



Emerging Technologies and Financial Management Performance: Survey Evidence from Companies Listed on the Shanghai Stock Exchange

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ARTICLE INFO	ABSTRACT
Article History: Received 10 April 2025 Received in revised form 29 July 2025 Accepted 12 September 2025 Available online 10 December 2025 Keywords: Emerging Technologies; Financial Management; Artificial Intelligence; Big Data Analytics; Blockchain; Financial Efficiency; Profitability	Purpose. This study examines how the use of three emerging technologies (artificial intelligence [AI], big data analytics, and blockchain) is associated with financial management performance in companies listed on the Shanghai Stock Exchange (SSE), and whether firms with higher technology utilization report better financial outcomes than firms with lower utilization. Design/methodology/approach. A cross-sectional descriptive survey was conducted among financial managers and corporate accountants (n = 200) using a researcher-developed questionnaire whose content validity, construct validity, and reliability were assessed. Data were analyzed with SPSS (descriptive statistics, Pearson correlations, linear regression, independent-samples <i>t</i>-tests) and SmartPLS (structural model). Findings. Technology utilization was positively and significantly associated with financial efficiency and profitability. AI showed the largest coefficients (0.45 for financial efficiency; 0.41 for profitability), followed by big data analytics (0.38; 0.35) and blockchain (0.32; 0.29). Reduced human error (0.39) and faster financial operations (0.36) were also positively associated with profitability. Firms with high technology utilization reported a return on assets 6.4 percentage points higher and a net profit margin 7.6 percentage points higher than low-utilization firms. Originality/value. The study compares the three technologies on the same two outcome dimensions within one emerging-market setting, and links technology use to operational mechanisms (error reduction and processing speed) rather than treating “fintech” as a single construct. Practical implications. The results support investment in emerging technologies, development of digital competencies among finance staff, and re-engineering of financial processes. Because the design is cross-sectional and based largely on self-reported data, the findings indicate association rather than causation.

1. INTRODUCTION

1.1. Background and problem statement

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Emerging technologies such as artificial intelligence (AI), machine learning (ML), big data analytics, blockchain, fintech platforms, and quantum computing are reshaping financial management. They are reported to improve operational efficiency and strategic decision-making, strengthen risk management, and widen access to financial services [1, 2]. Traditional financial management relied heavily on manual processes and legacy systems and now faces exponential data growth, demand for real-time analytics, and increasingly complex regulatory requirements. Emerging technologies are seen as a way to close these gaps while opening new opportunities for innovation [3, 4].

The topic matters because financial management, at both the organizational and national level, shapes resource allocation, economic sustainability, and growth. Fintech and AI have enabled financial institutions to detect fraud, forecast market trends, and personalize services. These advances are accompanied by cybersecurity threats, algorithmic risk, privacy concerns, and regulatory challenges [2, 5].

Much of the available evidence, however, comes from conceptual analyses and literature reviews, or from studies of banks and fintech providers in advanced or regional markets. Whether technology adoption translates into measurable improvements in the financial management of listed companies in an emerging economy such as China is less clear from the literature reviewed here.

1.2. Research gap and objectives

Three gaps motivate the study. First, recent contributions are dominated by narrative or systematic reviews [1, 2, 6, 7], while firm-level empirical tests of how specific technologies relate to specific financial outcomes are scarcer. Second, the empirical studies that exist focus mainly on banking [8, 9, 10], leaving the corporate finance function of listed companies less examined. Third, technologies are frequently studied individually or are bundled under a single “fintech” label, so their relative contributions to the same outcomes are rarely compared.

The study therefore pursues four objectives: (1) to estimate the association of AI, big data analytics, and blockchain with financial efficiency and profitability; (2) to examine whether reduced human error and faster financial operations are associated with profitability; (3) to compare firms with low and high technology utilization on financial and operational performance indicators; and (4) to assess, conceptually and where the data allow, the combined (synergistic) role of the three technologies. These objectives translate into the following research questions. RQ1: Do AI, big data analytics, and blockchain each relate positively to financial efficiency and profitability? RQ2: Do operational improvements (fewer errors, faster processing) relate to profitability? RQ3: Do high-utilization firms outperform low-utilization firms?

