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An Interpretivist Socio-Technical Research Framework for Understanding Antecedents for the integration of Artificial Intelligence in Financial Reporting

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Abstract

Artificial intelligence (AI) is increasingly entering accounting and financial reporting through automation, machine learning, natural-language processing, predictive analytics and generative AI. This expansion has generated a rapidly growing literature concerned with adoption, acceptance, implementation, performance and the consequences of human–AI interaction. Nevertheless, much of the literature continues to represent AI integration through technology-adoption models that privilege variables such as perceived usefulness, behavioural intention, technological readiness or organisational determinants. These approaches provide valuable explanations of adoption, but they can provide limited methodological guidance for understanding how financial professionals interpret AI through their prior technological histories, professional development and organisational circumstances. This paper develops an interpretivist socio-technical research framework for investigating antecedents of AI integration in financial reporting. Drawing on interpretivism in information systems research and Socio-Technical Systems Theory, the framework conceptualises AI integration as a socially interpreted, historically situated, organisationally embedded and recursively evolving process rather than as a discrete adoption event. Four antecedent domains are integrated: financial professionals' perceptions of AI; prior experience with traditional computer-based accounting and reporting systems; professional skills development; and organisational contextual factors. The paper makes a methodological contribution by translating these domains into a research architecture specifying how each can be investigated through semi-structured interviews, observation and document analysis. It further develops an interpretive analytical cycle linking experience, interpretation, interaction, organisational response and adaptation, and establishes methodological principles concerning contextuality, historical experience, socio-technical interdependence, practice orientation, triangulation, reflexivity and emergence. The framework is intended to guide qualitative and mixed-method research on AI-enabled financial reporting and is particularly relevant to organisational contexts in which technological transformation remains intertwined with professional capability, legacy systems, institutional expectations and resource constraints.

1. Introduction

Artificial intelligence is transforming the technological environment of accounting and financial reporting. Applications that were once limited to rule-based automation are increasingly supplemented by machine learning, natural-language processing, predictive analytics, computer vision and generative AI. These technologies can classify transactions, identify anomalies, extract information from documents, generate narratives, support forecasting, assist audit procedures and provide decision-support capabilities. As the technological frontier moves from repetitive automation towards systems capable of interpreting unstructured information and producing context-sensitive outputs, the question facing accounting organisations is no longer simply whether digital technologies should be used. It is how AI becomes embedded in established accounting information systems and professional work.

The growth of AI-accounting research reflects this transformation. Stratopoulos and Wang (2025), in the International Journal of Accounting Information Systems, classify recent AI-accounting research according to whether accounting or AI is the primary research focus and whether AI-based or traditional methods are used. Their review demonstrates the breadth of the field and identifies continued opportunities for traditional research approaches, including interviews, surveys, experiments, conceptual work and literature reviews, alongside AI-enabled research methods. Importantly for the present paper, their analysis shows that AI-accounting research is developing rapidly while still requiring higher-order theoretical and methodological contributions.

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Recent empirical research also demonstrates that AI integration is not a simple technological event. Choi and Xie (2026), for example, report substantial heterogeneity in accountants' adoption patterns, perceived benefits and concerns, and field evidence that AI use can reallocate effort away from routine data entry towards communication and quality-assurance activities. Their analysis also shows selective human intervention when AI confidence is low, suggesting complementarity between professional expertise and AI. Such findings reinforce the importance of examining the professional and organisational processes through which AI is actually used rather than assuming that technological capability automatically determines practice.

At the same time, accounting technology-adoption studies have established that organisational and technological conditions matter. Jackson and Allen (2024), using the Technology–Organisation–Environment framework and a mixed-method design involving accounting managers, identify security, privacy, organisational support, staff engagement and project management among the factors shaping technology adoption. Such evidence is important, but adoption frameworks tend to represent antecedents as relatively discrete determinants. They are less suited to examining how professionals interpret these conditions in context, how prior experience shapes their meanings, and how those meanings are translated into situated accounting practices.

