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Intelligence Layering in Accounting Information Systems: A Theory of Progressive AI Embedding in Financial Reporting

Misheck Mushani[1]*, Nchimunya Chaamwe[1], Joseph Phiri[1], Joe Likando[1]

[1] *Copperbelt University, Zambia*

* Corresponding Author

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Abstract

Artificial intelligence (AI) is increasingly embedded in accounting information systems (AIS), yet much of the emerging literature conceptualizes AI either as a collection of discrete technologies or as an organizational innovation whose adoption can be explained through established technology-acceptance and technology-adoption models. Such approaches provide limited theoretical explanation of what occurs between the decision to adopt AI and the emergence of an AI-enabled accounting information system. This paper develops intelligence layering as a theoretical construct that explains how AI capabilities are progressively embedded within established management information systems (MIS) and AIS architectures. Intelligence layering is defined as the progressive embedding, integration and orchestration of AI-enabled capabilities into an existing information-system architecture through which the system acquires enhanced capacities for automation, learning, language interpretation, prediction and adaptive decision support while remaining subject to human, organizational and governance controls. Drawing on the Technology Acceptance Model (TAM), Technology–Organization–Environment (TOE) framework, Resource-Based View (RBV), and socio-technical systems theory, the paper distinguishes adoption antecedents from the post-adoption mechanism through which AI changes information-processing capability. A multidimensional model is proposed comprising infrastructural compatibility, data readiness, integration depth, automation intelligence, learning intelligence, language intelligence, predictive intelligence, human interpretive integration, and governance integration. Nine propositions specify relationships among enabling conditions, intelligence layering, professional interpretation, governance and AI-enabled financial-reporting capability. A seven-level maturity model is proposed, ranging from conventional rule-based AIS to adaptive intelligent AIS. The paper also differentiates intelligence layering from a recently published multi-layered framework for AI in financial reporting by positioning layering not as an organizing taxonomy of AI themes but as a theoretical and architectural mechanism of post-adoption integration. Finally, the paper proposes an empirical operationalization strategy and research agenda. The contribution is to provide AIS scholarship with a middle-range theoretical mechanism linking technology adoption and resource conditions to progressive transformation of accounting information-processing capability..

1. Introduction

Artificial intelligence is changing the technological environment within which accounting information is generated, processed, interpreted and communicated. Machine learning, robotic process automation, natural language processing, predictive analytics, generative AI and large language models are increasingly capable of automating transactions, classifying information, identifying anomalies, interpreting documents, forecasting outcomes and producing narrative content. Recent empirical evidence shows that AI investment can be associated with improved audit quality and efficiency, that automation can reduce some internal-control weaknesses, and that generative AI can increase productivity while reallocating accounting effort toward communication and quality-assurance activities (Fedyk et al., 2022; Ashraf, 2025; Choi & Xie, 2026). These developments make AI increasingly relevant to accounting information systems rather than merely to isolated accounting applications.

Yet the growth of AI-accounting research has created a theoretical fragmentation problem. Recent reviews identify a rapidly expanding body of work spanning AI adoption, machine learning, robotic process automation, ChatGPT and large language models, auditing, financial reporting, management accounting, ethics and professional implications (Dong et al., 2024; Murphy et al., 2024; Stratopoulos & Wang, 2025). The literature is rich in applications, but many studies remain organized around individual technologies or individual accounting tasks. One study examines RPA, another machine learning, another natural-language processing, another generative AI, and another a particular auditing use case. This technology-specific orientation is useful for demonstrating what particular tools can do, but it provides a weaker explanation of how an established information-system architecture becomes progressively intelligent.

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The unresolved question is therefore not simply whether an organization adopts AI. It is: how does an existing MIS/AIS become progressively more intelligent when multiple AI capabilities are embedded within it? This question concerns the transformation of information-processing architecture. Traditional MIS and AIS provide the foundational infrastructure for transaction processing, data storage, controls, reporting and decision support. AI potentially extends this foundation by enabling systems to learn from data, recognize patterns, interpret language, generate content and anticipate future conditions. When these capabilities are integrated into existing workflows and combined with professional interpretation and governance, the resulting system may possess qualitatively different information-processing capabilities.

This paper introduces intelligence layering to conceptualize this transformation. Intelligence layering is defined as the progressive embedding, integration and orchestration of AI-enabled capabilities into an existing MIS/AIS architecture through which the system acquires enhanced capacities for automation, learning, language interpretation, prediction and adaptive decision support while remaining embedded within human, organizational and governance arrangements. The construct is deliberately broader than automation and narrower than digital transformation. It is also distinct from AI adoption because it focuses on the post-adoption process through which AI becomes structurally and operationally embedded.

The theoretical motivation is reinforced by recent developments in the literature. Stratopoulos and Wang (2025) demonstrate that AI-accounting research is fragmented across AI-centric and accounting-centric orientations and argue that theoretical depth remains an important source of scholarly value. Murphy et al. (2024) identify eleven topic clusters across 930 accounting-and-AI publications, confirming the breadth of the field. Dong et al. (2024) similarly show that ChatGPT research in accounting and finance spans applications, research uses and professional implications. These reviews establish the breadth of the field but also leave room for a higher-order mechanism that explains how different AI capabilities become integrated within accounting information architectures.

The contribution of this paper is consequently theoretical rather than empirical. It does not claim that intelligence layering has already been validated. Instead, it develops the construct, specifies its dimensions, positions it relative to established theories, proposes a formal mechanism and derives propositions that can be tested in future research. The paper also proposes a maturity model and an operationalization strategy to move the construct from conceptual language toward empirical measurement.

The paper makes four contributions. First, it introduces intelligence layering as a distinct middle-range construct in AIS research. Second, it specifies nine dimensions that capture the depth and configuration of intelligence embedded within an AIS. Third, it integrates TAM, TOE, RBV and socio-technical systems theory while assigning each a distinct explanatory role. Fourth, it develops a research program for measuring intelligence layering and testing whether deeper integration is associated with enhanced reporting capability under appropriate professional and governance conditions.

2 Literature Review

2.1 From Traditional MIS/AIS to AI-Enabled Information Systems

Management information systems developed as organizational mechanisms for collecting, processing, storing and communicating information to support operational and managerial decision-making. The evolution from transaction-processing systems to MIS, decision-support systems and executive information systems established the basic architecture through which organizations convert transactions and data into usable information. Accounting information systems are a specialized manifestation of this architecture, focused on capturing, processing, storing and communicating accounting information while supporting internal controls and financial reporting.

The traditional AIS remains the foundation for contemporary financial reporting. Enterprise resource planning systems, accounting databases, transaction-processing applications, reporting modules and control mechanisms continue to provide the infrastructure upon which financial information depends. AI does not make these components obsolete. Instead, AI introduces additional capabilities that can be connected to the existing architecture. The conceptual relationship is therefore not necessarily replacement but extension: traditional MIS/AIS infrastructure provides the information-processing foundation, while AI can add layers of automation, learning, interpretation and prediction.