1.3. Contributions and structure of the paper

The study contributes in three ways. Theoretically, it interprets technology utilization through the resource-based view and technology–organization–environment reasoning and tests whether the benefits attributed to different technologies differ in magnitude. Empirically, it provides survey evidence from SSE-listed companies on two outcome dimensions and six operational and financial indicators. Practically, it offers guidance on technology prioritization, workforce development, and process redesign. Section 2 reviews the theoretical background and the literature; Section 3 presents the conceptual model and hypotheses; Section 4 describes the methodology; Section 5 reports the results; Section 6 discusses them; and Sections 7 and 8 present limitations, future research directions, and conclusions.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1. Theoretical foundations

The resource-based view treats technological assets as firm resources whose contribution to performance depends on whether they are valuable, hard to imitate, and combined with complementary resources such as skills and processes [11]. Applied to finance, AI, analytics platforms, and distributed-ledger systems yield performance gains when they are embedded in capable teams and redesigned workflows, an argument that also underpins the study’s emphasis on human capital and process re-engineering. The technology–organization–environment framework

explains adoption and effectiveness through technological characteristics, organizational conditions (size, competencies, infrastructure), and the external environment (regulation, economic conditions) [12]. Diffusion-of-innovation theory adds that perceived advantage, compatibility, and complexity shape the depth of use [13]. The moderating and intervening factors in the conceptual model (Section 3.1) are drawn from these perspectives.

2.2. Emerging technologies in financial management

2.2.1. Artificial intelligence and machine learning

AI refers to systems that perform tasks that normally require human intelligence. In finance it is applied to market forecasting, risk management, fraud detection, and investment analysis. ML algorithms learn continuously from historical and real-time financial data and improve their accuracy over time [7]. Reported applications include fraud detection, credit risk assessment, and cash flow forecasting, with gains in operational efficiency [6]. By accelerating decisions and automating repetitive tasks, AI is also associated with lower costs and higher customer satisfaction [6].

2.2.2. Big data and advanced analytics

Big data denotes very large volumes of structured and unstructured data that traditional analytical methods cannot process effectively. Advanced analytics extracts patterns, trends, and risks from such data and supports better-informed financial decisions and strategy formulation [14, 15]. Analytical tools are also credited with enabling real-time analysis, more accurate forecasting, and data-driven decision-making in finance [14].

2.2.3. Blockchain and smart contracts

Blockchain is a decentralized, distributed ledger that records transactions transparently and securely. Smart contracts are self-executing agreements that enforce predefined terms automatically and reduce the need for intermediaries [16, 17]. Blockchain is argued to strengthen transparency and security in transactions and reporting by maintaining data integrity through immutable, shared records, while AI adds predictive analytics for decision support; their combination is reported to affect risk management, regulatory compliance, and operational efficiency [1]. Evidence linking blockchain to financial performance has been reported for major Australian banks [8].

2.2.4. The fintech ecosystem

Fintech, as an innovation ecosystem, has widened access to financial services for individuals and small businesses and promotes financial innovation and sustainable growth through advanced technologies [1, 2]. A review of fintech examined five major technologies (AI, ML, blockchain, augmented/virtual reality, and quantum computing) and described their applications in financial systems [1]. The present study concentrates on the three technologies most directly connected with the finance function of non-bank firms: AI/ML, big data analytics, and blockchain.

2.3. Dimensions of financial management performance

Financial efficiency is the extent to which an organization uses its financial resources optimally to achieve strategic objectives. Emerging technologies are expected to raise efficiency and profitability through automation, better decisions, and streamlined financial processes [18]. They are also expected to reduce costs and optimize resources by eliminating manual work, reducing operational errors, and improving allocation, which in turn raises productivity [9, 10]. A third dimension is forecasting accuracy and risk management: algorithms that exploit historical and real-time data support more reliable forecasts and more effective risk mitigation [7, 19]. The evidence of Rodríguez-Espíndola et al. [19] concerns risk management in digital manufacturing, so its transferability to financial management should be argued rather than assumed.

2.4. Prior evidence and the research gap

The literature has expanded rapidly since the early 2020s. Early studies emphasized the potential of digital technologies to raise efficiency; more recent work stresses sustainability, risk management, and technological integration [1, 2]. Systematic reviews conclude that emerging technologies enhance efficiency, transparency, and financial inclusion but also introduce cybersecurity vulnerabilities and algorithmic bias, and they identify recurring themes: the integration of technology with behavioral and regulatory frameworks, risk management practices, and sustainable finance [2, 5]. In public-sector and corporate financial management, technologies are reported to improve efficiency, decision quality, and accountability, although implementation challenges remain significant [3, 6].