This is the central methodological problem addressed by the present paper. Financial professionals do not encounter AI as blank-slate users. They encounter it through existing accounting information systems, previous experiences of computerisation and automation, established reporting routines, professional identities, continuing professional development, organisational structures, management expectations and regulatory requirements. A professional who has experienced unreliable legacy-system implementations may interpret AI differently from a professional whose previous experiences have been characterised by successful automation. A professional with strong analytical and AI-related training may approach an AI-enabled reporting system differently from one who has received little exposure to emerging technologies. Similarly, organisational support may be experienced differently depending on whether professionals have access to data, infrastructure, training, authority and effective governance.

The phenomenon is therefore socio-technical. Technology is embedded in social arrangements, while social arrangements are simultaneously reshaped through technological change. Socio-Technical Systems Theory (STS) provides a theoretical basis for examining this interdependence, while interpretivism provides an epistemological and methodological orientation for understanding how actors construct meanings around information technologies in particular contexts. Interpretive information systems research has long examined human actions and interpretations surrounding information systems (Walsham, 1995a, 1995b), while Klein and Myers (1999) established principles for conducting and evaluating interpretive field studies in information systems.

The present paper brings these traditions together for a specific methodological purpose: to develop a research framework for investigating the antecedents of AI integration in financial reporting. The framework focuses on four domains. First, financial professionals' perceptions are examined as meanings and evaluations concerning usefulness, trust, risk, professional identity and judgement. Second, prior experience with traditional computer-based accounting and reporting systems is treated as technological biography rather than merely years of work experience. Third, professional skills development is treated as a capability-building process involving AI literacy, digital competence, critical evaluation and professional judgement. Fourth, organisational contextual factors encompass management support, resources, infrastructure, data, culture, governance, policies and system compatibility.

Contribution and boundary of the claim. The contribution should be understood as a methodological architecture rather than a new list of antecedent variables or a new version of STS. Existing research has already examined perceptions, skills, organisational conditions and socio-technical relationships in technology and AI studies. The distinctive claim made here is narrower: the paper specifies how these established domains can be investigated together, interpretively and across complementary evidence sources, in the particular setting of AI-enabled financial reporting. The framework therefore addresses a translation problem between theory and empirical inquiry: it connects philosophical assumptions, STS concepts, sensitising domains, data-generation methods and recursive analysis in one research design. This distinction is important because the framework is proposed, not empirically validated, and its adequacy must ultimately be assessed through field application.

The paper makes three principal contributions. First, it reframes AI integration from a narrow adoption decision to an interpretive socio-technical process. Second, it provides an integrated conceptual architecture linking socio-professional antecedents with organisational-technical conditions. Third, it translates the framework into a detailed methodological protocol showing how interviews, observation and document analysis can be used to investigate each domain and their interactions. The framework is deliberately methodological rather than a validated causal model; its propositions are therefore sensitising propositions designed to guide qualitative inquiry.

The paper proceeds as follows. Section 2 distinguishes AI adoption from AI integration. Section 3 reviews relevant AI-accounting research and identifies the methodological gap. Section 4 establishes interpretivism as the philosophical foundation. Section 5 develops the STS theoretical argument. Section 6 examines the four antecedent domains. Section 7 presents the framework-development logic. Sections 8 through 12 establish the methodological architecture, including interviews, observation, document analysis, triangulation and interpretive analysis. Section 13 addresses quality and reflexivity, followed by ethics, sensitising propositions, comparison with established adoption theories, theoretical and methodological contributions, implications, limitations and conclusion.

1.1 From Technology Adoption to AI Integration

Technology adoption and technology integration are related but analytically distinct. Adoption generally concerns acceptance, acquisition, implementation or use. The Technology Acceptance Model explains acceptance through perceived usefulness and perceived ease of use (Davis, 1989), while UTAUT integrates performance expectancy, effort expectancy, social influence and facilitating conditions into an explanation of behavioural intention and use (Venkatesh et al., 2003). TOE explains innovation adoption through technological, organisational and environmental conditions (Tornatzky & Fleischer, 1990). These perspectives have generated extensive knowledge and remain useful for identifying important conditions associated with technology use.

The present framework begins from a different methodological question: how can researchers investigate how AI becomes incorporated into established financial-reporting work? Integration includes the incorporation of AI into workflows, reporting routines, control processes, professional judgement, decision-making and organisational governance. An organisation may adopt an AI application but leave it peripheral to the accounting process. Conversely, an organisation may gradually integrate AI through incremental modifications to existing systems, professional practices and controls. Integration therefore involves depth, adaptation and interaction rather than simply the presence or absence of a technology.