This distinction matters because a software application can be AI-enabled without transforming the information system into which it is connected. For example, an accountant may use a standalone generative-AI application to summarize a document. The activity is technologically AI-enabled, but the AIS itself may remain unchanged. In contrast, if the generative system is connected to authorized accounting records, automatically retrieves relevant transactions, applies reporting rules, generates a draft disclosure, records an audit trail and routes the output to a professional for validation, the AI capability has become embedded in the information architecture. Intelligence layering concerns the latter phenomenon.

The concept also builds on the longstanding recognition that information systems are socio-technical arrangements rather than purely technical artifacts. Accounting systems embody organizational routines, professional judgments, controls, institutional expectations and technological infrastructures. Consequently, AI integration must be understood as a change in a system of relationships rather than as the installation of an isolated algorithm.

The proposed conceptual shift can therefore be expressed as follows:

Traditional MIS/AIS → data and process integration → AI intelligence layer → professional interpretation → organizational embedding and governance → AI-enabled reporting capability.

The arrow between traditional AIS and AI-enabled reporting is the theoretical problem addressed by intelligence layering.

2.2 The Emerging AI-Accounting Literature

The contemporary AI-accounting literature provides strong evidence that AI is becoming relevant to core accounting activities. RPA research demonstrates the feasibility of automating repetitive processes. Perdana et al. (2023), for example, examine practical RPA scenarios in accounting firms and highlight implementation challenges. Machine-learning research examines classification, anomaly detection and other accounting tasks (Bavaresco et al., 2023; Booker et al., 2024). AI and auditing research has documented relationships between AI investment and audit quality, workforce composition and professional skills (Fedyk et al., 2022; Law & Shen, 2024). Explainable AI research addresses the challenge of making algorithmic outputs interpretable within auditing and evidence requirements (Zhang et al., 2022). More recent work on LLMs and GenAI examines audit planning, working papers, text generation, disclosure and human–AI interaction (Gu et al., 2024; Fotoh & Mugwira, 2025; Blankespoor et al., 2026; Choi & Xie, 2026).

The literature is increasingly moving beyond simple substitution narratives. Law and Shen (2024) find that AI use in audit offices is associated with changes in job demand and improvements in audit-related judgments, while Choi and Xie (2026) find evidence of selective human intervention when AI confidence is low. These findings are consistent with an augmentation perspective in which AI and professional expertise can be complementary.

The literature also highlights barriers and governance requirements. Jackson and Allen (2024) show that technological, organizational and environmental conditions influence technology adoption in accounting. Zhang et al. (2023) identify data security, accountability, accessibility, transparency and trust as important ethical concerns. Fotoh and Mugwira (2025) identify hallucinations, legal liability and ethical risks associated with LLM use in auditing. Lombardi et al. (2025) show that regulatory directives, skills, ethics and professional requirements are central to the future of audit technology.

However, the literature generally asks one of three questions: what can a particular technology do; what influences adoption; or what consequences follow from a particular implementation. Fewer studies conceptualize the mechanism through which multiple capabilities become progressively embedded in an existing AIS. This is the theoretical space for intelligence layering.

The need for such a mechanism is also evident from the 2026 multi-layered framework of Juma'ha et al. (2026). Their paper provides a useful review of AI in financial reporting and investment and uses TAM as a foundation for understanding adoption. The present paper takes a different theoretical position. Rather than organizing research themes into layers, intelligence layering explains the process by which AI capabilities become embedded in an information-system architecture after or alongside adoption. This distinction is developed explicitly in Section 6.

2.3 Construct Definition and Conceptual Boundaries

A rigorous construct requires a definition that identifies its essential properties and excludes neighboring concepts. Intelligence layering is defined as the progressive embedding, integration and orchestration of AI-enabled capabilities into an existing MIS/AIS architecture through which the system acquires enhanced capacities for automation, learning, language interpretation, prediction and adaptive decision support while remaining subject to human, organizational and governance controls.

The term progressive emphasizes that integration can occur over time. An organization may begin with automated data extraction, later introduce anomaly detection, subsequently integrate language models and eventually connect predictive systems. The sequence is not assumed to be universal, but the temporal possibility is important because it distinguishes layering from a static technology inventory.

Embedding means that AI capabilities become connected to the data, workflows and decision processes of the existing system. Integration refers to technical and process interoperability. Orchestration refers to the possibility that several capabilities operate together rather than as unrelated applications. Enhanced information-processing capability identifies the outcome at the system level. Finally, human, organizational and governance controls establish the socio-technical boundaries within which intelligence is deployed.

Intelligence layering is not equivalent to AI adoption. Adoption can occur without deep integration. A firm can purchase an AI tool, pilot it or allow employees to use a standalone application while the underlying AIS remains unchanged. Intelligence layering becomes visible when the AI capability is connected to organizational information flows and accounting work.

It is also not synonymous with automation. Automation is one dimension of intelligence layering, but learning, language and predictive capabilities extend beyond deterministic automation. Nor is intelligence layering equivalent to digital transformation, which is a broader organizational phenomenon involving business models, structures, processes and technologies. Intelligence layering focuses specifically on the information-processing architecture.

The construct is also distinct from AI maturity. AI maturity may describe an organization's readiness, sophistication or governance. Intelligence layering instead describes the configuration and depth of AI capabilities embedded in the AIS. Maturity can be an outcome or diagnostic expression of layering rather than a synonym for it.

Finally, intelligence layering is not a technological stack. A stack describes components of an IT environment. The proposed construct is theoretical: it explains how AI components become integrated with an existing system and how that integration changes information processing.

2.4 Dimensions of Intelligence Layering

The construct is conceptualized as multidimensional. Nine dimensions are proposed.

First, infrastructural compatibility captures the degree to which existing AIS architecture can communicate with and support AI capabilities. Compatibility includes interoperability, interfaces, scalability and integration with enterprise systems. Without compatibility, AI may remain peripheral.

Second, data readiness concerns the availability, quality, completeness, accessibility and interoperability of data. AI systems depend on data, and poor-quality or fragmented data constrain learning and prediction.

Third, integration depth captures how extensively AI is embedded within core accounting workflows. Peripheral use represents shallow layering; integration into transaction processing, reconciliation, reporting and control processes represents deeper layering.

Fourth, automation intelligence captures AI-enabled execution or augmentation of routine tasks. Examples include automated extraction, reconciliation, classification and matching.

Fifth, learning intelligence captures the ability of systems to identify patterns, classify cases, detect anomalies and adapt from data. It represents a shift from fixed rules toward data-driven inference.

Sixth, language intelligence captures the ability to interpret and generate natural language. Examples include document analysis, narrative reporting, disclosure summarization and natural-language querying.

Seventh, predictive intelligence captures the capacity to anticipate future conditions through forecasting, risk prediction, scenario analysis and predictive alerts.

Eighth, human interpretive integration captures the extent to which AI outputs are incorporated into professional judgment. It includes validation, review, contextualization and override mechanisms. This dimension prevents the construct from becoming purely technical.

Ninth, governance integration captures the embedding of controls around AI. It includes auditability, explainability, accountability, access control, monitoring and model-risk management.

The dimensions should initially be treated as potentially formative rather than automatically reflective. Each dimension represents a different capability that contributes to the overall configuration. An organization can have high automation and low language intelligence, or strong prediction and weak governance. This variation is theoretically meaningful.