Empirical work on performance outcomes has concentrated on banks: fintech and the financial performance of Islamic banks [9], fintech and the profitability of listed banks [10], and blockchain and financial performance in major Australian banks [8]. The literature thus leaves open the question addressed here: how do AI, big data analytics, and blockchain compare in their association with financial efficiency, profitability, and operational indicators in the finance functions of listed companies in an emerging market?

3. CONCEPTUAL MODEL AND HYPOTHESES

3.1. Conceptual model

The conceptual model explains the impact of emerging technologies on financial management. AI and ML, big data and advanced analytics, and blockchain and smart contracts are the independent variables. Financial management is the dependent construct, represented by three dimensions: financial efficiency and profitability; cost reduction and resource optimization; and the accuracy of financial forecasting and risk management. Moderating factors (organizational characteristics, human resource competencies, and technological infrastructure) and intervening factors (economic conditions, laws and regulations, and organizational culture) are incorporated because they may affect the strength and direction of the relationship between technology and financial outcomes. The framework provides a basis for testing the hypotheses below.

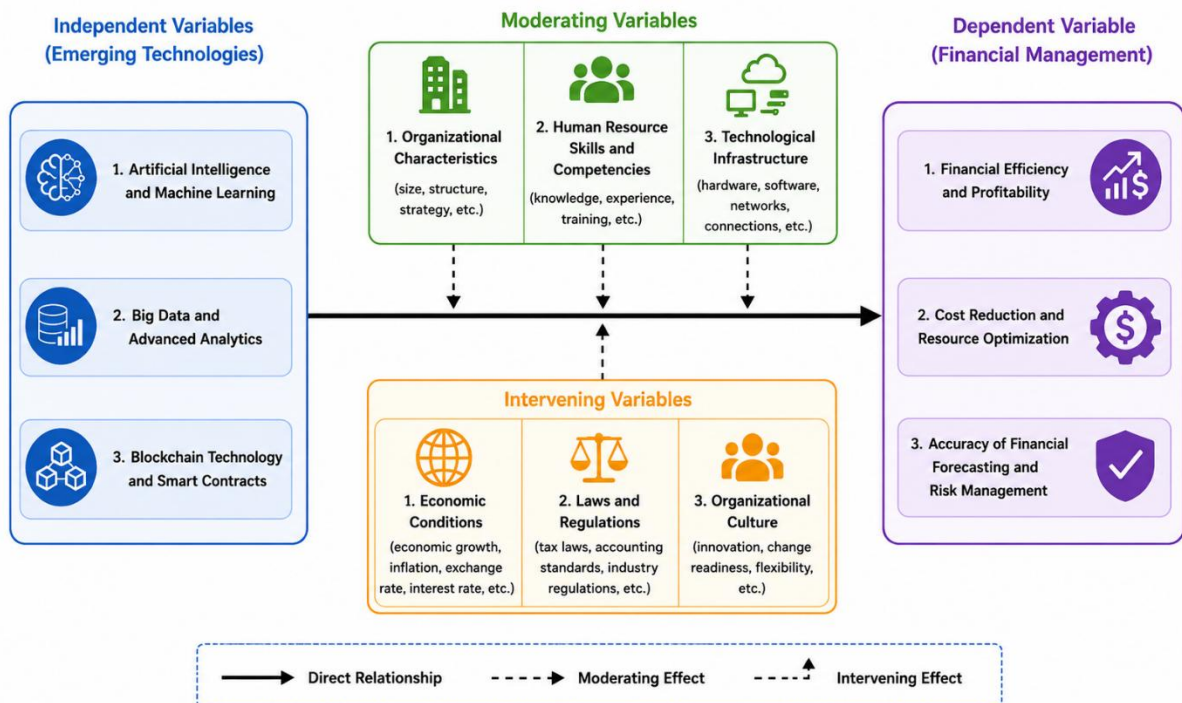


Fig. 1. Conceptual research model

Only the direct paths from the three technologies to the financial management dimensions are estimated in the results reported in Section 5; the moderating and intervening factors are part of the theoretical model and are not yet reflected in reported estimates.

