Enterprise Development & Microfinance, 35:1, 462-491

Digital Transformation and Financial Reporting Quality in Corporate Finance: Evidence from Internal Control Practices using Artificial Intelligence

AFFRIN NIZAMI, JAFFRIN NIZAMI, DR. KAMAL GULATI

Abstract: *This paper develops an integrative explanation of how digital transformation can improve financial reporting quality through artificial intelligence (AI)-enabled internal control practices. Rather than treating technology adoption as a direct guarantee of better reporting, the analysis positions digital capability as an enabling condition whose value depends on process design, data governance, control ownership, and human review. The study combines an integrative conceptual review with a structured evidence-coding dataset of 30 cited sources published between 1977 and 2026. The dataset records publication period, source class, evidence design, primary literature stream, and non-exclusive relevance to digital transformation, AI and automation, internal control, financial reporting quality, and governance or ethics. It is used for descriptive transparency rather than effect estimation. Of the 30 sources, 24 are peer-reviewed articles and six are official standards or governance frameworks; 16 are review or conceptual works, eight provide empirical evidence, and six are standards or frameworks. Evidence is organized around recurring corporate-finance processes: invoice verification, bank reconciliation, journal-entry and period-close controls, management information system reporting, continuous monitoring, and audit documentation. The synthesis shows that AI can increase transaction coverage, accelerate matching and exception detection, strengthen traceability, and shorten reporting cycles. These gains improve relevance, faithful representation, timeliness, comparability, verifiability, and understandability only when AI is embedded in an effective system of internal control. Poor-quality data, weak access controls, opaque models, automation bias, model drift, cyber exposure, and ungoverned generative AI can instead scale errors and weaken accountability.*

Affrin Nizami (affrinnizami@gmail.com) BBA (BFSI), Amity School of Insurance, Banking and Actuarial Science, Amity University, Uttar Pradesh, India,
Jaffrin Nizami (jaffrin.nizami03@gmail.com) M. A Business Economics (MBE), Amity School of Economics, Amity University, Uttar Pradesh, India,
Dr. Kamal Gulati (drkamalgulati@gmail.com) Associate Professor, Amity School of Insurance, Banking and Actuarial Science, Amity University, Noida, Uttar Pradesh, India,
Orcid ID: 0000-0002-1186-1426
Corresponding Author: Dr. Kamal Gulati

The paper proposes a process-based framework in which AI-enabled control capability strengthens internal control over financial reporting, which then mediates the relationship between digital transformation and reporting quality. It also presents testable propositions, an implementation roadmap, descriptive figures, a source-level dataset, and illustrative measures for future empirical research. The central conclusion is that AI should be governed as a control capability, not deployed merely as a productivity tool.

Keywords: Digital transformation; financial reporting quality; artificial intelligence; internal control over financial reporting; corporate finance; structured review dataset

Introduction

Corporate finance is undergoing a transformation to become more integrated, automated, cloud-based, analytical and AI-driven. Sequential handoffs and spreadsheet checking can now be replaced with activities that can be performed continuously across enterprise systems. Invoices can be extracted and matched in seconds, bank transactions can be reconciled against ledger transactions all day long, unusual journals can be scored prior to posting and management reports can be produced from live operational data. The changes impact more than just the pace of accounting work. They change who does a control, when evidence is created, how exceptions are elevated and what management can know prior to the formal reporting date.

The lure is simple: digital tools can help eliminate repetitive work, expand the scope of samples to encompass larger numbers of transactions, and provide information earlier. However, defects can also be transmitted on a large scale with the same architecture. A misconfigured rule can incorrectly classify thousands of transactions, a machine-learning model trained on incomplete data can smooth out an unwanted trend, and a generative-AI system can generate grammatically correct explanations that don't have any supporting data. So faster processing does not equal to better quality reporting. The result will be based on disciplined processes, reliable information, clear accountability and good internal control.

The quality of financial reporting is a suitable outcome to measure this transformation as it reflects the decision usefulness and representational integrity of financial information. According to the IFRS Conceptual Framework, there are two fundamental qualitative characteristics: relevance and faithful representation, which are complemented by comparability, verifiability, timeliness and understandability (IFRS Foundation, 2018). Digital tools have the potential to impact all dimensions, but not necessarily in a positive way. A hasty close could lead to increased timeliness but also increased classification errors, a complex model could lead to relevant forecasts but decreased verifiability and automated standardization of the close could lead to increased comparability but decreased context-specific judgment. It therefore needs to look at the mechanisms and safeguards linking technology to reporting outcomes to be meaningful.

That link is provided by internal control over financial reporting. Previous studies link deficiencies with lower accrual quality, reporting issues, and operational inefficiency, and remediation with better reporting and business processes (Altamuro & Beatty, 2010; Ashbaugh-Skaife et al., 2008; Doyle et al., 2007; Feng et al., 2015). Digital transformation is not the elimination of authorization, segregation of duties, evidence, review and remediation, but instead a shift in the method of control, from manual inspection to embedded validation, automated matching, continuous monitoring, and algorithmic exception analysis. The Committee of Sponsoring Organizations of the Treadway Commission (COSO) also provides technology-specific guidance that states that new systems provide new control objects and new control opportunities (COSO, 2024, 2026).

There is still a disconnect between the general statements about digital transformation and the reality of how it is actually achieved in terms of processes and how financial statements are produced. The literature on digital transformation tends to be on enterprise strategy and organizational change, and accounting literature tends to be on either reporting quality, audit technology or internal control as stand-alone literatures. Recent research indicates that digitalization can positively impact the effectiveness of finance functions and the nature of reporting, but this depends on resources, finance-function maturity and governance (Bedford et al., 2025; Kerrouche & Belouadah, 2025). AI research in auditing provides evidence regarding both an increase in the scope of analysis and questions of explainability, privacy, reliability, and workforce (Abdo-Salloum & Chehade, 2026; Kokina et al., 2025).

1.1 Research questions and contribution

The review addresses the following questions:

1. Through which process-level mechanisms does digital transformation affect financial reporting quality in corporate finance?
2. How do different AI technologies change the design and operation of internal controls in routine finance processes?
3. Which governance conditions strengthen or weaken the reporting benefits of AI-enabled internal control practices?

The paper makes three contributions. First, it reframes AI as an organizational control capability rather than a stand-alone automation tool. Second, it develops a process-based model that explains why internal-control effectiveness mediates the relationship between digital transformation and reporting quality. Third, it converts the conceptual model into practical and research-ready outputs: a process-control matrix, testable propositions, an implementation roadmap, and suggested measures for empirical validation. The analysis remains conceptual; it does not claim primary field evidence or causal estimates.

Conceptual and Theoretical Foundations

2.1 Financial reporting quality

Financial reporting quality is a multi-faceted concept. At the most general level, high quality reporting is information that is useful for making economic decisions, and that captures the economic phenomena to the extent it is complete, neutral and free from any material error. Relevance relates to whether the information would be useful to make a decision and faithful representation relates to whether the information is a representation of the substance of the transaction or event. Comparability, verifiability, timeliness and understandability increase the usefulness of relevant and faithfully represented information (IFRS Foundation, 2018).
There are a number of empirical proxies for reporting quality in accounting research, such as accrual quality, persistence, restatements, timeliness, value relevance, disclosure quality and enforcement or control weaknesses. There is no single proxy that represents the whole construct and a proxy that is valid in one context may not be valid in another (Dechow et al., 2010; Sahi et al., 2022). In this paper, the quality of reporting is considered a composite outcome, which consists of six dimensions: relevance, faithful representation, timeliness, comparability, verifiability and understandability. This definition is wide-ranging enough to relate internal management reporting to the external reporting and yet maintains the distinction between the two.

The internal and external reporting are connected by the same transaction information, accounting policies, close procedures, reconciliations, and review procedures. Management information systems can encompass operational activities and forecasts which are not necessarily reflected in published financial statements, but deficiencies in data definitions, interfaces or review procedures may impact both. A reliable internal information environment helps management make judgments and estimates, and provides explanations; otherwise, it can lead to late adjustments and inconsistent explanations. Thus, this paper does not only assess the quality of financial statements but also of the reporting pipeline.

2.2 Digital transformation of the finance function

Digital transformation is more than just going from paper to electronic records. The difference between digitization and digitalization is that the latter is the use of digital technologies to enhance existing activities, while the former is the conversion of analog information into digital information, and the latter is coordinated changes to strategy, processes, structures, capabilities, and value creation (Vial, 2019; Verhoef et al., 2021). Transformation, in the context of finance, thus encompasses process redesign, enterprise-system integration, governed data architecture, automation, analytics and changes in professional roles. Such technologies are also changing the scope and expectations of accounting job (Moll & Yigitbasioglu, 2019). When you install the software without changing the workflow, it's more of a "tool adoption" than a "transformation.