This distinction is especially significant in accounting because financial reporting is an established socio-technical practice. Reporting processes depend on interconnected systems, procedures, professional standards, review hierarchies and judgement. AI is therefore inserted into an existing infrastructure rather than introduced into an empty organisational environment. Traditional systems, spreadsheets, ERP platforms, reporting packages and manual controls continue to shape how professionals understand new technologies. The history of previous technological change can become an antecedent of current AI interpretation.

Integration can also be recursive. A new technology can alter professional roles; changed roles can create new training requirements; training can change confidence and interpretation; new interpretations can affect use; unexpected system outcomes can lead to revised controls; and revised controls can alter how the technology is configured. A linear model such as antecedents → adoption → outcome therefore misses an important feature of socio-technical transformation: the outcome of one phase can become an antecedent of the next.

The distinction also clarifies the contribution of this framework to existing accounting research. Jackson and Allen (2024) explicitly examine technology adoption in accounting through TOE and identify organisational, technological and environmental factors. Their findings are important for understanding why adoption decisions occur, but the present framework asks how professionals experience and interpret those conditions during integration. Choi and Xie (2026) provide field evidence of actual human–AI complementarity in accounting, demonstrating that professional expertise continues to matter after adoption. The methodological framework developed here is intended to provide researchers with tools for examining that post-adoption and interactional terrain in depth.

Accordingly, the central conceptual distinction is: adoption asks whether AI is accepted, acquired or used; integration asks how AI becomes part of accounting work, how actors make sense of it, how existing practices are reconfigured and how organisational conditions enable or constrain the process.

2 Literature Review: AI, Accounting Information Systems and the Emerging Research Gap

2.1 AI in Accounting and Financial Reporting

AI research in accounting has expanded across audit, financial reporting, management accounting, disclosure, fraud detection, forecasting and decision support. Earlier work emphasised automation and rule-based technologies, while recent research increasingly addresses machine learning and generative AI. The development has shifted the focus from whether accounting tasks can be automated towards how AI changes the nature of accounting work and information processing.

Kokina and Davenport (2017) identified AI as an emerging force in auditing and highlighted the changing distribution of tasks between people and technologies. Fedyk et al. (2022) examined AI in auditing and found associations with audit quality and labour-market effects. Perdana et al. (2023) investigated robotic process automation in accounting firms, demonstrating both benefits and implementation challenges. Bavaresco et al. (2023) examined machine-learning automation of accounting services, illustrating how AI capabilities can move beyond fixed-rule automation. These studies establish that AI can alter accounting processes, but they also indicate that implementation is dependent on organisational and professional conditions.

Research on natural-language and generative AI has expanded the problem further. Gu et al. (2024) developed the concept of AI-copiloted auditing, highlighting human–AI collaboration. Fotoh and Mugwira (2025) discuss the opportunities and ethical risks associated with large language models in external audit, including hallucination and liability concerns. Blankespoor et al. (2026) document the increasing presence of generative AI in financial reporting disclosures. Choi and Xie (2026) provide field evidence that GenAI can increase productivity while shifting professional effort towards communication and quality assurance. Together, these studies show that AI does not simply replace accounting activities; it can redistribute them and change the relationship between routine processing and professional judgement.

The emerging literature therefore creates a need for research that explains the conditions under which professionals and organisations can translate AI capability into useful and governed accounting practice. The methodological question is not simply whether AI performs a task accurately. It is also how professionals interpret outputs, how prior experience shapes trust, how training affects the capacity to evaluate results, and how organisational systems support or constrain the integration of AI into reporting routines.

2.2 Accounting Technology Adoption Research

Accounting research has long investigated the adoption of information technologies. Technology adoption models have been useful because they provide parsimonious explanations of user acceptance and organisational implementation. In contemporary accounting, however, the diversity and complexity of AI technologies create challenges for a purely adoption-oriented perspective. AI can be used for automation, prediction, language interpretation, anomaly detection and decision support, and these capabilities have different implications for professional judgement and control.