3.2. Hypothesis development

H1. Emerging technologies (AI, big data, and blockchain) have a positive and significant effect on financial efficiency and organizational profitability. Grounded in the resource-based view, technologies that automate processing and improve information quality should raise the efficiency with which financial resources are converted into returns [1, 11].

H1a. AI and ML improve financial efficiency and increase profitability through the automation of financial processes and the analysis of complex data [6].

H1b. Big data analytics optimizes financial decision-making and enhances profitability by identifying hidden patterns and providing deeper insight [14, 15].

H1c. Blockchain improves financial efficiency and increases profitability by enhancing transparency, reducing fraud, and eliminating intermediaries [8, 16].

H1d. The integration of the three technologies creates a synergistic effect on financial efficiency and profitability. This follows the complementarity logic of the resource-based view, whereby resources combined with one another yield more than the sum of separate effects, and the reported complementarity between blockchain and AI [1].

H1e. The use of emerging technologies reduces human error and increases the speed of financial operations, ultimately improving profitability. H1e implies a mediating chain (technology → error reduction and speed → profitability); its empirical treatment is discussed in Sections 4.5 and 5.5.

4. RESEARCH METHODOLOGY

4.1. Research design

The study is applied in purpose and uses a cross-sectional descriptive-survey design. Hypotheses were examined with correlation and linear regression, group comparisons (independent-samples *t*-tests), and a structural model estimated in SmartPLS.

4.2. Population and sampling

The population comprised financial managers and corporate accountants working in companies listed on the SSE. The sample comprised 200 respondents selected by simple random sampling. Under Cochran's [20] formula for an unlimited population with conventional parameters (95% confidence, $p = 0.5$, $e = 0.05$), the required size is about 384; a sample of 200 therefore corresponds to a margin of error of about $\pm 6.9\%$ at the same confidence level and p . This should be considered when generalizing, and the sample is adequate for the correlation, regression, and group-comparison analyses reported here (for a correlation of $r = .30$, $n = 200$ gives power above .95 at $\alpha = .05$).

4.3. Instrument and measurement

Data were collected with a researcher-developed questionnaire based on the theoretical foundations and the literature. Section 1 recorded respondents' demographic information; Section 2 contained specialized items on emerging technologies and financial management. Constructs were AI, big data, blockchain, financial efficiency, profitability, reduction of human errors, and financial operations speed.

4.4. Validity and reliability

Content validity was assessed by ten experts in finance and technology. Construct validity was evaluated with confirmatory factor analysis (CFA), and all goodness-of-fit indices are reported to have been within acceptable

ranges. Reliability was assessed with Cronbach's alpha and composite reliability (CR); alpha exceeded 0.70 for all variables (Table 1). Two inter-construct correlations are high (financial efficiency–profitability $r = .77$; error reduction–speed $r = .76$), so discriminant validity should be demonstrated with the Fornell–Larcker criterion or HTMT [22, 23].

4.5. Data analysis

Descriptive statistics comprised means, standard deviations, minima, and maxima. Pearson correlations examined bivariate associations, and linear regression tested the hypotheses. Independent-samples t -tests compared low- and high-utilization groups. Descriptive, correlation, regression, and t -test analyses were conducted in SPSS version 26. The structural model, including the moderating role of organizational factors, was analyzed in SmartPLS [24]. Because the three technology variables are intercorrelated ($r = .52$ – $.68$), regression diagnostics (variance-inflation factors, residual normality, linearity, and homoscedasticity) and an assessment of common-method bias [25] are required given that all variables come from one respondent source.

4.6. Ethical considerations

Respondents' information was kept confidential, informed consent was obtained, and sensitive or intrusive questions were avoided.

5. RESULTS

5.1. Descriptive statistics and reliability

Table 1 presents descriptive statistics and Cronbach's alpha for the seven variables ($n = 200$). Mean scores were highest for AI ($M = 4.32$, $SD = 0.65$), followed by big data ($M = 3.95$) and blockchain ($M = 3.78$), indicating that respondents' firms rely on AI more than on the other two technologies. All alpha coefficients ranged from 0.83 to 0.89 and exceeded the 0.70 threshold, indicating satisfactory internal consistency.