The proposed construct can therefore be represented as:

IL = f(IC, DR, ID, AI, LI, NI, PI, HI, GI)

where IL is intelligence layering; IC is infrastructural compatibility; DR is data readiness; ID is integration depth; AI is automation intelligence; LI is learning intelligence; NI is language intelligence; PI is predictive intelligence; HI is human interpretive integration; and GI is governance integration.

The expression is conceptual rather than a claim about a final statistical functional form. Future scale-development studies should determine whether a formative second-order model, composite index or configurational approach best represents the construct.

2.5 Distinguishing Intelligence Layering from the 2026 Multi-Layered Framework

The emergence of a 2026 paper explicitly titled “Integrating AI into financial reporting and investment: multi-layered framework” makes conceptual differentiation essential. Juma’ha, Chuang and Harfouche (2026) review AI applications in financial reporting and investment, use TAM as a theoretical foundation and organize major themes and research directions around AI adoption and applications. Their contribution is valuable because it maps a rapidly developing research domain.

The present construct differs in purpose and ontological status. A multi-layered framework can organize domains, technologies, contexts or themes. Intelligence layering is proposed as a theoretical mechanism that explains a process of architectural integration. The unit of analysis is therefore different. The multi-layered framework focuses on the field of AI in financial reporting and investment; intelligence layering focuses on the AIS architecture and its progressive transformation.

The distinction is especially important because the word “layer” can be used descriptively or theoretically. Descriptively, layers may represent categories of technology or research themes. Theoretically, layering refers to a mechanism through which one capability becomes embedded in another system and changes its operation. This paper adopts the latter meaning.

The distinction can be summarized in five propositions. First, intelligence layering is post-adoption in orientation. Second, it is architectural rather than primarily thematic. Third, its dimensions represent information-processing capabilities rather than literature categories. Fourth, human interpretation and governance are constitutive components rather than external considerations. Fifth, the construct is intended to be operationalized and empirically tested as a determinant of AI-enabled reporting capability.

This distinction also protects the manuscript from a weak novelty claim. The paper does not claim that no researcher has used the word “layer” or proposed a multi-layered AI framework. Instead, it claims that existing literature provides limited theorization of progressive AI embedding as a mechanism linking adoption conditions to transformed AIS information-processing capability. This is a narrower and more defensible theoretical contribution.

3 Methods

3.1 Theoretical Foundations: TAM, TOE, RBV and Socio-Technical Systems

TAM explains user acceptance of information technology through perceived usefulness, perceived ease of use, attitudes and behavioral intentions (Davis, 1989). UTAUT extends technology-use explanations through performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). These models are valuable for understanding whether users and organizations are willing to use AI. They do not, however, specify how accepted technologies become embedded within an AIS.

TOE focuses on technological, organizational and environmental conditions affecting innovation adoption (Tornatzky & Fleischer, 1990). Recent accounting research demonstrates the relevance of TOE to AI, RPA and other technologies (Jackson & Allen, 2024). TOE can therefore explain important antecedents of intelligence layering, including infrastructure, organizational readiness and institutional pressure. Yet adoption conditions alone do not constitute the post-adoption integration mechanism.

RBV emphasizes the strategic role of valuable resources and capabilities (Barney, 1991). In AI-enabled accounting, relevant resources include data, technology infrastructure, AI skills, accounting expertise and governance capability. RBV explains why organizations with different resource configurations may have different AI capabilities. It does not specify how these resources become embedded into information-system architecture.

Socio-technical systems theory provides the strongest conceptual connection to human–AI integration because it treats technical and social elements as interdependent. Accounting systems are socio-technical arrangements, and AI integration necessarily affects roles, skills, decision rights and professional judgment. However, socio-technical theory is broad. It does not provide a specific construct for measuring the depth of AI integration within an AIS.

Intelligence layering therefore complements rather than replaces these theories. TAM/UTAUT can explain acceptance; TOE can explain adoption conditions; RBV can explain resources and capabilities; socio-technical theory can explain human–technology interaction; and intelligence layering can explain the transition from adopted AI to embedded AI-enabled information processing.

This division of explanatory labor is important. The contribution is not a new grand theory of technology. It is a middle-range mechanism that connects established theoretical perspectives to a specific phenomenon in AIS.

3.2 Formal Theoretical Mechanism

The central mechanism proposed in this paper is:

Enabling conditions → Intelligence layering → Enhanced information processing → Professional interpretation → Governed organizational embedding → AI-enabled reporting capability.

The first stage comprises technological, organizational and resource conditions. Infrastructure compatibility and data readiness are particularly important technological conditions. Organizational readiness, leadership support and professional competence are organizational conditions. Resources include data, skills, financial investment and technological capabilities.

The second stage is intelligence layering itself. AI capabilities become connected to existing workflows and information flows. The system can then perform activities that were previously impossible or impractical through rule-based processing alone.

The third stage is enhanced information processing. Intelligence layering changes the system's ability to process information by adding automation, pattern recognition, language interpretation and prediction. This stage is the immediate system-level consequence of layering.

The fourth stage is professional interpretation. AI outputs do not automatically become accounting judgments. Professionals assess relevance, accuracy, context and compliance. They may accept, modify or override outputs. The recent field evidence of Choi and Xie (2026), which documents selective human intervention when AI confidence is low, is consistent with this mechanism.

The fifth stage is governed organizational embedding. AI outputs become part of accounting processes only when workflows, roles, controls and accountability structures accommodate them. Governance is therefore not simply an external ethical issue; it conditions whether increased intelligence produces reliable outcomes.

The sixth stage is AI-enabled reporting capability. Potential outcomes include greater timeliness, richer analytical capability, improved anomaly detection, enhanced forecasting and more efficient reporting. These outcomes are conditional rather than automatic.

The formal conceptual expression is:

IL = f(IC, DR, ID, AI, LI, NI, PI, HI, GI)

and:

AI-enabled reporting capability = f(IL, professional interpretation, governance, organizational embedding, institutional context).

The model therefore separates antecedents, mechanism and outcomes. This separation is central to the theoretical contribution.

3.3 Proposition Development

P1. Greater infrastructural compatibility between existing MIS/AIS architecture and AI capabilities positively influences intelligence-layering depth.

Compatibility determines whether AI can communicate with existing databases, enterprise systems and workflows. Highly fragmented legacy systems may restrict integration even when an organization has strong AI resources.

P2. Greater data readiness positively influences intelligence-layering effectiveness.

AI systems require accessible, sufficiently complete and appropriately structured data. Data readiness therefore provides the informational substrate for learning and prediction.

P3. Greater integration of AI capabilities into core accounting workflows produces deeper intelligence layering than peripheral or standalone AI use.

The proposition distinguishes embedded intelligence from individual tool use. A standalone AI application can support a task without transforming the AIS.

P4. Integration of complementary AI capabilities produces greater intelligence-layering potential than isolated deployment of individual capabilities.

The proposition reflects the possibility of orchestration. Automated extraction can feed machine-learning classification; machine learning can identify anomalies; language models can interpret supporting documents; predictive systems can assess future risk. The combined configuration can create capabilities that are difficult to obtain from any one technology alone.

P5. Professional interpretation mediates the relationship between intelligence layering and AI-enabled financial-reporting capability.