Jackson and Allen (2024) provide a particularly relevant example. Their mixed-method study surveyed 585 accounting managers and interviewed 20 Australian accounting managers, using TOE to investigate enablers, barriers and strategies for technology adoption. The study identified security and privacy as particularly important concerns and highlighted staff engagement, technological awareness and project management. This demonstrates the value of organisational-context research but also shows the dominant framing of antecedents as adoption factors.

A methodological limitation emerges when such factors are treated as variables without investigating how actors experience them. Management support, for example, may exist formally but be experienced as inconsistent. Training may be available but poorly aligned with actual work. Infrastructure may exist but lack interoperability. A technology may be considered useful in principle but distrusted because of previous system failures. Interpretive research can reveal these differences because it examines meaning and practice rather than only the presence or strength of a variable.

2.3 The Importance of Professional Experience

Professional experience has become increasingly important as AI moves into judgement-intensive accounting work. Choi and Xie (2026) find evidence that experienced accountants selectively intervene when AI confidence is low, suggesting that professional expertise and AI capability can be complementary. This finding has methodological significance because it indicates that the impact of AI cannot be fully understood without examining how professionals use experience to evaluate technology outputs.

Prior experience with traditional accounting systems is conceptually distinct from experience with AI itself. Professionals develop expectations about system reliability, data quality, automation and organisational change through interaction with earlier systems. These expectations may become interpretive resources when AI is introduced. A researcher who asks only whether participants have used AI may therefore miss an important historical antecedent: the professional's accumulated experience of computerisation.

This paper conceptualises that accumulated history as technological biography. Technological biography includes previous systems, transitions, failures, successful implementations, workarounds, training experiences and interactions with IT personnel. It provides a temporal bridge between traditional AIS and emerging AI-enabled AIS. Investigating technological biography can therefore help explain why professionals facing similar AI technologies may respond differently.

2.4 Professional Skills Development

AI integration also changes the competence requirements of accounting. Earlier digitalisation increased demand for spreadsheet, ERP and analytics capabilities. AI introduces additional requirements involving data literacy, model limitations, prompt and language-model literacy, critical evaluation, ethical judgement and the ability to interpret AI-generated outputs. Professional skills development is therefore not merely a facilitating condition but a process through which professionals construct the capacity to work with AI.

The significance of skills is reinforced by the movement towards human–AI collaboration. If AI performs routine classification or generates analytical recommendations, professionals may spend more time evaluating outputs, communicating findings and resolving exceptions. Choi and Xie (2026) report precisely such a reallocation of work. This suggests that professional development should encompass both technical capabilities and higher-order human capabilities such as scepticism, contextual interpretation and judgement.

An interpretive framework asks how professionals understand these changing competence requirements. Some may see AI literacy as an opportunity for professional growth; others may perceive it as an additional burden or threat to professional identity. These meanings can influence engagement with training and willingness to experiment with new systems. Skills development is therefore connected to perception and organisational support rather than functioning as an isolated antecedent.

2.5 Organisational Context

Organisational context encompasses the conditions through which technologies are funded, governed, implemented and used. These conditions include leadership, resources, infrastructure, data, culture, policies, governance and the relationships among professional and technical departments. Accounting research using TOE demonstrates that such factors are important to technology adoption (Jackson & Allen, 2024). STS extends the argument by suggesting that organisational arrangements cannot be understood separately from the social and technical systems they coordinate.

Organisational context is particularly important in financial reporting because reporting processes involve accountability, auditability and regulatory expectations. AI-generated outputs may require review, explanation and documentation. Data quality may affect system reliability. Governance may determine who is allowed to use an AI tool and who is accountable for its output. The organisational context therefore shapes not only whether AI can be used but how it can be used responsibly.

2.6 Research Gap

The literature reveals three connected gaps. First, adoption-oriented research explains important technological and organisational determinants but provides limited methodological guidance for understanding how those determinants are interpreted by financial professionals in context. Second, AI-accounting studies increasingly examine specific technologies and outcomes, but less attention is given to the historical relationship between traditional accounting systems and emerging AI. Third, professional skills and organisational context are often treated as separate facilitating conditions rather than as elements of an interconnected socio-technical process.