The finance function is a mix of volume and rules-based work and judgment-based work. Automation can be very useful for repetitive processing and standardized controls, while analytics can be useful for pattern detection, prediction and decision support. Studies on the digitalization of the finance function have shown that both can contribute to better performance, but that combined use can lead to a strain of resources if data, skills or change capacity are limited (Bedford et al., 2025). This is significant because it challenges the notion of a linear maturity model based on greater technology. Fit is the key – does the technology fit the process, risk, data structure and available control capacity?

The temporal structure of finance is also affected by enterprise systems and business analytics. Data can be collected once and then be used for reporting, forecasting and control; deviations can be highlighted on dashboards before the month-end reporting date; and some activities can be completed continuously and not deferred to a reporting date. Appelbaum et al. (2017) explain how enterprise systems and analytics can be used to move managerial accounting from a descriptive to a predictive and prescriptive model. The advantage though is dependent upon data integrity and common definitions. Integration without governance can result in a single source of error, instead of a single source of truth.

2.3 Internal control over financial reporting

Internal control is not a checklist, but a system. The COSO framework consists of five interrelated components of an effective control: control environment, risk assessment, control activities, information and communication, and monitoring activities (COSO, 2013). In the context of financial reporting, the components provide reasonable assurance that transactions are authorized, recorded in the proper period and account, evidenced and reported in accordance with the reporting framework involved.

There are differences between the controls for different objectives and modes. Preventive controls attempt to prevent an error or unauthorized action from entering the records; detective controls are used to detect errors after or during processing; corrective controls ensure that any exceptions are resolved. Control can be manual, automated or manual controls that are IT dependent. Entity-level controls have an impact on culture, accountability and oversight, and process-level controls relate to specific assertions, including existence, completeness, accuracy, valuation, rights and obligations, presentation and disclosure. Automated application controls are supported by IT general controls, which include access security, change management, operations, backups and interface controls.

With digital transformation, the nature of control evidence and the frequency of control change. An automated three-way match can be used for all invoices, an anomaly model can prioritize the entire journal population and process-mining software can identify deviations from an approved process. These features can help to improve coverage and timeliness, but they also focus on configurations, data pipelines and models. If the parameters of a control are wrong, then it may be consistently wrong even though it looks as though it is being performed consistently. Assurance over the technology that processes or evaluates the business transaction is therefore important for effective internal control in a digital environment (Chalmers et al., 2019, COSO, 2024).

2.4 AI technologies relevant to finance controls

AI is used in such a generic manner. There are at least five different families of technology that are applicable to finance controls. Robotic process automation (RPA) is a set of deterministic rules that are used to move data or perform repetitive steps. Machine learning is used to find statistical patterns for classification, prediction and anomaly detection.

Information is captured from narrative disclosures, statements, contracts and invoices via optical character recognition and natural-language processing. Process mining is a technique that can be used to reconstruct the actual workflows from the event logs and compare them to the expected workflows. Generative AI generates or transforms text, code, and other content using a probabilistic model. They vary in their explainability, errors, validation requirements, and autonomous execution (Huang & Vasarhelyi, 2019; Issa et al., 2016; Kokina & Davenport, 2017; Sutton et al., 2016).
Rules-based automation is typically best suited for a process that is stable and has decision logic that can be defined in advance. Machine learning can be helpful when the pattern that is relevant is too complicated to be expressed by simple rules, but historical data are available. Generative AI is particularly helpful for summarisation, retrieval, drafting and interaction, and outputs are probabilistic and might include unsupported statements. COSO (2026) thus considers generative AI a unique control challenge that includes the manipulation of prompts, opaque reasoning, model drift, frequent configuration changes, and potential amplifications of errors and/or bias. The technology used for a control should be commensurate with the risk of failure, the amount of judgment involved and the capacity of the organization to validate and monitor the performance.

2.5 A socio-technical and governance lens

A socio-technical approach provides an understanding of the need for co-design of technology and work systems to achieve outcomes of digital-control. Information systems are not autonomous of incentives, roles, skills, communication and organizational norms (Bostrom & Heinen, 1977). In corporate finance, a technically correct model can be wrong for a variety of reasons: users may not be aware of its boundaries, reviewers may routinely ignore alerts without explanation, and process owners may consider the AI output to be a passing of the buck. On the other hand, a small automation can make a big difference if it's well integrated into a stable process, has clear accountability and has good follow-up.

It's the same with ethics and with trust. AI-assisted accounting decisions are a concern, as they involve issues of objectivity, privacy, transparency, accountability and trustworthiness (Lehner et al., 2022; Munoko et al., 2020). These are not “side issues” — they impact the ability to contest evidence, to comprehend the basis of an alert or recommendation, and to see who is responsible. Data governance, IT controls, model governance, human oversight, and control culture are therefore considered to be cross-cutting conditions and are not optional implementation details for the analytical model developed below.

Table 1. Core constructs and their roles in the proposed framework

Construct	Working definition	Illustrative dimensions	Role in the framework
Digital transformation capability	The organizational ability to redesign finance using integrated digital systems and data.	System integration; process standardization; cloud/ERP architecture; automation and analytics capacity.	Enabling antecedent.

Construct	Working definition	Illustrative dimensions	Role in the framework
AI-enabled internal-control capability	The ability to use rules, analytics, machine learning, language technologies, or generative AI to perform or support controls.	Validation; matching; anomaly detection; continuous monitoring; controlled reporting and documentation.	Proximal process mechanism.
Internal-control effectiveness	The extent to which controls prevent, detect, explain, and remediate financial-reporting risk with reliable evidence.	Authorization; segregation; accuracy; completeness; traceability; review; remediation.	Mediator.
Financial reporting quality	The decision usefulness and representational integrity of financial information.	Relevance; faithful representation; timeliness; comparability; verifiability; understandability.	Outcome.
Governance conditions	The technical and organizational safeguards that make AI use controllable and accountable.	Data and IT governance; cybersecurity; model validation; explainability; human oversight; skills and culture.	Moderators / boundary conditions.

Integrative Review Methodology

An integrative conceptual review is used in the study. This approach is suitable if the research question is to explain a phenomenon that is addressed in multiple literatures and when a pooled effect is not being estimated. The review is a synthesis of peer-reviewed literature in accounting, auditing, management accounting, and information systems, as well as authoritative literature on financial reporting, internal control, and AI risk. It's not a systematic meta-analysis and it doesn't present the number of hits in the database searches, the number of observations at the firm level, or the primary survey responses.

Conceptual relevance to the themes was used as a guideline to select the sources: financial reporting quality, internal control over financial reporting, digital transformation of finance, AI and analytics in accounting or auditing, governance of automated and generative systems. Studies which formed the foundation of the concepts were kept, and studies and guidance that have been conducted recently were given priority for the use of current technology. Definitions and governance principles were anchored in the official materials of the IFRS Foundation, COSO and NIST. There was minimal use of practitioner claims with no transparent methods and these were not used as causal evidence.

The analysis was done in three steps. The literature was then coded according to the mechanisms: standardization, integration, anomaly detection, continuous monitoring, decision support, documentation and governance. Secondly, these mechanisms were assigned to the usual finance processes and to the qualitative characteristics of reporting. Third, the recurring benefits, failure modes and safeguards were compared across the sources to draw out the conceptual framework and propositions. This way, it is possible to integrate theory while maintaining claims in proportion to the evidence.
Quality safeguard was done by triangulation. Claims to reporting quality were compared with accounting research, claims to control design were compared with COSO guidance and claims to AI risk were compared with NIST and emerging accounting literature. The paper makes conditional statements instead of causal statements, where the literature is still emerging, such as for generative AI in transaction processing. The resulting framework is designed to guide the empirical testing and practical control design.

Table 2. Review design and analytical safeguards

Review element	**Approach used**	**Quality safeguard**
Scope	Accounting, auditing, management accounting, information systems, internal control, and AI-risk governance.	Claims retained only when directly relevant to finance processes or reporting quality.
Source types	Peer-reviewed research plus authoritative IFRS, COSO, and NIST guidance.	Official frameworks anchor definitions; practitioner claims are not treated as causal evidence.
Time orientation	Foundational literature plus recent studies and guidance, with emphasis on current AI applications.	Classic concepts are separated from emerging, still-conditional claims.
Analytical method	Thematic coding and narrative synthesis across mechanisms, processes, benefits, risks, and safeguards.	Cross-source triangulation and explicit treatment of contradictory or contingent evidence.
Research output	Structured source-level dataset, descriptive figures, conceptual framework, propositions, process-control matrix, implementation roadmap, and measurement suggestions.	No fabricated firm-level observations, effect estimates, or causal claims; all source records are traceable to the reference list.