AI output becomes organizationally useful through professional evaluation and contextualization. This proposition incorporates accounting judgment into the mechanism.

P6. Organizational readiness positively influences the extent to which intelligence layering becomes embedded in accounting processes.

Readiness includes leadership support, skills, change-management capacity, infrastructure and resources. Technology alone cannot guarantee embedding.

P7. Governance integration positively moderates the relationship between intelligence layering and reporting reliability.

Without appropriate governance, greater AI capability may increase rather than reduce reporting risk. Explainability, audit trails, access controls and human oversight are therefore boundary conditions.

P8. Institutional and regulatory conditions shape the form and depth of intelligence layering.

Accounting is institutionally embedded. Regulatory requirements, professional standards, data-protection expectations and audit requirements can encourage, constrain or redirect AI integration.

P9. Greater intelligence-layering depth is positively associated with AI-enabled financial-reporting capability when professional interpretation and governance integration are adequately developed.

This final proposition represents the overall outcome relationship. The conditional wording prevents the theory from becoming technologically deterministic.

3.4 Conceptual Architecture

The conceptual architecture has six interconnected stages. The first is the traditional MIS/AIS foundation: transactions, databases, accounting processes, controls and reporting infrastructure. The second comprises enabling conditions, including infrastructure compatibility, data readiness, organizational readiness and professional capability. The third is the intelligence layer, which contains automation, learning, language and predictive capabilities. The fourth is professional interpretation. The fifth is governance and organizational embedding. The sixth is AI-enabled reporting capability.

The architecture emphasizes that intelligence is layered onto an existing system rather than introduced into an organizational vacuum. The traditional AIS remains important because it provides the data, processes and control structures upon which AI depends.

The architecture also distinguishes capability from outcome. The presence of an AI model is not equivalent to improved reporting. The model must be integrated, interpreted, governed and embedded. This distinction responds directly to the tendency in technology research to infer organizational transformation from technology availability.

The architecture further allows different organizations to follow different trajectories. One organization may move from traditional AIS to automation and then prediction. Another may introduce language intelligence first because narrative reporting is its primary problem. A third may possess advanced AI models but shallow organizational integration. Intelligence layering therefore does not imply a universal sequence; it provides a framework for analyzing different configurations and trajectories.

3.5 Maturity Model

A seven-level maturity model is proposed.

Level 0, Traditional AIS, is characterized by rule-based transaction processing and conventional reporting.

Level 1, Automated AIS, introduces automation into repetitive processes such as reconciliation, extraction, classification and matching.

Level 2, Learning-enabled AIS, introduces machine-learning capabilities for pattern recognition, anomaly detection and classification.

Level 3, Language-enabled AIS, introduces natural-language interpretation and generation. The system can analyze documents, answer queries and assist with narrative reporting.

Level 4, Predictive AIS, adds forecasting, risk prediction and scenario analysis. The system moves from describing historical information toward anticipating future conditions.

Level 5, Integrated Intelligent AIS, combines multiple intelligence capabilities within common workflows. Automation, learning, language and prediction interact rather than operating as independent tools.

Level 6, Adaptive Intelligent AIS, represents continuous learning, dynamic human–AI collaboration and adaptive decision support. This is a theoretical endpoint rather than an assumption that all organizations should pursue it.

Maturity should not be interpreted simply as “higher is better.” Higher intelligence can increase complexity, governance requirements and exposure to model risk. The relevant question is whether the level of intelligence is appropriate to the organization's objectives, risk tolerance and regulatory environment.

Maturity also differs from depth. Two organizations can both operate at Level 4 while having different integration depth, governance quality and human-interaction patterns. Future empirical research should therefore combine categorical maturity with multidimensional depth measurement.

3.6 Construct Operationalization and Empirical Testing

The next stage in developing intelligence layering is empirical validation. A construct cannot remain purely metaphorical if it is intended to support theory development. This paper therefore proposes a measurement architecture that future researchers can refine.

Infrastructural compatibility can be measured through interoperability, system connectivity, API availability, ERP compatibility and scalability. Data readiness can be assessed through data quality, accessibility, completeness, standardization and integration. Integration depth can be assessed through the proportion of core reporting workflows that incorporate AI, the degree of real-time integration and the extent to which AI outputs enter operational decision processes.

Automation intelligence can be assessed through the number and criticality of accounting tasks supported or executed automatically. Learning intelligence can be measured through anomaly detection, adaptive classification and model updating. Language intelligence can be measured through document interpretation, natural-language querying, summarization and narrative generation. Predictive intelligence can be assessed through forecasting, risk prediction and scenario analysis.

Human interpretive integration requires measures of professional review, validation, override, contextual interpretation and human-in-the-loop design. Governance integration requires measures of auditability, explainability, accountability, access control, monitoring and model-risk management.

The construct should initially be treated as potentially formative because its dimensions are conceptually distinct. Researchers should not assume that all nine dimensions are interchangeable manifestations of a single underlying trait. A formative second-order construct, composite index or configurational approach may be more appropriate than a simple reflective scale.

A possible empirical model is:

Technological readiness → Intelligence layering → AI-enabled reporting capability

with organizational readiness, professional competence and governance as moderators or mediators, depending on theoretical specification.

Construct development could proceed through four stages. First, generate items from the conceptual dimensions and qualitative evidence. Second, conduct expert assessment for content validity. Third, use exploratory factor analysis or related techniques to examine dimensional structure where appropriate. Fourth, use confirmatory factor analysis and structural-equation modeling to test the proposed relationships.

Qualitative research is equally important. Longitudinal case studies could trace how organizations move from automation to learning, language and prediction. Interviews could ask how AI is introduced, integrated, reviewed, governed and embedded. Process tracing could identify whether intelligence layering actually occurs as theorized.

Mixed methods may provide the strongest validation strategy. Qualitative research can refine the construct, followed by quantitative scale development and structural testing. This sequence would help ensure that the measurement instrument reflects organizational reality rather than imposing an abstract technology taxonomy.

4 Results

4.1 Human–AI Collaboration and Professional Interpretation

The human component of intelligence layering is theoretically central. Accounting information systems are not autonomous technical systems; they operate within professional and institutional environments. AI can produce predictions, classifications, summaries and recommendations, but accounting professionals remain responsible for interpreting these outputs within standards, organizational objectives and reporting circumstances.

The human–AI relationship can therefore be conceptualized as complementarity rather than simple substitution. Choi and Xie (2026) find that accountants selectively intervene when AI confidence is low and report productivity and reporting-quality improvements associated with GenAI use. Law and Shen (2024) similarly find changes in skills associated with AI use in audit offices rather than a simple disappearance of professional work. Commerford et al. (2024) and Commerford et al. (2022) show that professional reliance on AI can be influenced by how AI recommendations are presented and how they compare with human advice.

These findings imply that deeper intelligence layering may require more sophisticated professional roles, not fewer. As routine processing becomes automated, accountants may devote more effort to interpretation, communication, quality assurance, exception handling and governance.

This is also why human interpretive integration is a dimension of the construct. A highly intelligent AIS that produces outputs that professionals cannot interpret or challenge may be less useful than a moderately intelligent system embedded in effective professional workflows.