The theoretical issue is therefore not that STS is absent from AI research. It is that broad socio-technical models often operate at a high level of subsystem categories, whereas an interpretive financial-reporting study requires a more explicit bridge from those categories to professional meaning, technological biography, capability development and enacted organisational practice. The present framework is intended to provide that bridge. It should consequently be evaluated against the quality of the resulting empirical explanation, rather than against the novelty of STS itself.

The gap is therefore not an absence of research on perceptions, experience, skills or organisational factors. Rather, the gap concerns the lack of an integrated interpretive research architecture that examines how these antecedents interact in the lived practice of AI-enabled financial reporting. This paper addresses that gap by combining interpretivism with STS and translating the combination into a domain-specific qualitative framework.

This positioning is important in light of Stratopoulos and Wang (2025), whose IJAIS framework explicitly distinguishes AI-accounting research using traditional methods from AI-based methods. Their analysis shows that traditional methods remain valuable for examining AI systems, adoption, ethics and organisational questions. The present framework occupies this traditional-method, accounting-centric space while offering a specific methodological contribution: it explains how researchers can investigate the meanings and interactions through which AI becomes integrated into financial reporting.

3 Interpretivism as the Philosophical Foundation

Interpretivism provides the epistemological foundation of the framework because the central phenomenon involves meaning, interpretation and situated action. Rather than assuming that AI integration can be understood entirely through objective measures of readiness or adoption intention, interpretivism asks how actors understand their world and how those understandings shape action. This orientation is well established in information systems research, particularly in studies of organisational change and technology implementation.

Walsham's work is foundational. Walsham (1995a) describes interpretive case studies as concerned with human actions and interpretations surrounding the development and use of computer-based information systems. Walsham (1995b) further examines the emergence of interpretivism in IS research and explains its philosophical and methodological implications. His later methodological reflection emphasises that interpretive research involves the interaction of theory and data, the use of multiple interpretations and attention to context (Walsham, 2006). These principles are directly relevant to AI integration because AI is experienced through organisational and professional contexts rather than as a universally identical artefact.

Klein and Myers (1999) provide an additional methodological foundation by articulating principles for conducting and evaluating interpretive field studies. Their work emphasises contextual understanding, the hermeneutic relationship between parts and whole, interaction between researcher and participants, abstraction and generalisation, dialogical reasoning, multiple interpretations and suspicion. These principles provide a basis for the quality criteria proposed later in this paper.

The interpretive stance changes how the four antecedents are understood. Perceptions are not fixed scores; they are meanings constructed through experience and interaction. Prior experience is not simply the number of years using software; it is a history through which professionals learn what systems are reliable, controllable and useful. Skills development is not merely training hours; it is the development of confidence and interpretive capability. Organisational context is not only a set of resources; it is experienced through relationships, power, routines and institutional expectations.

Interpretivism also supports attention to contradiction. If a participant states that AI is useful but repeatedly checks every AI output, the researcher should not simply select one statement as the correct measure. The contradiction can reveal a more nuanced meaning: AI may be valued for efficiency while remaining distrusted for high-stakes judgement. Such complexity is precisely what interpretive research is designed to capture.

The framework therefore adopts a contextual and reflexive interpretive stance toward organisational reality. It does not require the researcher to claim that reality is entirely subjective. Rather, it recognises that access to organisational reality is mediated by actors' interpretations, language, practices and institutional contexts. The objective is to produce credible, contextually grounded explanations of how AI integration is experienced and enacted.

4 Socio-Technical Systems Theory: Theoretical Argument

4.1 Origins and Core Assumptions

Socio-Technical Systems Theory originated in work concerned with the relationship between technological arrangements and social organisation. Trist and Bamforth's (1951) study of coal-mining work demonstrated that changes in technical arrangements could disrupt established social patterns and that effective work organisation required attention to both. The broader STS tradition subsequently developed the principle that social and technical systems should be designed and analysed as interdependent components of work systems.

In information systems, the socio-technical perspective has been used to challenge purely technical approaches that treat system performance as a property of software or hardware. Baxter and Sommerville (2011), for example, argue that socio-technical systems engineering can bridge organisational change and system development by bringing together technical, organisational and human concerns. The theoretical implication is that a system's value depends on its fit and interaction with the social arrangements in which it is embedded.