3.1 Review dataset and coding protocol

For the sake of easier auditing of the synthesis, the final reference list of 30 items was considered as a structured review dataset. The unit of analysis is a cited source, not a firm, finance department, transaction, employee or AI system. The data set includes publication year and period, source class, broad evidence design, primary literature stream, five non-exclusive construct flags, an analytical evidence role, and the DOI or website cited in the reference for each source. The construct flags are based on substantive relevance for digital transformation, AI and automation, internal control, financial reporting quality and governance/ethics.

The coding is congruent with the focus of each source and its purpose in this paper. It must not be regarded as a methodological quality score. Years were divided into four periods; source class distinguishes peer-reviewed research from official standards or governance guidance and evidence design differentiates between empirical evidence, review or conceptual work, and standards or frameworks. One primary literature stream is assigned to each source, and may be assigned several construct flags. This way, the descriptive analysis is allowed, while at the same time the conceptual nature of the paper is maintained and unsupported effect estimates are avoided.

Table 3. Structured review dataset and coding rules

Variable	Operational definition	Coding rule
Unit of analysis	One cited source in the manuscript reference list.	Thirty source-level records; no firm-level or transaction-level observations.
Publication profile	Publication year and four time periods.	Through 2010; 2011-2018; 2019-2022; 2023-2026.
Source class	Publication or authority category.	Peer-reviewed article; official framework or guidance; official standard or framework.
Evidence design	Broad form of knowledge contribution.	Empirical evidence; review or conceptual; standard or framework.
Primary literature stream	Dominant literature represented by a source.	One stream per source for descriptive profiling.
Construct coverage	Substantive relevance to the paper's five core domains.	Five non-exclusive binary flags: DT, AI, IC, FRQ, and GOV.
Traceability	Link between each record and its cited source.	Short citation, full reference, evidence role, and DOI or website where supplied.

3.2 Descriptive profile of the evidence base

There are 30 sources in the dataset, ranging from 1977 to 2026. Twenty-four are peer-reviewed articles and six are authoritative standards and governance frameworks. There are six sources published up to 2010 and eight sources in the three later timeframes. The profile thus brings together basic evidence with a significant amount of recent research on digital finance and AI-governance.

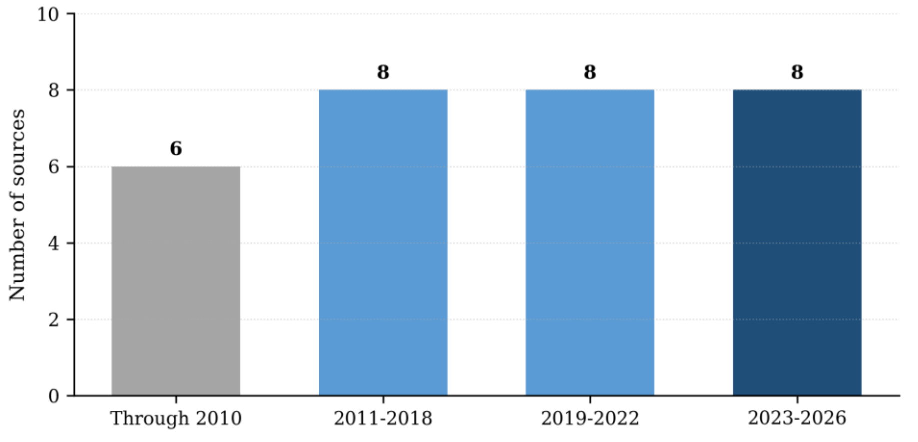

Figure 1. Distribution of reviewed sources by publication period

The evidence-design profile is weighted toward theory development and synthesis. Sixteen sources are review or conceptual works, eight provide empirical evidence, and six are standards or frameworks. This mix is appropriate for building a cross-disciplinary model, but it also explains why the paper treats causal effects as propositions requiring additional testing.

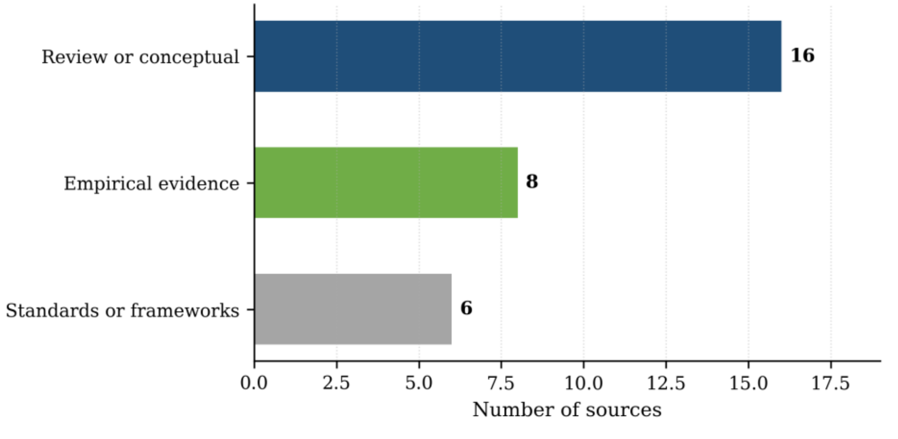

Figure 2. Evidence-design composition of the review dataset

Construct coding is non-exclusive as a source can tell more than one part of the framework. The terms governance and ethics are mentioned in 21 sources, AI and automation in 16, financial reporting quality in 14 and digital transformation and internal control in 13. The focus on governance has highlighted the critical role of accountability, data quality, model risk and human oversight in the growing literature. Conversely, the low and relatively even coverage of the aspects of digital transformation, internal control and reporting quality suggest that relatively few studies incorporate the full process pathway.

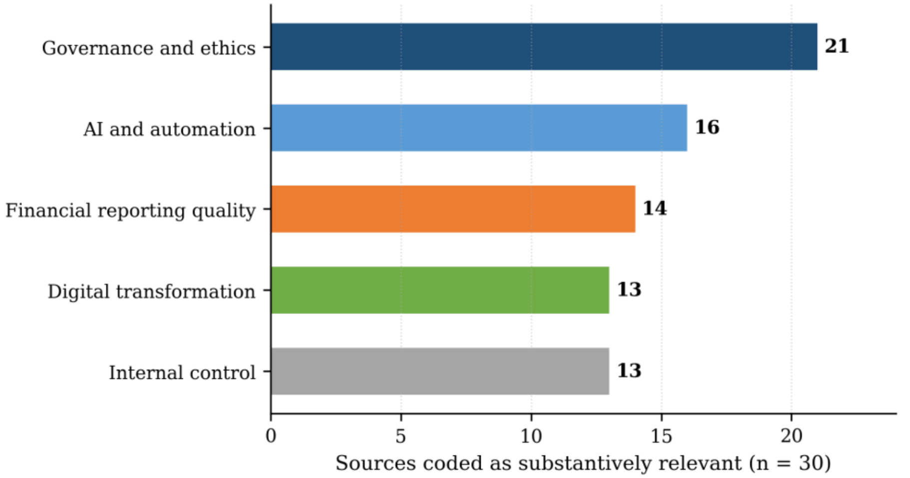

Figure 3. Construct coverage across the coded literature

The evidence map reveals that the literatures are still specialized. Internal-control sources are consistent in looking at the quality of reporting and seldom look directly at AI. AI-governance sources focus on automation, accountability, and risk, but only a small portion of them are talking about reporting outcomes. Digital-transformation research focuses on redesign and governance using technology and offers less direct evidence about control operation. The discontinuous pattern reinforces the need for an integrative process model, as opposed to the study of these topics individually: technology, control performance, and reporting quality.