The theoretical implication is that intelligence layering changes the division of cognitive labor between humans and systems. It is therefore not merely an IT architecture concept. It is an architecture of human–machine information processing.

4.2 Governance as a Boundary Condition

AI integration creates opportunities and risks. Explainability is particularly important in auditing and financial reporting because professionals must be able to understand and support the basis for important outputs (Zhang et al., 2022). Generative AI introduces additional risks involving hallucinations, confidentiality, accountability and inappropriate reliance (Fotoh & Mugwira, 2025). Ethical research in managerial accounting similarly identifies data security, privacy, accountability, accessibility and transparency as major concerns (Zhang et al., 2023).

These concerns justify treating governance as a boundary condition rather than an optional add-on. Intelligence layering can increase system capability while simultaneously increasing the need for controls. Governance therefore determines whether additional intelligence produces reliable organizational outcomes.

Governance integration includes audit trails, explainability, model monitoring, access control, human oversight, accountability and escalation procedures. In financial reporting, these mechanisms are particularly important because errors can affect investors, regulators and other stakeholders.

The theoretical model consequently rejects technological determinism. It does not assume:

More AI = better reporting.

Instead, it proposes:

More intelligence + professional interpretation + appropriate governance = greater potential for AI-enabled reporting capability.

This conditional logic makes the theory compatible with evidence showing both benefits and risks from AI integration.

4.3 Organizational and Institutional Embedding

Technological integration becomes organizational transformation only when workflows, roles, skills, decision rights and controls change. Research on emerging digital technologies in auditing indicates that AI and RPA can influence organizational structures, recruitment and the division of expertise (Vitali & Giuliani, 2024). Institutional research in AIS also emphasizes that digital transformation is embedded in broader processes of institutional change (Schiavi et al., 2024).

Intelligence layering therefore has an organizational dimension. Organizations must decide who owns AI systems, who validates outputs, who can override recommendations, who is accountable for errors and how AI-generated evidence enters reporting processes. These decisions affect the depth of layering.

Institutional conditions also shape what organizations can implement. Accounting standards, audit requirements, professional codes, privacy regulation and sector-specific rules can encourage or constrain AI deployment. This is especially relevant in public-sector and regulated environments.

The model therefore positions institutional conditions around the entire architecture rather than treating them as a one-time adoption variable. Institutional conditions can affect the choice of technologies, the depth of integration and the governance requirements associated with each layer.

4.4 Implications for Financial Reporting

The proposed theory suggests several pathways through which intelligence layering may influence financial reporting.

First, automation can reduce processing time and manual errors in routine activities. Ashraf (2025) provides empirical evidence that automation in financial reporting is associated with fewer internal-control material weaknesses.

Second, learning intelligence can identify anomalies and patterns that may be difficult to detect through conventional procedures. AI investment in auditing has been associated with improved audit outcomes (Fedyk et al., 2022).

Third, language intelligence can support the interpretation and production of narrative information. Blankespoor et al. (2026) provide early evidence that GenAI has begun to appear in corporate disclosures, demonstrating that generative systems are already entering the reporting environment.

Fourth, predictive intelligence can support forward-looking assessment. Forecasting systems may provide earlier signals of financial risks, liquidity pressures or operational changes.

Fifth, integrated intelligence may support continuous reporting and monitoring by linking multiple information sources and analytical capabilities.

However, none of these outcomes should be assumed automatically. The theory predicts that outcomes depend on integration, professional interpretation and governance. A highly capable model connected to poor-quality data may produce poor outputs. A technically sophisticated system that professionals do not trust may remain peripheral. A useful model without auditability may be unacceptable for high-stakes reporting.

The contribution of intelligence layering is therefore to connect technological capability to organizational reporting outcomes through explicit intermediate mechanisms.

4.5 Theoretical Contributions

The first contribution is the introduction of intelligence layering as a distinct AIS construct. The construct provides language for discussing progressive AI embedding without reducing the phenomenon to adoption or individual technology applications.

The second contribution is theoretical integration. TAM, TOE, RBV and socio-technical theory are not treated as competing explanations. They perform different explanatory roles. Adoption and resource theories explain enabling conditions; socio-technical theory explains human–technology interaction; intelligence layering explains post-adoption architectural integration.

The third contribution is a shift from technology-centric to capability-centric analysis. RPA, machine learning, NLP, predictive analytics and generative AI are not the theoretical endpoints. They are technologies through which automation, learning, language and predictive capabilities can be layered into the AIS.

The fourth contribution is a bridge between MIS/AIS theory and contemporary AI research. Traditional AIS theory explains information processing; AI research demonstrates new computational capabilities. Intelligence layering connects these streams by asking how new intelligence becomes embedded in existing information architectures.

The fifth contribution is empirical tractability. The proposed dimensions, maturity model and operationalization strategy provide a pathway through which the construct can be measured and tested.

Finally, the paper contributes to the emerging debate about human–AI collaboration. By making professional interpretation constitutive of deep layering, the model rejects both purely technological and purely human explanations of AI-enabled accounting.

4.6 Research Agenda

The construct creates a broad empirical research agenda. First, future studies should validate the dimensions and determine whether intelligence layering is best represented as a formative construct, composite index or configuration. Second, longitudinal studies should examine how organizations move across maturity levels. Third, comparative studies should examine differences between private and public organizations, large and small firms, and highly regulated and less regulated environments.

Fourth, researchers should examine whether governance maturity develops in parallel with intelligence maturity. Fifth, studies should investigate how professional skills change as AI becomes more deeply embedded. Sixth, archival research can test whether intelligence-layering depth is associated with reporting timeliness, audit fees, internal-control weaknesses, restatements or disclosure quality. Seventh, qualitative studies can trace the organizational processes through which AI capabilities become embedded.

The proposed construct also opens research opportunities in emerging economies. AI integration may differ where organizations face legacy systems, constrained infrastructure, skills shortages and different regulatory environments. Such contexts can test whether the proposed dimensions are universal or context-dependent.

The construct is therefore intended to function as a research platform rather than a closed theory. Its value will ultimately depend on whether future empirical studies confirm, refine or challenge its dimensions and relationships.

4.7 Limitations

The paper has several limitations. First, intelligence layering is a proposed construct and has not yet been empirically validated. Second, the nine dimensions are theoretically derived and may not capture every form of AI integration. Third, the maturity model is conceptual and should not be treated as a validated diagnostic instrument. Fourth, different industries and institutional environments may produce different layering trajectories. Fifth, the model may understate forms of AI integration that are difficult to observe because they occur within proprietary systems.

These limitations are appropriate for a theory-development paper but create clear requirements for subsequent research. Construct validity, measurement invariance, predictive validity and boundary conditions must be examined empirically before the construct can be treated as established.

5 Conclusion

Artificial intelligence is increasingly embedded in accounting and financial reporting, but the theoretical vocabulary for explaining this transformation remains incomplete. Existing adoption theories explain why organizations accept technology. Resource-based approaches explain why capabilities differ. Socio-technical theory explains the interaction between people and technology. Contemporary AI-accounting research demonstrates what individual technologies can accomplish. What remains less developed is a mechanism explaining how AI becomes progressively embedded within the information-system architecture through which accounting information is generated and communicated.