Table 1. Descriptive statistics and internal consistency of research variables ($n = 200$)

Variable	Mean	SD	Min	Max	Cronbach's α
Artificial intelligence	4.32	0.65	2.5	5.0	0.87
Big data	3.95	0.71	2.1	4.9	0.83
Blockchain	3.78	0.69	2.3	4.8	0.85
Financial efficiency	4.18	0.62	2.8	5.0	0.89
Profitability	4.05	0.58	2.9	4.9	0.88
Reduction of human errors	4.22	0.64	2.7	5.0	0.86
Financial operations speed	4.15	0.61	2.6	4.9	0.84

Note. Values are construct means on the response scale used in the questionnaire (minimum and maximum values are consistent with a five-point scale).

5.2. Correlation analysis

Table 2 shows positive and statistically significant correlations among all variables ($p < .01$). AI had the strongest correlation among the technologies with financial efficiency ($r = .71$) and with profitability ($r = .69$), indicating a substantial association between technology utilization and financial performance. The highest coefficients in the matrix, however, are between the outcome variables themselves (financial efficiency–profitability, $r = .77$) and between error reduction and operational speed ($r = .76$), which raises the question of discriminant validity addressed in Section 4.4.

Table 2. Pearson correlation matrix of research variables

Variable	1	2	3	4	5	6	7
1. Artificial intelligence	1						
2. Big data	.68**	1					
3. Blockchain	.59**	.52**	1				
4. Financial efficiency	.71**	.66**	.61**	1			
5. Profitability	.69**	.63**	.58**	.77**	1		
6. Reduction of human errors	.65**	.58**	.54**	.72**	.68**	1	
7. Financial operations speed	.67**	.61**	.56**	.74**	.71**	.76**	1

Note. n = 200. **p < .01 (two-tailed).

5.3. Regression analysis

Table 3 reports the regression results for the sub-hypotheses. In every model the coefficient was positive and the reported significance level was below .05. AI had the largest coefficients for financial efficiency ($\beta = 0.45$) and profitability ($\beta = 0.41$), followed by big data analytics (0.38 and 0.35) and blockchain (0.32 and 0.29). Reduction of human errors ($\beta = 0.39$) and financial operations speed ($\beta = 0.36$) were positively associated with profitability.

Table 3. Regression results for the sub-hypotheses

Predictor	Outcome	Coef.	SE	t	p	R ²
Artificial intelligence	Financial efficiency	0.45	0.07	6.42	< .001	0.51
Artificial intelligence	Profitability	0.41	0.06	5.83	< .001	0.48
Big data	Financial efficiency	0.38	0.06	5.33	0.001	0.44
Big data	Profitability	0.35	0.05	4.92	0.002	0.40
Blockchain	Financial efficiency	0.32	0.05	4.45	0.003	0.37
Blockchain	Profitability	0.29	0.04	4.12	0.004	0.34
Reduction of human errors	Profitability	0.39	0.05	5.21	0.001	0.42
Financial operations speed	Profitability	0.36	0.05	4.87	0.002	0.39

Note. Values are those of the original analysis.

Because each row appears to be a separate one-predictor model, the table does not show the unique contribution of each technology when the others are controlled. The three technology variables are intercorrelated ($r = .52-.68$), so a multiple regression (or the PLS-SEM structural model) with variance-inflation factors is needed to test H1 jointly.

5.4. Comparison of low- and high-utilization firms

Table 4 compares firms with low and high technology utilization. High-utilization firms had higher mean ROA (14.70% versus 8.30%) and net profit margin (17.80% versus 10.20%), and they reported larger reductions in operating costs, higher forecasting accuracy, larger reductions in financial errors, and faster transaction processing. Differences are expressed in percentage points: 6.4 for ROA, 7.6 for net profit margin, 6.7 for operating-cost reduction, 16.5 for forecasting accuracy, 23.2 for error reduction, and 18.6 for processing speed. Reported effect sizes ranged from 0.65 to 0.81, conventionally medium to large [26].

Table 4. Group comparison by level of emerging-technology utilization

Indicator	Low use (M)	High use (M)	Difference (pp)	p	Effect size
Return on assets (ROA)	8.30%	14.70%	6.40	0.001	0.68
Net profit margin	10.20%	17.80%	7.60	< .001	0.72
Reduction in operating costs	6.50%	13.20%	6.70	0.002	0.65
Financial forecasting accuracy	72.40%	88.90%	16.50	< .001	0.75
Reduction in financial errors	68.30%	91.50%	23.20	< .001	0.81
Transaction processing speed	74.60%	93.20%	18.60	< .001	0.78

Note. pp = percentage points.