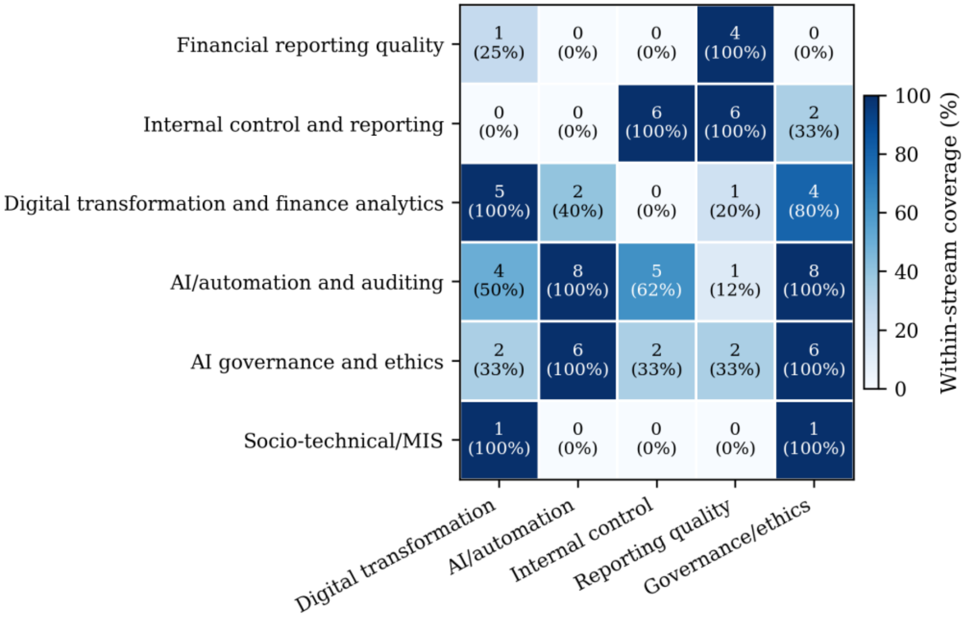

Figure 4. Literature-stream evidence map

The complete source-level coding is reproduced in Appendix B and supplied as Supplementary File S1, Structured_Review_Evidence_Dataset.xlsx. Because the dataset contains only bibliographic and analytical coding, it includes no personal, confidential, or proprietary organizational data.

AI-Enabled Internal Control Practices in Corporate Finance

The usefulness of the framework becomes clearer at the process level. The following sections examine how AI changes recurring finance controls, the reporting dimensions that may benefit, and the safeguards needed to prevent technology from creating an uncontrolled dependency.

4.1 Invoice verification and procure-to-pay

Procure-to-pay is a good fit for AI-powered control due to its high volume of transactions, recurring document types, clearly defined authorization rules and recurring exceptions. Supplier name, invoice number, date, tax information, line items and payment terms can be extracted using optical character recognition and natural-language processing. Those fields can then be compared with purchase orders, goods-receipt records, contract terms, approved vendor files, and historical patterns using rules and/or machine-learning models. Duplicate Invoices, changed Bank Information, abnormal Unit Prices, Split Purchases and charges that are not supported can be referred for review prior to payment/posting.

The reporting benefit is through a number of assertions. Matching supports occurrence and accuracy, document completeness supports verifiability, date and receipt checks support cut-off, account and tax mapping supports classification and presentation and faster exception resolution supports timeliness. However, bad vendor master data, missing purchase orders, incorrect tolerance rules, manipulated documents and automation bias are all risks that can be present in the process. An effective design thus maintains independent approval, separates the changes of the vendor-masters from the execution of the payment, records the changes of the rules and models, verifies the correctness of the extraction and calls for documented disposition of exceptions. While generative AI could summarize a contract or explain a variance, it shouldn't generate or authorize a payment without deterministic validations and accountable authorization.

4.2 Bank reconciliation and cash management

Bank Reconciliation is the process of reconciling the internal cash records with the external evidence and is thus at the heart of completeness and accuracy. Digital bank feeds and matching engines will match transactions by amount, date, reference, payers, and probabilistic similarity – only unmatched or suspicious transactions will need to be reviewed. The analytics can be used to detect recurring reconciling items, inactive accounts, round-dollar payments, recipients not associated with the entity, and timing that is not typical of normal processes. These capabilities can help minimize the number of unreconciled items and enhance the accuracy of cash position for financial statement reporting and cash position decisions.

Automation doesn't reduce the risk of reconciliation. The false sense of completion can occur when bank-feed changes are made without authorization, matching tolerances are lax, bank accounts are not recorded, reconciling items are not up to date, or too many manual overrides are used. Security features are authenticated interfaces, full bank-account inventory, limitation on configuration access, independent review of unresolved items and overrides, aging thresholds and matching of the final reconciliation to the general ledger. Forecasts should be seen as a tool to help in relevance and planning, but not as evidence to support the cash that has been recognised.

4.3 Journal entries and the period close

The record-to-report cycle focuses risk as the journal entries, estimates, consolidations, and late close adjustments can have a significant impact on the final statements. RPA can take care of recurring postings and roll-forwards, workflow can take care of close calendars and dependency, and machine learning models can score journal entries based on user, time, amount, account, description, source system and reversal behaviour. Continuous controls can detect entries made by users that are not usual, outside of regular working hours, to accounts that are not often used or just below approval limits. This yields a more targeted review than random sampling or a rules-based list.

The benefit will be based upon the interpretation of alerts. If a model generates too many false positives, it can lead to mechanical clearance, if a model is trained on historical approvals it can reproduce historical control weaknesses, and if an automated posting is not properly credentialed or has not been configured correctly for the workflow rules, it can go around the rules. Governance should comprise of an approved model objective, documented features, validation against known risk cases, performance thresholds, monitoring for drift and periodic review of false negatives and a clear distinction between recommendation and authorization. Management continue to have responsibility for the accounting judgements and estimates and the supporting evidence.

4.4 MIS reporting, analytics, and governed narrative

Management information systems convert transaction and operational information into dashboards, variance reports, forecasts and explanations. They often play an indirect but key role in the quality of reporting, including in the areas of budgeting, going concern assessment, impairment analysis, provisioning, disclosure preparation and management review, all of which are reliant on reliable information. These analytics can tell managers what is driving the results, not just the numbers, and natural-language interfaces can help managers who are not data specialists understand complex data (Appelbaum et al., 2017).

The main risk is that the words are semantically inconsistent. Business units can have varying definitions of revenue, overdue receivables, active customers or operating cash flow, making a dashboard technically accurate yet misleading. Generative AI takes it one step further: it can generate commentary in no time, but it can also make up causes, leave out conflicting evidence, or put forward uncertain forecasts as facts. Some of these controls are a controlled metric dictionary, documented data lineage, key performance indicator data reconciliation to source systems, version control, access restrictions, data only retrieved from approved data, and managerial review of all narratives that are externally significant. The system should not conceal uncertainty, but should make it visible, by not using language that suggests certainty.

4.5 Continuous monitoring and process mining

Continuous monitoring and process mining get the control evaluation closer to the time of the transaction. Event logs can show if purchase orders were created after the invoices, if approvals were skipped, if the same user was the one to do incompatible steps or if exceptions were not resolved within policy limits. The test of analytics can be applied to a higher percentage of the population than a month-end sample, and can detect changes in process behaviour which would not be apparent in a month-end sample. Initial continuous-auditing studies showed the potential and difficulties of incorporating automated tests into operational systems, and subsequent data-analytics studies highlighted the importance of linking the technical ability with audit judgment and quality of audit evidence (Alles et al., 2008; Earley, 2015).

These tools are the best when they are used to take corrective action. Exceptions that are left to build up on a monitoring dashboard isn't an effective control. Risk based thresholds, named owners, due dates, escalation rules, evidence of closure and analysis of recurring root causes are all needed within an organisation. The monitoring should also include changes to the controls, such as changes in rules, interfaces, models, user access and data quality. In this way, digital control is recursive, technology is monitoring transactions and governance is monitoring technology.

4.6 Audit documentation and knowledge support

An evidentiary chain is the basis for financial reporting. The availability and connectivity of contracts, invoices, approvals, reconciliations, calculations, policy interpretations and review sign-offs must be available and connected to the amounts reported. Digital document repositories enhance the retrieval and version management of documents, while natural-language tools can categorize evidence, find missing support, summarize lengthy agreements, and assist staff in finding relevant policies. These tools, when designed properly, decrease the delays in audits and enhance verifiability.

The hazards are confidentiality, origin and dependence. Sensitive information might be presented in the external models; a summary might contain a clause that alters the accounting conclusion; and workpapers generated might appear complete, but fail to show actual review. Control should be ensured on approved models and data environment, source-document links, prompts and outputs for material uses, reviewers confirmation of critical facts, version history and not accepting of unsupported generated evidence. While AI can help structure and provide insights on evidence, it cannot replace evidence that does not exist.

Table 4. Process-level applications, reporting contributions, and safeguards

Finance process	AI-enabled practice	Expected reporting contribution	Essential safeguards
Invoice verification and procure-to-pay	Document extraction, three-way matching, duplicate detection, vendor and price anomaly scoring.	Accuracy, occurrence, cut-off, classification, timeliness, and audit trail.	Vendor-master controls; independent approval; extraction testing; thresholds; override logs; exception follow-up.
Bank reconciliation and cash	Automated matching, unresolved-item aging, unusual-payment detection, cash forecasting.	Cash completeness and accuracy; faster close; timely liquidity insight.	Authenticated feeds; complete account inventory; restricted configuration; independent review; ledger agreement.
Journal entries and period close	Recurring automation, close orchestration, journal anomaly scoring, late-adjustment monitoring.	Consistency, timeliness, focused review, and fewer unsupported entries.	Model validation; feature documentation; access control; approval boundaries; drift and false-negative review.
MIS and management reporting	Integrated dashboards, variance analytics, governed narrative drafting, metric retrieval.	Relevance, understandability, comparability, and support for estimates and disclosures.	Metric dictionary; data lineage; source reconciliation; grounded retrieval; fact review; version control.