This paper proposes intelligence layering as that mechanism.

Intelligence layering conceptualizes AI integration as a progressive process through which automation, learning, language and predictive capabilities become embedded within an existing MIS/AIS architecture and interact with professional interpretation, organizational embedding and governance. The construct comprises nine dimensions and is represented through a maturity model ranging from traditional rule-based AIS to adaptive intelligent AIS.

The theoretical contribution is intentionally modest but specific. Intelligence layering is not presented as a replacement for TAM, TOE, RBV, socio-technical systems theory or AIS theory. Instead, it is positioned as a middle-range mechanism connecting adoption conditions to post-adoption information-processing transformation.

The central proposition is therefore:

AI transformation in accounting does not occur merely when an organization adopts artificial intelligence. It occurs when intelligence capabilities become progressively embedded within the information architecture through which accounting information is generated, interpreted, governed and communicated.

Future research should now test this proposition rather than assume it. The proposed operationalization strategy, maturity model and propositions provide a basis for doing so. If empirical research validates the construct, intelligence layering may provide a useful theoretical bridge between traditional AIS research and the emerging era of AI-enabled accounting information systems.

Table 1. Construct dimensions and proposed operationalization

Dimension	Construct meaning	Illustrative indicators	Measurement status
Infrastructural compatibility	Alignment of existing MIS/AIS infrastructure with AI capabilities.	Interoperability; APIs; ERP integration; scalability.	Formative candidate
Data readiness	Availability, quality and accessibility of usable organizational data.	Completeness; quality; standardization; accessibility.	Formative candidate
Integration depth	Degree to which AI is embedded in core accounting workflows.	Workflow integration; real-time access; reporting-process coverage.	Formative candidate
Automation intelligence	AI-enabled execution or augmentation of routine accounting tasks.	Automated extraction; reconciliation; classification; matching.	Formative candidate
Learning intelligence	Capacity to identify patterns and improve inference from data.	Anomaly detection; classification; model updating.	Formative candidate
Language intelligence	Capacity to interpret and generate natural language.	Document analysis; summarization; narrative generation; querying.	Formative candidate
Predictive intelligence	Capacity to anticipate future states or risks.	Forecasting; scenario analysis; predictive alerts.	Formative candidate
Human interpretive integration	Integration of AI outputs with professional judgment.	Review; validation; override; contextualization.	Formative candidate
Governance integration	Embedding of controls and accountability around AI.	Audit trails; explainability; monitoring; access control.	Formative candidate

Note. The measurement status is intentionally described as a candidate rather than a validated scale. Future scale-development research should determine whether intelligence layering is formative, reflective, composite or configurational.

Table 2. Refined theoretical propositions

Proposition	Construct	Proposition statement	Role in model
P1	Infrastructure compatibility	Greater infrastructural compatibility positively influences intelligence-layering depth.	Core antecedent
P2	Data readiness	Greater data readiness positively influences intelligence-layering effectiveness.	Core antecedent
P3	Integration depth	Deeper workflow integration produces deeper intelligence layering than peripheral AI use.	Mechanism
P4	AI complementarity	Complementary AI capabilities produce greater layering potential than isolated applications.	Mechanism
P5	Professional interpretation	Professional interpretation mediates the relationship between intelligence layering and reporting capability.	Mediator
P6	Organizational readiness	Organizational readiness positively influences embedding of intelligence layers.	Enabler
P7	Governance	Governance integration strengthens the relationship between intelligence layering and reporting reliability.	Boundary condition
P8	Institutional environment	Institutional and regulatory conditions shape the form and depth of intelligence layering.	Context
P9	Reporting capability	Greater layering depth is positively associated with reporting capability when interpretation and governance are adequate.	Outcome

Table 3. Distinguishing intelligence layering from adjacent concepts

Concept	Primary question	Why intelligence layering differs
AI adoption	Will / does the organization adopt AI?	Layering concerns depth and configuration after or alongside adoption.
Digital transformation	How does digital technology transform organizations?	Layering focuses specifically on AI-enabled information-processing architecture.
Automation	Which tasks can be executed automatically?	Automation is one intelligence dimension, not the whole construct.
AI capability	What can an AI system do?	Layering concerns embedding capabilities into an existing AIS.
AI maturity	How sophisticated or ready is the organization?	Maturity can describe layering trajectories but is not synonymous with the construct.
Multi-layered AI framework	How can AI applications/themes be organized?	Layering is proposed as an architectural and post-adoption mechanism intended for empirical testing.

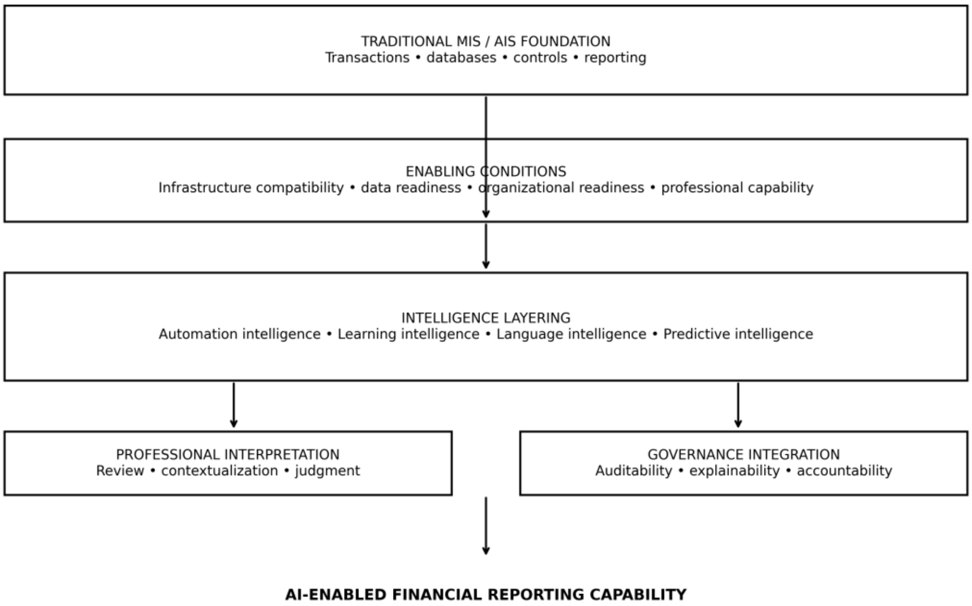

Figure 1. Intelligence-layering architecture.

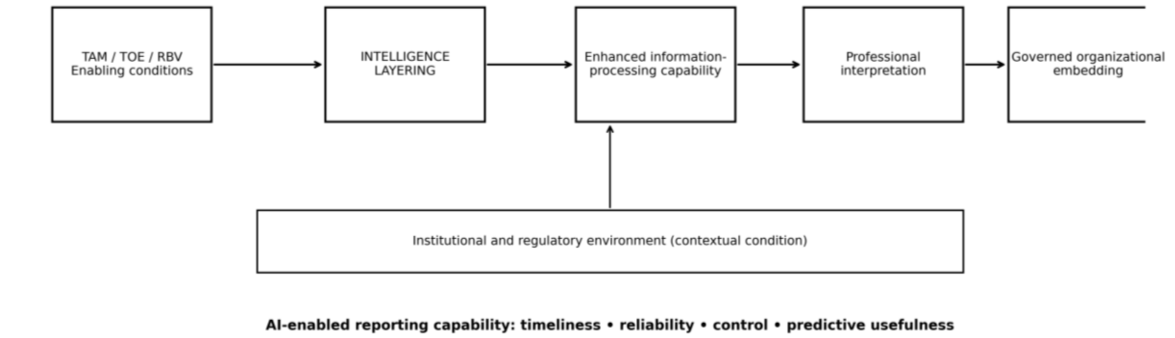

Figure 2. Formal theoretical mechanism.

