [Internet]. Deloitte; [cited 2025 Oct 4]. Available from: https://www2.deloitte.com
4. Reuters. Yellen to warn of 'significant risks' from use of AI in finance. Reuters; 2024 Jun 5.
5. Kokina J, Davenport TH. The emergence of artificial intelligence: how automation is changing auditing. J Emerg Technol Account. 2017;14(1):115-122.

6. Vancsura L, *et al.* Navigating AI-Driven Financial Forecasting: A Systematic Review. Mathematics. 2025;13(1).
7. Deloitte. Automation with intelligence (RPA and intelligent automation overview). Deloitte Insights; 2022.
8. U.S. Department of the Treasury. Digital Assets and the Treasury Market (TBAC report). Washington, DC: U.S. Treasury; 2024.
9. AAA. Cloud ERP data processing practices. J Enterp Technol Account. 2024.
10. Nguyen Phu G, *et al.* The impact of cloud computing technology on corporate financial management. Humanit Soc Sci Commun. 2025.
11. Elia G, *et al.* The digital transformation canvas: a conceptual framework for successful digital initiatives. J Bus Res. 2024.
12. Li Y. Artificial intelligence, dynamic capabilities, and corporate finance. J Corp Finance. 2024.
13. ResearchGate. Robotic process automation impacts in financial institutions [conference paper]. 2025.
14. Schneider J. AI governance decomposition: data, models, systems. Gov AI J. 2023.
15. GFMA, IRE Journals. Treasury analyses on distributed ledger and treasury market implications. Policy Brief. 2024-2025.
16. Kokina J, Davenport TH. AI and the finance function: complementarity and governance. J Financ Technol. 2025.
17. Deloitte. Robotic process automation and intelligent automation in finance. Deloitte Insights; 2022.
18. Hamad MJ. ERP post-implementation effects and cloud migration. J Inf Syst. 2022.
19. Rahman S, *et al.* Technology adoption and finance outcomes in emerging markets. Emerg Mark Rev. 2023.
20. Basdekidou A, Papapanagos A. Blockchain, auditability and financial reporting. Account Forum. 2024.