5.5. Summary of hypothesis tests

Table 5 summarizes the status of each hypothesis according to the analyses actually reported. The original manuscript concludes that all hypotheses are supported; for H1, H1d, and H1e the reported analyses do not fully match what the hypotheses assert.

Table 5. Hypothesis status based on the reported analyses

Hypothesis	Analysis reported	Evidence as reported	Assessment
H1a (AI)	Simple regression; correlation	Positive coefficients on both outcomes	Supported, subject to re-verification of Table 3
H1b (big data)	Simple regression; correlation	Positive coefficients on both outcomes	Supported, subject to re-verification of Table 3
H1c (blockchain)	Simple regression; correlation	Positive coefficients on both outcomes	Supported, subject to re-verification of Table 3
H1 (joint effect)	Three separate simple regressions; SEM not reported	No joint model	Not yet tested jointly; a multiple regression or PLS-SEM result is required
H1d (synergy)	None	No interaction term, composite, or moderated path	Not tested; requires an interaction/integration analysis
H1e (error reduction and speed)	Simple regression on profitability	Positive coefficients (0.39; 0.36)	Partially tested: technology → error/speed → profitability mediation not estimated

6. DISCUSSION

6.1. Interpretation of the principal findings

The results show that the utilization of each of the three technologies is positively associated with perceived financial efficiency and profitability, and that the ordering of coefficients (AI, then big data analytics, then blockchain) is the same for both outcomes. Two features of this pattern merit interpretation. First, the leading position of AI is consistent with how closely AI applications are tied to core finance tasks such as forecasting, credit and fraud analytics, and process automation [6]. Gains from such applications materialize inside the finance function and are therefore easier for respondents to observe. Second, the ranking mirrors descriptive utilization levels (AI M = 4.32; big data M = 3.95; blockchain M = 3.78). More widely diffused technologies may be more deeply embedded in routine processes, as diffusion theory would suggest [13]. Since adoption intensity and coefficient size rank identically, the data cannot separate technology-specific effects from maturity of use.

The smaller blockchain coefficients may also reflect context. Benefits that theory attributes to blockchain, namely transparency, fraud reduction, and disintermediation, depend on shared infrastructure, counterparties that participate, and a clear regulatory footing. Where those conditions are only partly present, realized benefits can lag potential benefits. This explanation is tentative and should be tested in future work with measures of institutional and infrastructure readiness.

The associations of reduced human errors (0.39) and faster financial operations (0.36) with profitability are similar in size to those of the technologies themselves. This is compatible with the operational mechanism proposed in H1e: technology improves profitability partly by making processes more accurate and faster. Yet error reduction and speed were entered as direct predictors, so the mediating chain is inferred and not demonstrated. A bootstrapped indirect-effects analysis within the PLS-SEM model would test it directly.

The group comparison shows that firms with higher utilization report higher ROA (+6.4 pp) and net profit margin (+7.6 pp), together with stronger operational indicators. The coherence between the regression and group-comparison results increases the substantive plausibility of the findings. However, if the group-comparison indicators were obtained from the same respondents, the two analyses are not independent confirmations of one another. Reverse causality is also plausible: more profitable firms may have the slack resources to invest in technology.

6.2. Relation to prior research

The positive associations agree in direction with review-based conclusions that emerging technologies improve efficiency, transparency, and decision quality [1, 2, 3], and with studies that link fintech or blockchain to bank financial performance [8, 9, 10]. Effect magnitudes are not directly comparable with those studies because their samples (banks), constructs (fintech or blockchain), and measures differ. The study adds firm-level, technology-specific estimates from the finance functions of listed companies, a level at which the reviewed literature is mostly conceptual.

The results differ in emphasis from literature that foregrounds blockchain's potential for transparency and data integrity [1, 8]: here blockchain shows the weakest, though still positive, association. This is a difference of degree rather than direction and may reflect the setting discussed above. The study also measured only benefits. Reviews stress that the same technologies introduce cybersecurity, privacy, and algorithmic-bias risks [2, 5, 7]. The uniformly positive results should therefore be read as the perceived net benefit among adopters, not as evidence that adoption is risk-free.