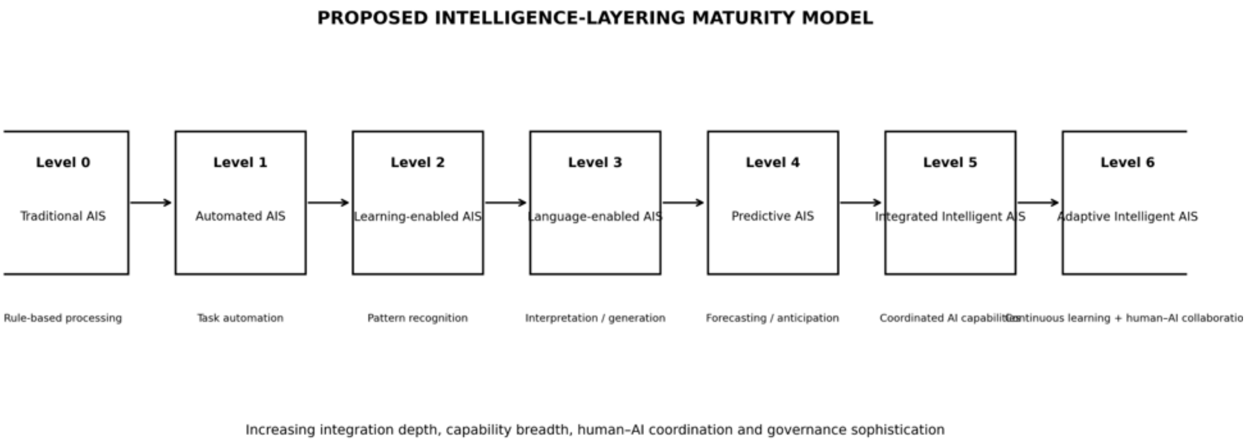

Figure 3. Proposed intelligence-layering maturity model.

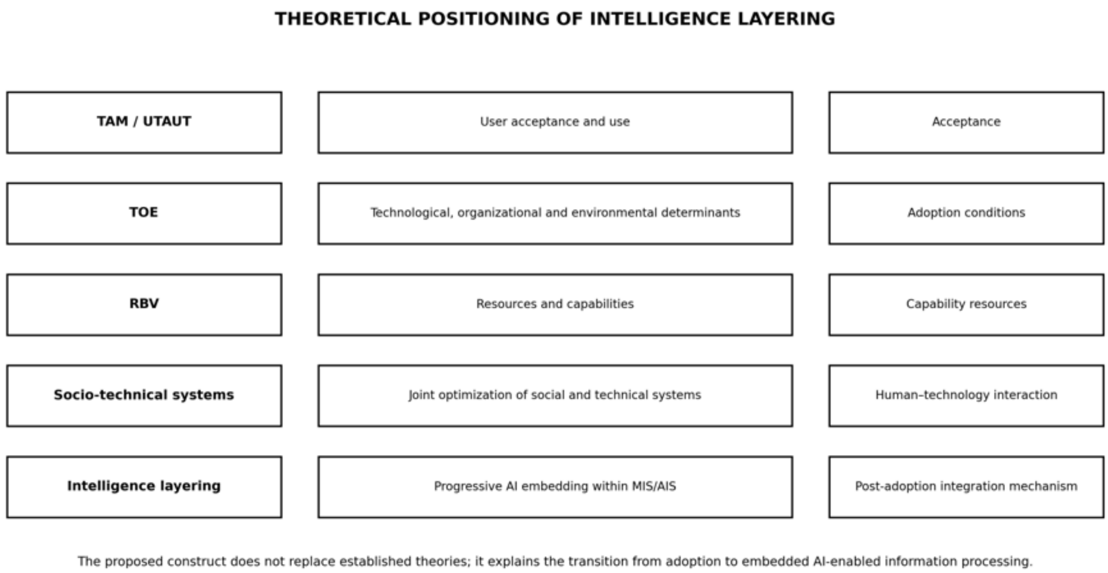

Figure 4. Theoretical positioning relative to established theories.

References

Abbas, K. (2026). Management accounting and artificial intelligence: A comprehensive literature review and recommendations for future research. The British Accounting Review, 58(2), 101551. https://doi.org/10.1016/j.bar.2025.101551

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

Al-Okaily, M., et al. (2025). Artificial intelligence and its applications in the context of accounting and disclosure. Journal of Financial Reporting and Accounting, 23(4), 1387–1401. https://doi.org/10.1108/JFRA-04-2024-0209

Ashraf, M. (2025). Does automation improve financial reporting? Evidence from internal controls. Review of Accounting Studies, 30, 436–479. https://doi.org/10.1007/s11142-024-09822-y

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Bavaresco, R. S., Nesi, L. C., Barbosa, J. L. V., Antunes, R. S., Righi, R. R. D., da Costa, C. A., Vanzin, M., Dornelles, D., Junior, S. C., Gatti, C., Ferreira, M., & Silva, E. (2023). Machine learning-based automation of accounting services: An exploratory case study. International Journal of Accounting Information Systems, 49, 100618. https://doi.org/10.1016/j.accinf.2023.100618

Berkin, A., Aerts, W., & Van Caneghem, T. (2023). Feasibility analysis of machine learning for performance-related attributional statements. International Journal of Accounting Information Systems, 48, 100597. https://doi.org/10.1016/j.accinf.2022.100597

Blankespoor, E., deHaan, E., & Li, Q. (2026). Generative AI in financial reporting. Journal of Accounting Research, 64(3), 1189–1232. https://doi.org/10.1111/1475-679X.70050

Booker, A., Chiu, V., Groff, N., & Richardson, V. J. (2024). AIS research opportunities utilizing machine learning: From a meta-theory of accounting literature. International Journal of Accounting Information Systems, 52, 100661. https://doi.org/10.1016/j.accinf.2023.100661

Cebi, S., Karakurt, N. F., Kurtulus, E., & Tokgoz, B. (2024). Development of a decision support system for client acceptance in independent audit process. International Journal of Accounting Information Systems, 53, 100683. https://doi.org/10.1016/j.accinf.2024.100683

Choi, J. H., & Xie, C. L. (2026). Human + AI in accounting: Early evidence from the field. Journal of Accounting Research, 64(3), 1333–1373. https://doi.org/10.1111/1475-679X.70052

Commerford, B. P., Dennis, S. A., Joe, J. R., & Ulla, J. W. (2022). Man versus machine: Complex estimates and auditor reliance on artificial intelligence. Journal of Accounting Research, 60(1), 273–305. https://doi.org/10.1111/1475-679X.12407

Commerford, B. P., Eilifsen, A., & Hatfield, R. C. (2024). Control issues: How providing input affects auditors' reliance on artificial intelligence. Contemporary Accounting Research. https://doi.org/10.1111/1911-3846.12974

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Dong, M. M., Stratopoulos, T. C., & Wang, V. X. (2024). A scoping review of ChatGPT research in accounting and finance. International Journal of Accounting Information Systems, 55, 100715. https://doi.org/10.1016/j.accinf.2024.100715

Duan, H. K., Vasarhelyi, M. A., Codesso, M., & Alzamil, Z. (2023). Enhancing the government accounting information systems using social media information: An application of text mining and machine learning. International Journal of Accounting Information Systems, 48, 100600. https://doi.org/10.1016/j.accinf.2022.100600

Eisikovits, N., Johnson, W. C., & Markelevich, A. J. (2024). Should accountants be afraid of AI? Risks and opportunities of incorporating artificial intelligence into accounting and auditing. Accounting Horizons.