Finance process	AI-enabled practice	Expected reporting contribution	Essential safeguards
Continuous monitoring and process mining	Full-population testing, workflow-deviation detection, control-performance dashboards.	Earlier detection, traceability, and faster remediation of control failures.	Risk-based thresholds; named owners; aging and escalation; evidence of closure; monitoring of control changes.
Audit documentation and knowledge support	Evidence classification, policy retrieval, contract summarization, workpaper assistance.	Verifiability, completeness of support, and audit readiness.	Approved environments; confidentiality controls; source links; prompt/output logs; reviewer confirmation; version history.

Conceptual Framework and Propositions

The literature synthesis suggests an indirect (process) relationship. Digital transformation establishes the base for data integration, uniform work processes and scalable automation. That infrastructure allows for validation, matching, anomaly detection, monitoring, reporting and documentation with the assistance of AI. These practices enhance reporting only if they increase the organization's internal-control capability - its ability to prevent, detect, explain, and remediate reporting risks in a timely and accountable manner. Thus, internal control is the mechanism of transformation from technological potential to the quality of reporting.

Boundary conditions are also included in the framework. Data quality and lineage are important in determining if an AI control is analyzing the correct data. Integrity of interfaces, configurations, and access are impacted by IT general controls and cybersecurity. The impact of model governance and explainability on the validation and challenge of results. Exceptions can be mechanically cleared or investigated based on human supervision and control. Skills and resources are key to whether or not organizations can maintain automation and analytics without compromising other finance roles. These relationships are summarized in figure 5.

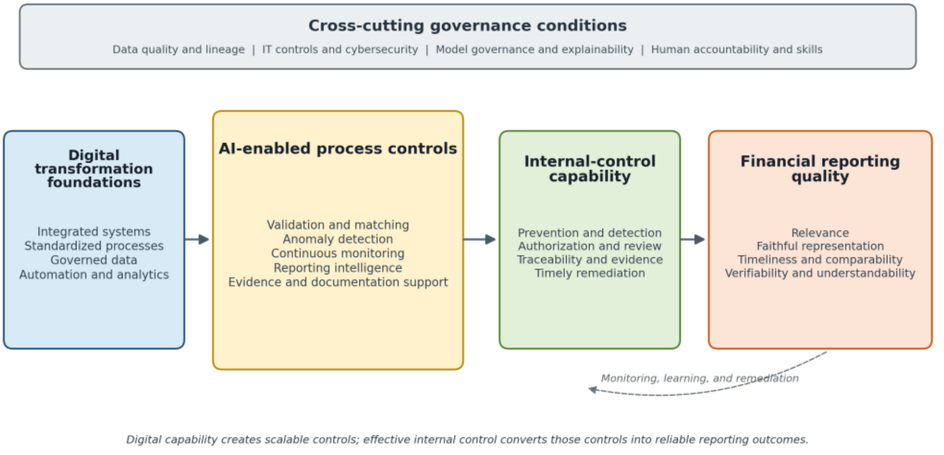

Figure 5. Digital transformation, AI-enabled internal control, and financial reporting quality

Proposition 1 - Digital foundations. Greater integration, process standardization, and governed data availability are positively associated with the development of AI-enabled internal-control capability.

Proposition 2 - Control mechanism. AI-enabled control capability improves internal-control effectiveness by increasing transaction coverage, consistency, traceability, and the timeliness of exception detection and remediation.

Proposition 3 - Mediation. Internal-control effectiveness mediates the positive relationship between digital transformation and financial reporting quality.

Proposition 4 - Data and IT governance. The positive effect of AI-enabled controls on internal-control effectiveness is stronger when data governance, access controls, change management, interface controls, and cybersecurity are effective.

Proposition 5 - Model governance and human oversight. Explainability, validation, accountable human review, and documented override procedures strengthen the reporting benefits of AI; their absence increases the risk that automation scales errors or bias.

Proposition 6 - Process fit. AI-enabled controls produce larger net benefits in high-volume, structured processes than in low-volume, judgment-intensive processes, unless the latter are supported by stronger evidence and review safeguards.

Proposition 7 - Complementary capability. Finance skills, control culture, and implementation resources positively moderate the relationship between digital transformation and reporting quality by reducing adoption strain and improving remediation quality.

Table 5. Summary of testable propositions

Proposition	Expected relationship	Primary mechanism
P1	Digital foundations -> AI-enabled internal-control capability (+)	Integrated data and standardized processes make controls programmable and scalable.
P2	AI-enabled controls -> internal-control effectiveness (+)	Wider coverage, consistent execution, traceability, and timely exception detection.
P3	Internal control mediates digital transformation -> reporting quality	Controls convert technological capacity into prevented, detected, and remediated reporting risk.
P4	Data and IT governance strengthen P2	Reliable inputs, secure access, controlled changes, and dependable interfaces.
P5	Model governance and human oversight strengthen P2 and P3	Validation, explainability, accountable challenge, and documented override decisions.
P6	Process structure moderates net benefit	Benefits are greater where volume is high and decision criteria are observable.
P7	Skills, resources, and control culture strengthen the overall pathway	Complementary capability reduces implementation strain and improves remediation.

Note. *A plus sign indicates an expected positive relationship. The propositions are conceptual and require empirical testing.*

Proposition 1 makes a distinction between infrastructure and outcomes. While integrated systems and standardized processes don't guarantee reliable reports, they increase the ability to program controls, reuse data, and expose exceptions. Different systems mean different definitions and interfaces that need to be manually reconciled, making AI unscalable. The proposition is in line with research on digital transformation which focuses on the change of organizations and processes instead of the acquisition of technologies (Vial, 2019; Verhoef et al., 2021).

Propositions 2 and 3 explain the mechanism in the centre. The reporting benefit comes from control performance: exceptions are found and corrected, and documented and reflected in the accounts; AI can help with the expansion of coverage and speed up the detection. This is why it is not a sign of quality that there is a high rate of model alerts. The meaningful indicators are the reduction in the number of unresolved exceptions, reduction in aging, reduction in late adjustments, improved evidence and reduction in control failures. The overall finding of the relationship between effective internal-control and better reporting and operations is corroborated by previous internal-control studies (Ashbaugh-Skaife et al., 2008; Doyle et al., 2007; Feng et al., 2015).

Technological dependence and accountability is represented by Propositions 4 and 5. The weaknesses of the data, interfaces, configuration and access environment are carried over to the automated controls. Validation, explainability and drift risks are added with machine-learning and generative systems. The NIST's AI Risk Management Framework categorizes AI governance into four activities: governing, mapping, measuring, and managing risk; COSO's technology-specific guidance relates the concerns to the well-known internal-control components (COSO, 2024, 2026; NIST, 2023, 2024). The bottom line is that in finance, the practical effect is that a model owner cannot substitute for a control owner, and that a technically accurate output cannot replace an accounting conclusion given by an authorized accounting firm.

Proposition 6 and 7 are against universal automation. Validation criteria for structured matching and reconciliation processes are typically more transparent than impairment, valuation or disclosure judgments. In judgment intensive environments, AI can enhance research and consistency, but with a need for more robust assumptions, evidence from sources, and uncertainty. Likewise, adoption has to be complemented by other resources. Bedford, et al., (2025) demonstrate how automation and analytics can put pressure on the effectiveness of the finance function, if resources are not considered. So, digital ambition needs to be sequenced with capability development.

Discussion

The framework shifts from the unit of analysis of the tool to the control system. When people start talking about AI in finance, they often start by discussing what a technology can do, such as reading a document, finding an anomaly, creating a narrative or predicting cash. The more relevant issue regarding reporting quality is whether such ability affects the likelihood of avoiding, identifying, understanding and rectifying a material error. This change eliminates the possibility that organisations can rely on pilot accuracy, processing speed or user enthusiasm as proof of the effectiveness of their control.

The analysis also helps to understand the difference between deterministic and probabilistic automation. RPA and configured application controls are typically used to perform a set of logic, and the primary threats to these controls are design issues, access, change management and exceptions. Machine-learning controls need to be tested to ensure they are performing correctly, monitored for drift, and have false-positive and false-negative considerations. Generative AI does not generate a fixed classification, but rather content – that needs to be grounded, traced back to the source, protected in terms of confidentiality and checked for facts. This approach to the technologies as interchangeable leaves control gaps as the same approval or testing process will not cover all failure modes.