6.3. Theoretical contributions

The study offers three contributions. First, it supports a resource-based reading of financial technology: coefficients are positive across technologies and outcomes, while the emphasis on skills and process redesign in the managerial implications reflects the premise that technology yields returns when combined with complementary resources [11]. Second, by disaggregating three technologies against the same two outcomes, it shows that the benefits of “emerging technology” are not uniform and may depend on maturity of use and context, consistent with technology–organization–environment reasoning [12]. Third, it proposes error reduction and processing speed as operational mechanisms linking technology to profitability, a hypothesis that future mediation studies can test formally.

6.4. Managerial and policy implications

Strategy and governance. Organizations should develop digital transformation strategies that align technology investment with long-term objectives, supported by data-governance mechanisms and integrated business intelligence systems that generate timely, actionable financial insight. Given the cross-sectional design, firms should sequence investments and evaluate returns through pilots rather than assume uniform gains. On the present evidence, AI and analytics show the strongest association with outcomes, whereas blockchain may be best targeted at processes where multi-party transparency is essential.

Human capital. The finding that benefits depend on people as well as systems supports sustained professional development in digital competencies for financial managers and staff, recruitment of specialists in fintech, data analytics, and AI, and knowledge-sharing and mentoring programs within finance departments.

Operations. Firms should automate repetitive financial activities through robotic process automation (RPA) and intelligent decision-support systems, and re-engineer processes around AI-driven analytics and blockchain-based solutions to improve transparency, reduce costs, minimize errors, and speed up decision-making.

Policy. Regulators and professional bodies can foster an enabling environment by developing appropriate regulatory frameworks, ethical guidelines for AI use, and digital auditing mechanisms that strengthen trust and ensure legal and professional compliance. Collaboration among financial institutions, technology providers, and regulators can support a sustainable fintech ecosystem.

7. LIMITATIONS AND FUTURE RESEARCH

Several limitations qualify the findings. (1) The cross-sectional design supports association, not causation, and reverse causality or self-selection cannot be excluded. (2) All constructs derive from a single respondent group using self-reported, perceptual measures, which exposes the results to common-method and social-desirability bias; the high correlations among outcome variables heighten this concern. (3) The sample is limited to respondents from SSE-listed companies and to a survey methodology, restricting generalizability across industries, firm sizes, and countries; the basis for the sample size also requires clarification. (4) The reported regressions treat each technology separately, so unique effects, synergy (H1d), and mediation (H1e) are not established. (5) Moderating and intervening factors in the conceptual model are acknowledged theoretically but not reported empirically. (6) The study measures benefits but not costs or risks of adoption.

Future research should (a) use longitudinal or quasi-experimental designs; (b) combine survey data with objective financial-statement data matched at firm level; (c) replicate the model across industries and countries; (d) apply mixed-method designs to capture implementation processes; (e) test moderation by human-resource competence, infrastructure, and organizational culture, and mediation by error reduction and processing speed; and (f) examine other dimensions of financial management, including liquidity management, working capital optimization, financial resilience, and sustainability performance, as well as the risk side of technology adoption.

8. CONCLUSION

This study examined the association of AI, big data analytics, and blockchain with financial management performance in SSE-listed companies. Within the limits of a single-source, cross-sectional survey, technology utilization was positively associated with financial efficiency and profitability. AI showed the strongest coefficients (0.45 and 0.41), followed by big data analytics (0.38 and 0.35) and blockchain (0.32 and 0.29), and high-utilization firms reported ROA and net profit margins 6.4 and 7.6 percentage points higher than low-utilization firms.

The findings suggest that digital transformation is shifting the finance function from a supportive and reporting role toward a strategic, value-creating capability, with AI, big data, and blockchain as its main technological pillars. Realizing that value depends on aligning three components: technology, human resources, and business processes. Continuous employee development, process redesign, and a supportive organizational culture are therefore as important as the technology itself. Organizations must also manage data privacy, cybersecurity, initial investment costs, and resistance to change, for example through comprehensive technology strategies, partnerships with providers, and gradual implementation. Emerging technologies should accordingly be treated as drivers of strategic transformation and not merely as tools for efficiency, while recognizing that the present evidence is associative and should be confirmed with longitudinal and objective data.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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