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? Review of Accounting Studies, 27, 938–985. https://doi.org/10.1007/s11142-022-09697-x

Fotoh, L. E., & Mugwira, T. (2025). Exploring large language models in external audits: Implications and ethical considerations. International Journal of Accounting Information Systems, 56, 100748. https://doi.org/10.1016/j.accinf.2025.100748

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. A. (2024). Artificial intelligence co-piloted auditing. International Journal of Accounting Information Systems, 54, 100698. https://doi.org/10.1016/j.accinf.2024.100698

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California Management Review, 61(4), 5–14. https://doi.org/10.1177/0008125619864925

Han, H., Shiwakoti, R. K., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial intelligence: A literature review. International Journal of Accounting Information Systems, 48, 100598. https://doi.org/10.1016/j.accinf.2022.100598

Harrast, S. A. (2020). Robotic process automation in accounting systems. Journal of Corporate Accounting & Finance, 31(4), 209–213. https://doi.org/10.1002/jcaf.22457

Jackson, D., & Allen, C. (2024). Enablers, barriers and strategies for adopting new technology in accounting. International Journal of Accounting Information Systems, 52, 100666. https://doi.org/10.1016/j.accinf.2023.100666

Jones, M., & Free, C. (2026). What accountants need to know about artificial intelligence and machine learning: A review and call for future research. Journal of Accounting Literature, 48(5), 133–158. https://doi.org/10.1108/JAL-12-2025-0693

Juma'ha, A. H., Chuang, M., & Harfouche, A. (2026). Integrating AI into financial reporting and investment: Multi-layered framework. Journal of Decision Systems, 35(1), Article 2645969. https://doi.org/10.1080/12460125.2026.2645969

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Knudsen, D.-R. (2020). Elusive boundaries, power relations, and knowledge production: A systematic review of the literature on digitalization in accounting. International Journal of Accounting Information Systems, 36, 100441. https://doi.org/10.1016/j.accinf.2019.100441

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

Law, K. K. F., & Shen, M. (2024). How does artificial intelligence shape audit firms? Management Science. https://doi.org/10.1287/mnsc.2022.04040

Libby, R., & Witz, P. D. (2024). Can artificial intelligence reduce the effect of independence conflicts on audit firm liability? Contemporary Accounting Research. https://doi.org/10.1111/1911-3846.12941

Lombardi, D. R., Kim, M., Sipior, J. C., & Vasarhelyi, M. A. (2025). The increased role of advanced technology and automation in audit: A Delphi study. International Journal of Accounting Information Systems, 56, 100733. https://doi.org/10.1016/j.accinf.2025.100733

Murphy, B., Feeney, O., Rosati, P., & Lynn, T. (2024). Exploring accounting and AI using topic modelling. International Journal of Accounting Information Systems, 55, 100709. https://doi.org/10.1016/j.accinf.2024.100709

Pei, D., & Vasarhelyi, M. A. (2020). Big data and algorithmic trading against periodic and tangible asset reporting: The need for U-XBRL. International Journal of Accounting Information Systems, 37, 100453. https://doi.org/10.1016/j.accinf.2020.100453

Perdana, A., Lee, W. E., & Kim, C. M. (2023). Prototyping and implementing robotic process automation in accounting firms: Benefits, challenges and opportunities to audit automation. International Journal of Accounting Information Systems, 51, 100641. https://doi.org/10.1016/j.accinf.2023.100641

Rikhardsson, P., & Dull, R. (2016). An exploratory study of the adoption, application and impacts of continuous auditing technologies. International Journal of Accounting Information Systems, 20, 1–19.

Rikhardsson, P., & Yigitbasioglu, O. (2018). Business intelligence and analytics in management accounting research: Status and future focus. International Journal of Accounting Information Systems, 29, 37–58. https://doi.org/10.1016/j.accinf.2018.03.001

Rikhardsson, P., & Yigitbasioglu, O. (2022). Artificial intelligence and auditing in small- and medium-sized firms: Expectations and applications. AI Magazine. https://doi.org/10.1002/aaai.12066

Rodgers, W. (2020). Accounting by and for digital technology: The role of AI and machine learning in accounting. In related accounting technology scholarship.

Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Saxena, D. (2022). A conceptual framework for assessing the application of artificial intelligence for financial reporting. Universal Journal of Accounting and Finance, 10(5), 897–911. https://doi.org/10.13189/ujaf.2022.100502

Schiavi, G. S., Behr, A., & Marcolin, C. B. (2024). Institutional theory in accounting information systems research: Shedding light on digital transformation and institutional change. International Journal of Accounting Information Systems, 52, 100662. https://doi.org/10.1016/j.accinf.2023.100662

Stratopoulos, T. C., & Wang, V. X. (2025). Artificial intelligence and accounting research: A framework and agenda. International Journal of Accounting Information Systems, 56, 100760. https://doi.org/10.1016/j.accinf.2025.100760

Tiron-Tudor, A., Lacurezeanu, R., Bresfelean, V. P., & Dontu, A. N. (2024). Perspectives on how robotic process automation is transforming accounting and auditing services. Accounting Perspectives.

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. Human Relations, 4(1), 3–38. https://doi.org/10.1177/001872675100400101

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Vitali, S., & Giuliani, M. (2024). Emerging digital technologies and auditing firms: Opportunities and challenges. International Journal of Accounting Information Systems, 53, 100676. https://doi.org/10.1016/j.accinf.2024.100676

Warren, J. D., Moffitt, K. C., & Byrnes, P. (2015). How big data will change accounting. Accounting Horizons, 29(2), 397–407. https://doi.org/10.2308/acch-51069

Zhang, C. A., Cho, S., & Vasarhelyi, M. A. (2022). Explainable artificial intelligence (XAI) in auditing. International Journal of Accounting Information Systems, 46, 100572. https://doi.org/10.1016/j.accinf.2022.100572

Zhang, C., et al. (2024). The role of IT governance in the integration of AI in accounting and auditing operations. Economies.

Zhang, C., Zhu, W., Dai, J., Wu, Y., & Chen, X. (2023). Ethical impact of artificial intelligence in managerial accounting. International Journal of Accounting Information Systems, 49, 100619. https://doi.org/10.1016/j.accinf.2023.100619.