The second implication relates to the seemingly conflicting nature of timeliness and reliability. While there is some benefit to accelerating the close, the speed is only useful when there's evidence and review to go with it. The goal isn't necessarily to get the month end faster, it's to get more continuous reporting, where recon, data quality and exception reviews are done throughout the month. The continuous work makes it possible to spread out the risk of any unusual items prior to the deadline, which allows management to investigate the items before publication.

A third implication is that the quality of reporting might not be uniform. Templatization and controlled data definitions can improve the comparability and understandability. Automated Matching and Data Lineage can enhance verifiability and faithful representation. Predictive analytics can enhance relevance and quicker processing can enhance timeliness. However, complexity in the model can create less understandability and high levels of automation can diminish the faithful representation as employees may no longer question the economic substance of a transaction. Governance needs to therefore not only optimize one aspect of the quality profile, but monitor the complete quality profile.

The framework also highlights that internal control does not stand in the way of innovation. Without effective control, innovation can't be trusted and scaled. Having clear ownership, controlled change, reliable evidence, and monitored performance facilitates the ability to scale an AI use case beyond a pilot. On the other hand, shadow AI, unmanaged spreadsheets and undocumented overrides make it difficult to provide assurance and build resistance as stakeholders cannot determine what the system did or why. So control discipline is not just a cost of compliance, it is a source of capacity for adoption.

Lastly, the ongoing importance of professional judgment is really about accountability and not resistance to technology. While AI can prioritize, compare, retrieve and explain, management should determine if accounting estimates are reasonable, if evidence is sufficient, if an exception is material, and if a disclosure is a faithful representation of the underlying economics. AI in auditing is also found to emphasize the importance of explainability, robustness, privacy, bias, and rethinking the human-machine collaboration (Kokina et al., 2025; Munoko et al., 2020). The best operating model is thus not one that is completely manual or one that operates without human oversight; it is a mixture of machine scale and human responsibility and accountability.

Managerial and Governance Implications

Implementation should start with the reporting objective and control risk not with an overall directive to “use AI.” A finance leader needs to understand where there are errors, delays, judgment bottlenecks or evidence gaps in reporting and then assess the suitability of rules, analytics, machine learning, or generative AI. The technology should be the simplest way of achieving the control objective at an acceptable risk and cost.

Table 6 shows COSO's internal-control logic in the roadmap alongside NIST's AI-risk lifecycle. It's aimed at CFOs, controllers, process owners, CIOs, information-security leaders, internal auditors and audit committees. For each stage, evidence is generated which can be reviewed separately. The roadmap also distinguishes between model performance and control performance, which is the ability of the model to provide alerts that are acted on in time and remediated.

Table 6. Implementation roadmap for AI-enabled finance controls

Stage	Management actions	Control evidence	Illustrative measures
1. Define the objective	Specify reporting assertion, risk, materiality, user, and acceptable consequence of error.	Approved use-case charter and risk assessment.	Baseline error rate; cycle time; value at risk.
2. Map process and data	Document workflow, interfaces, data lineage, ownership, exceptions, and existing controls.	Process map, data dictionary, control inventory, access matrix.	Data completeness; duplicate rate; interface failures.
3. Select and design the technology	Choose the least complex suitable tool; define decision boundaries and human review.	Design specification, model card or rule logic, approval matrix.	Expected precision/recall; coverage; human-review threshold.
4. Validate and pilot	Test representative, edge, and adverse cases; reconcile outputs; assess user behavior and failure modes.	Validation report, test scripts, exception results, go-live approval.	False positives/negatives; override rate; unresolved exceptions.
5. Operate and evidence	Run the control, investigate alerts, retain source links, document decisions, and remediate root causes.	Logs, reviewer sign-off, exception files, evidence of closure.	Aging; completion rate; late journals; post-close adjustments.
6. Monitor and govern change	Track drift, access, configuration, vendor changes, cyber events, and control outcomes; reassess materiality.	Periodic performance review, change approvals, incident and remediation records.	Model drift; access exceptions; control failures; audit adjustments; close time.

Note. *The roadmap should be repeated when a model, vendor, data source, reporting objective, or materiality threshold changes significantly.*

Governance roles and responsibilities should be clearly defined. The reporting objective, accounting policy, materiality judgments and control conclusions are the responsibility of the CFO and the controller. Exception investigation/remediation is the responsibility of the process owners. The ownership of technology and security functions, architecture, access, interfaces, resilience and technical change. Model-risk specialists or analytics specialists validate performance and monitor drift. Internal audit is an assessment of the design of governance and control, but not management's responsibility. The audit committee is responsible for important reporting and AI risks particularly in areas where AI models may impact material judgements or external narratives.

There are a number of other guardrails needed for Generative AI. The material posting and approvals should not be done just from a generative response. Systems should get material from approved sources, keep track of sources of material, log material prompts and material produced, protect confidential information, test for manipulation using prompts, and show uncertainty. Users should be educated on how to check facts and how to differentiate drafting assistance and accounting evidence. All overrides of models or rules need to be documented with the person responsible, the reason, supporting evidence and final disposition.

Performance measures need to be a combination of efficiency, control and reporting quality. Match rates, false-positive and false-negative rates, override frequency, unresolved-exception aging, reconciliation completion, late journal entries, close-cycle time, post-close adjustments, evidence completeness and user review time are examples of useful operational metrics. Outcome measures can encompass control deficiencies, restatements, audit adjustments, forecast error, report timeliness and user evaluations of relevance and understandability. By using a balanced scorecard, management cannot take the chance of celebrating the speed of the process and compromising the quality of control.

Limitations and Future Research

This paper is conceptual and thus can not be used to draw causal inferences. The evidence examined includes a variety of technologies, sectors, regions and research approaches, and many new uses of AI are captured in early field evidence, not necessarily in the context of long-term studies. The framework proposes mechanisms and boundary conditions that are plausible, but need to be empirically tested. Materiality, complexity of processes, regulations, and digital maturity are also unique across organizations, and a control design that works in one context might not apply to another.

The structured review data set enhances transparency, but is not comprehensive. It indexes the 30 sources mentioned in this manuscript, but not all the publications that might be pertinent to the field. Assignments to the primary streams and the construction of flags are based on author judgment, and the dataset does not formally assess methodological quality, publication bias or weighting studies by sample size. The descriptive figures should thus be seen as a profile of the evidence gathered for this paper and not as a full bibliometric map.

The model can be tested at a number of levels in future research. Archival studies may be conducted to determine if there is a relationship between controlled AI adoption and other outcomes, such as: reduced reporting lags, reduced audit adjustments, improved accrual quality, and reduced control deficiencies. The difference-in-differences designs would be able to compare firms before and after the implementation as long as the adoption event and the control changes are properly measured. Process-log research could be performed to determine if exception aging is reduced or if unauthorized exceptions in the workflow are reduced due to continuous monitoring. Field studies might examine the shared responsibilities for model validation and the shared ownership of controls between controllers, data scientists and internal auditors.

Behavioral experiments are required as well. Reviewers can be over-reliant on an algorithmic recommendation, ignore correct alerts when there have been false alerts previously, or take fluent generative explanations at face value without checking the evidence. Experiments may be conducted to examine the impact of explainability, confidence displays, accountability cues and the need for justification on professional skepticism. Other studies should be conducted using the same control task, and comparing deterministic rules, machine learning and generative AI, and not comparing AI as a group.

Development of measurement is another priority. Research needs to differentiate between digital infrastructure, the use of AI for control, the effectiveness of internal-control, governance quality, and reporting results and not use a single adoption index. Illustrative measures and data sources are included in Appendix A and the source level coding used for the descriptive review figures is included in Appendix B and the companion workbook. Research can then be carried out cross country to analyze the influence of enforcement, data protection, audit regulation and professional capacity on the relationships. This would shift the focus from the general optimism or fear of technology to the data on which processes, governance and technology mix to better reporting.

Conclusion

Digital transformation can have a real impact on the quality of financial information production and use, but its impact on the quality of financial information is not automatic or purely technical. Integrated systems, automation, analytics and AI provide the ability to validate more transactions, uncover exceptions sooner, streamline processes, enhance evidence and deliver results quicker. Those capabilities turn into reporting quality only if they are made to work as effective internal control.

The process level analysis illustrates how that conversion takes place. The use of AI for invoice verification aids in occurrence, accuracy, and cut-off; automated bank reconciliation assists with cash completeness and reliability; journal analytics highlight unusual transactions for attention; management information systems enhance decision support; continuous monitoring detects control drift; and digital documentation provides a boost to verifiability. Every application also brings in dependency on data, access, configurations, models, cyber security and human review. Control can be scaled up with technology, but so can error.

The paper thus proposes a simple yet significant idea: AI should be regulated within the framework of the internal-control system. Organizations should start with reporting goals, establish the process and evidence, select appropriate technology, retain human judgment and accountability and track the performance of the model and control. In such a situation, digital transformation can help generate reports that are faster, more relevant, faithfully represented, comparable, verifiable and understandable.

References

Abdo-Salloum, A. M., & Chehade, S. (2026). The role of artificial intelligence in transforming accounting and auditing practices: A systematic review. SAGE Open, 16(1), 1-13. https://doi.org/10.1177/21582440251403296

Alles, M. G., Kogan, A., & Vasarhelyi, M. A. (2008). Putting continuous auditing theory into practice: Lessons from two pilot implementations. Journal of Information Systems, 22(2), 195-214. https://doi.org/10.2308/jis.2008.22.2.195

Altamuro, J., & Beatty, A. (2010). How does internal control regulation affect financial reporting? Journal of Accounting and Economics, 49(1-2), 58-74. https://doi.org/10.1016/j.jacceco.2009.07.002

Appelbaum, D., Kogan, A., Vasarhelyi, M. A., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems, 25, 29-44. https://doi.org/10.1016/j.accinf.2017.03.003

Ashbaugh-Skaife, H., Collins, D. W., Kinney, W. R., Jr., & LaFond, R. (2008). The effect of SOX internal control deficiencies and their remediation on accrual quality. The Accounting Review, 83(1), 217-250. https://doi.org/10.2308/accr.2008.83.1.217

Bedford, D. S., Derichs, D., Hoozee, S., Malmi, T., Messner, M., Sinha, V. K., Van der Kolk, B., & Verbeeten, F. (2025). Digitalization of the finance function: Automation, analytics, and finance function effectiveness. Management Accounting Research, 67, Article 100942. https://doi.org/10.1016/j.mar.2025.100942

Bostrom, R. P., & Heinen, J. S. (1977). MIS problems and failures: A socio-technical perspective. Part I: The causes. MIS Quarterly, 1(3), 17-32.

Chalmers, K., Hay, D., & Khlif, H. (2019). Internal control in accounting research: A review. Journal of Accounting Literature, 42, 80-103. https://doi.org/10.1016/j.acclit.2018.03.002

Committee of Sponsoring Organizations of the Treadway Commission. (2013). Internal control - Integrated framework. https://www.coso.org/guidance-on-ic

Committee of Sponsoring Organizations of the Treadway Commission. (2024). Achieving effective internal control over robotic process automation: Integrating RPA governance with the COSO Internal Control - Integrated Framework.

Committee of Sponsoring Organizations of the Treadway Commission. (2026). Achieving effective internal control over generative AI (GenAI).

Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of Accounting and Economics, 50(2-3), 344-401. https://doi.org/10.1016/j.jacceco.2010.09.001

Doyle, J. T., Ge, W., & McVay, S. (2007). Accruals quality and internal control over financial reporting. The Accounting Review, 82(5), 1141-1170. https://doi.org/10.2308/accr.2007.82.5.1141

Earley, C. E. (2015). Data analytics in auditing: Opportunities and challenges. Business Horizons, 58(5), 493-500. https://doi.org/10.1016/j.bushor.2015.05.002

Feng, M., Li, C., McVay, S. E., & Skaife, H. (2015). Does ineffective internal control over financial reporting affect a firm's operations? Evidence from firms' inventory management. The Accounting Review, 90(2), 529-557. https://doi.org/10.2308/accr-50909

Huang, F., & Vasarhelyi, M. A. (2019). Applying robotic process automation (RPA) in auditing: A framework. International Journal of Accounting Information Systems, 35, Article 100433. https://doi.org/10.1016/j.accinf.2019.100433

IFRS Foundation. (2018). Conceptual framework for financial reporting. https://www.ifrs.org/issued-standards/list-of-standards/conceptual-framework/

Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. Journal of Emerging Technologies in Accounting, 13(2), 1-20. https://doi.org/10.2308/jeta-10511

Kerrouche, N., & Belouadah, F. (2025). Digital transformation and the quality of financial reports: Evidence from Saudi listed companies. International Journal of Data and Network Science, 9(1), 243-252. https://doi.org/10.5267/j.ijdns.2024.7.012

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115-122. https://doi.org/10.2308/jeta-51730

Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. International Journal of Accounting Information Systems, 56, Article 100734. https://doi.org/10.1016/j.accinf.2025.100734

Lehner, O. M., Ittonen, K., Silvola, H., Strom, E., & Wuhrleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: Ethical challenges and normative thinking. Accounting, Auditing & Accountability Journal, 35(9), 109-135. https://doi.org/10.1108/AAAJ-09-2020-4934

Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. The British Accounting Review, 51(6), Article 100833. https://doi.org/10.1016/j.bar.2019.04.002

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. A. (2020). The ethical implications of using artificial intelligence in auditing. Journal of Business Ethics, 167(2), 209-234. https://doi.org/10.1007/s10551-019-04407-1

National Institute of Standards and Technology. (2023). Artificial Intelligence Risk Management Framework (AI RMF 1.0) (NIST AI 100-1). https://doi.org/10.6028/NIST.AI.100-1

National Institute of Standards and Technology. (2024). Artificial Intelligence Risk Management Framework: Generative Artificial Intelligence Profile (NIST AI 600-1). https://doi.org/10.6028/NIST.AI.600-1

Sahi, A. M., Sahi, A. M., Abbas, A. H., & Khatib, S. F. A. (2022). Financial reporting quality of financial institutions: Literature review. Cogent Business & Management, 9(1), Article 2135210. https://doi.org/10.1080/23311975.2022.2135210

Sutton, S. G., Holt, M., & Arnold, V. (2016). "The reports of my death are greatly exaggerated" - Artificial intelligence research in accounting. International Journal of Accounting Information Systems, 22, 60-73. https://doi.org/10.1016/j.accinf.2016.07.005

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118-144. https://doi.org/10.1016/j.jsis.2019.01.003

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889-901. https://doi.org/10.1016/j.jbusres.2019.09.022

Sobia Wassan, Chen Xi, Tian Shen, Kamal Gulati, Kinza Ibraheem, Rana M. Amir Latif Rajpoot, "The Impact of Online Learning System on Students Affected with Stroke Disease", Behavioural Neurology, vol. 2022, Article ID 4847066, 14 pages, 2022. https://doi.org/10.1155/2022/4847066

Sobia Wassan, Tian Shen, Chen Xi, Kamal Gulati, Danish Vasan, Beenish Suhail, "Customer Experience towards the Product during a Coronavirus Outbreak", Behavioural Neurology, vol. 2022, Article ID 4279346, 18 pages, 2022. https://doi.org/10.1155/2022/4279346

Dhiman, G.; Juneja, S.; Viriyasitavat, W.; Mohafez, H.; Hadizadeh, M.; Islam, M.A.; El Bayoumy, I.; Gulati, K. A Novel Machine-Learning-Based Hybrid CNN Model for Tumor Identification in Medical Image Processing. Sustainability 2022, 14, 1447. https://doi.org/10.3390/su14031447

Akanksha, E., Sharma, N., & Gulati, K. (2021, January). OPNN: Optimized Probabilistic Neural Network based Automatic Detection of Maize Plant Disease Detection. In 2021 6th International Conference on Inventive Computation Technologies (ICICT) (pp. 1322-1328). IEEE.

Gulati, K., Boddu, R. S. K., Kapila, D., Bangare, S. L., Chandnani, N., & Saravanan, G. (2021). A review paper on wireless sensor network techniques in Internet of Things (IoT). Materials Today: Proceedings.

Gulati, K., Kumar, S. S., Boddu, R. S. K., Sarvakar, K., Sharma, D. K., & Nomani, M. Z. M. (2021). Comparative analysis of machine learning-based classification models using sentiment classification of tweets related to COVID-19 pandemic. Materials Today: Proceedings.

Wisetsri, W., R.T.S., Julie Aarthy, C.C., Thakur, V., Pandey. D. and Gulati K. (2021), Systematic Analysis and Future Research Directions in Artificial Intelligence for Marketing. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(11), 43-55.

Akanksha, E., Sharma, N., & Gulati, K. (2021, April). Review on Reinforcement Learning, Research Evolution and Scope of Application. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1416-1423). IEEE.

Singh, U. S., Singh, N., Gulati, K., Bhasin, N. K., & Sreejith, P. M. (2021). A study on the revolution of consumer relationships as a combination of human interactions and digital transformations. Materials Today: Proceedings.

Gulati, K., Boddu, R. S. K., Kapila, D., Bangare, S. L., Chandnani, N., & Saravanan, G. (2021). A review paper on wireless sensor network techniques in Internet of Things (IoT). Materials Today: Proceedings.

SANGEETHA, D. M., PRIYA, D. R., ELIAS, J., MAMGAIN, D. P., WASSAN, S., & GULATI, D. K. (2021). Techniques Using Artificial Intelligence to Solve Stock Market Forecast, Sales Estimating and Market Division Issues. Journal of Contemporary Issues in Business and Government, 27(3), 209-215.

Dovhan, O.D., Yurchenko, O.M., Naidon, J.O., Peliukh, O.S., Tkachuk, N.I. and Gulati, K. (2021), "Formation of the counter intelligence strategy of Ukraine: national and legal dimension", World Journal of Engineering, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/WJE-06-2021-0358

Billewar, S.R., Jadhav, K., Sriram, V.P., Arun, D.A., Mohd Abdul, S., Gulati, K. and Bhasin, D.N.K.K. (2021), "The rise of 3D E-Commerce: the online shopping gets real with virtual reality and augmented reality during COVID-19", World Journal of Engineering, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/WJE-06-2021-0338

Sanil, H.S., Singh, D., Raj, K.B., Choubey, S., Bhasin, N.K.K., Yadav, R. and Gulati, K. (2021), "Role of machine learning in changing social and business eco-system – a qualitative study to explore the factors contributing to competitive advantage during COVID pandemic", World Journal of Engineering, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/WJE-06-2021-0357

L. M. I. L. Joseph, P. Goel, A. Jain, K. Rajyalakshmi, K. Gulati and P. Singh, "A Novel Hybrid Deep Learning Algorithm for Smart City Traffic Congestion Predictions," 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), 2021, pp. 561-565, doi: 10.1109/ISPCC53510.2021.9609467.

S. L. Bangare, S. Prakash, K. Gulati, B. Veeru, G. Dhiman and S. Jaiswal, "The Architecture, Classification, and Unsolved Research Issues of Big Data extraction as well as decomposing the Internet of Vehicles (IoV)," 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), 2021, pp. 566-571, doi: 10.1109/ISPCC53510.2021.9609451.

V. P. Sriram, K. B. Raj, K. Srinivas, H. Pallathadka, G. S. Sajja and K. Gulati, "An Extensive Systematic Review of RFID Technology Role in Supply Chain Management (SCM)," 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), 2021, pp. 789-794, doi: 10.1109/ISPCC53510.2021.9609414.

Appendix A. Illustrative Operationalization for Empirical Validation

The indicators below are not presented as a previously validated scale. They provide a starting point for researchers who wish to test the framework using surveys, process logs, control-testing records, archival data, or mixed methods. Constructs should be measured separately, and the selected reporting-quality proxies should match the research setting.

Table A1. Suggested constructs, indicators, and data sources

Construct	Illustrative indicators	Possible data source	Caution
Digital transformation capability	ERP integration; percentage of straight-through processing; standardized process coverage; governed data domains; analytics adoption.	System inventory, process maps, configuration data, management survey.	Adoption breadth should not be assumed to equal effective use.
AI-enabled internal-control capability	Automated control coverage; anomaly models in production; continuous-monitoring frequency; explainable alerts; retained logs.	Control inventory, model register, application logs, interviews.	Separate deterministic automation, machine learning, and generative AI.
Internal-control effectiveness	Control failure rate; exception aging; remediation speed; repeat exceptions; override quality; evidence completeness.	GRC system, internal-audit findings, exception logs, management testing.	Frequency alone does not establish effectiveness; consider severity and materiality.
Governance quality	Data-quality controls; access and change effectiveness; model validation; drift monitoring; human-review compliance; training.	ITGC testing, model-risk files, security records, training data.	Governance may be endogenous to digital maturity; research designs should address selection effects.
Financial reporting quality	Accrual quality; restatements; audit adjustments; reporting lag; forecast error; qualitative-characteristic survey; disclosure readability.	Financial statements, audit records, market data, survey or experiment.	Use multiple proxies because no single measure captures the full construct.

Appendix B. Structured Review Evidence Dataset

Table B1 reproduces the 30 source records used for Figures 1-4; the companion workbook provides all 15 variables, source links, the codebook, formulas, and charts.

Table B1. Source-level evidence-coding dataset (n = 30)

ID	Short citation	Year	Source class	Evidence design	Primary literature stream	Construct coverage
S01	Abdo-Salloum & Chehade (2026)	2026	Peer-reviewed article	Review/conceptual	AI/automation & auditing	DT; AI; GOV
S02	Alles et al. (2008)	2008	Peer-reviewed article	Empirical	AI/automation & auditing	AI; IC; FRQ; GOV
S03	Altamuro & Beatty (2010)	2010	Peer-reviewed article	Empirical	Internal control & reporting	IC; FRQ
S04	Appelbaum et al. (2017)	2017	Peer-reviewed article	Review/conceptual	Digital transformation & finance analytics	DT; AI
S05	Ashbaugh-Skaife et al. (2008)	2008	Peer-reviewed article	Empirical	Internal control & reporting	IC; FRQ
S06	Bedford et al. (2025)	2025	Peer-reviewed article	Empirical	Digital transformation & finance analytics	DT; AI; FRQ; GOV
S07	Bostrom & Heinen (1977)	1977	Peer-reviewed article	Review/conceptual	Socio-technical/MIS	DT; GOV
S08	Chalmers et al. (2019)	2019	Peer-reviewed article	Review/conceptual	Internal control & reporting	IC; FRQ; GOV
S09	COSO (2013)	2013	Official guidance	Framework	Internal control & reporting	IC; FRQ; GOV
S10	COSO (2024)	2024	Official guidance	Framework	AI governance & ethics	DT; AI; IC; FRQ; GOV
S11	COSO (2026)	2026	Official guidance	Framework	AI governance & ethics	DT; AI; IC; FRQ; GOV
S12	Dechow et al. (2010)	2010	Peer-reviewed article	Review/conceptual	Financial reporting quality	FRQ
S13	Doyle et al. (2007)	2007	Peer-reviewed article	Empirical	Internal control & reporting	IC; FRQ
S14	Earley (2015)	2015	Peer-reviewed article	Review/conceptual	AI/automation & auditing	AI; IC; GOV
S15	Feng et al. (2015)	2015	Peer-reviewed article	Empirical	Internal control & reporting	IC; FRQ
S16	Huang & Vasarhelyi (2019)	2019	Peer-reviewed article	Review/conceptual	AI/automation & auditing	DT; AI; IC; GOV
S17	IFRS Foundation (2018)	2018	Official standard	Framework	Financial reporting quality	FRQ
S18	Issa et al. (2016)	2016	Peer-reviewed article	Review/conceptual	AI/automation & auditing	AI; IC; GOV
S19	Kerrouche & Belouadah (2025)	2025	Peer-reviewed article	Empirical	Financial reporting quality	DT; FRQ
S20	Kokina & Davenport (2017)	2017	Peer-reviewed article	Review/conceptual	AI/automation & auditing	DT; AI; GOV
S21	Kokina et al. (2025)	2025	Peer-reviewed article	Empirical	AI/automation & auditing	DT; AI; IC; GOV
S22	Lehner et al. (2022)	2022	Peer-reviewed article	Review/conceptual	AI governance & ethics	AI; GOV

ID	Short citation	Year	Source class	Evidence design	Primary literature stream	Construct coverage
S23	Moll & Yigitbasioglu (2019)	2019	Peer-reviewed article	Review/conceptual	Digital transformation & finance analytics	DT; GOV
S24	Munoko et al. (2020)	2020	Peer-reviewed article	Review/conceptual	AI governance & ethics	AI; GOV
S25	NIST (2023)	2023	Official guidance	Framework	AI governance & ethics	AI; GOV
S26	NIST (2024)	2024	Official guidance	Framework	AI governance & ethics	AI; GOV
S27	Sahi et al. (2022)	2022	Peer-reviewed article	Review/conceptual	Financial reporting quality	FRQ
S28	Sutton et al. (2016)	2016	Peer-reviewed article	Review/conceptual	AI/automation & auditing	AI; GOV
S29	Vial (2019)	2019	Peer-reviewed article	Review/conceptual	Digital transformation & finance analytics	DT; GOV
S30	Verhoef et al. (2021)	2021	Peer-reviewed article	Review/conceptual	Digital transformation & finance analytics	DT; GOV

Note. DT = digital transformation; AI = artificial intelligence and automation; IC = internal control; FRQ = financial reporting quality; GOV = governance and ethics. Flags are non-exclusive and indicate substantive relevance within this review. The complete dataset with full references and source links is provided in Supplementary File S1.