The present paper extends this logic to AI-enabled financial reporting. AI is not merely another software module. Its outputs can be probabilistic, opaque, adaptive or language-based, creating new requirements for professional evaluation and organisational governance. The social system therefore matters not only for implementation but for interpretation, validation and accountability.

4.2 STS and AI Integration

Contemporary AI research increasingly uses STS to explain adoption and application. Yu, Xu and Ashton (2022) develop a socio-technical framework for AI adoption and application in the workplace and identify personnel, technical, organisational-structure and environmental subsystems as relevant antecedent domains. This work demonstrates the value of STS for AI research and provides a broad theoretical foundation for considering human and organisational factors alongside technology.

Other AI research similarly emphasises the need to consider employees and AI together. Raisch and Fomina (2020) develop a socio-technical perspective on bringing AI into organisations and emphasise AI socialisation, collaboration and the cognitive, relational and structural implications of human–AI integration. These studies support the present framework's central claim that AI integration is a relationship between technological capability and organisational actors rather than a technology-only process.

However, the present paper differs in its methodological purpose and accounting-specific focus. It does not seek to produce another general AI-adoption taxonomy. Instead, it asks how an interpretivist researcher can investigate the socio-technical antecedents of AI integration in financial reporting. This requires moving from abstract subsystem categories to questions about professional meaning, technological history, skills development and organisational context.

4.3 Socio-Professional and Organisational-Technical Domains

The framework therefore distinguishes two analytical domains while recognising their interdependence. The socio-professional domain includes perceptions, prior experience and professional skills development. The organisational-technical domain includes organisational contextual conditions and the technical environment in which AI is embedded. This classification is methodological rather than a claim that organisation is itself a technical subsystem. It is used to organise the researcher's attention to the professional side and the organisational/system side of the phenomenon.

The distinction is useful because it prevents two common analytical errors. The first is technological determinism, in which AI is treated as causing changes independently of human interpretation. The second is social reductionism, in which AI is treated merely as a symbolic object without examining its actual technical properties and constraints. A socio-technical framework requires both dimensions to remain visible.

4.4 Emergence and Recursivity

A key STS implication is emergence. The resulting socio-technical arrangement cannot necessarily be predicted by examining each component separately. A highly capable AI tool may fail to produce useful reporting outcomes if data are poor, skills are inadequate or governance is absent. Conversely, a technically modest system may generate meaningful improvements when professionals adapt workflows and organisational arrangements effectively.

The framework therefore treats AI integration as emergent and recursive. Perceptions shape use; use produces experience; experience changes perceptions; skills influence interaction; interaction reveals new training needs; organisational responses change system conditions; and new system conditions reshape professional practice. This recursive logic is a central feature of the proposed research architecture, although its explanatory value remains to be established through empirical application.

5 Framework Development: From Theory to Research Architecture

The framework was developed through a theory-to-method translation process. First, the problem was defined as the limitations of treating AI integration solely as technology adoption. Second, interpretivism was selected because the research problem concerns meaning, experience and contextual interpretation. Third, STS was selected because the phenomenon involves reciprocal relationships between professional and technological-organisational arrangements. Fourth, the literature was used to identify recurring antecedent domains in AI-accounting and technology-adoption research. Fifth, the domains were reformulated as sensitising concepts suitable for qualitative inquiry rather than as fixed measurable variables. Sixth, each concept was mapped to appropriate data-generation methods and analytical questions.

This process is important because methodological frameworks can become superficial when theoretical concepts are simply listed beside methods. The present framework instead requires a logical chain: philosophical assumptions determine what counts as knowledge; theoretical assumptions determine what relationships should be examined; conceptual domains determine what should be explored; and methodological techniques determine how evidence about those domains can be generated and interpreted.

Construct-selection criteria. The four domains were retained only where they met four criteria: (1) relevance to the accounting/AI literature, (2) conceptual distinctiveness, (3) observability through more than one evidence source, and (4) compatibility with interpretivist and socio-technical assumptions. This screening logic reduces the risk that the framework becomes an unstructured catalogue of factors. It also makes the framework amendable: an empirical study may add or remove domains where evidence shows that the proposed architecture does not adequately represent the case.

The four constructs were selected because they jointly connect the individual professional, historical technological and organisational dimensions of AI integration. Perceptions capture meaning. Prior experience captures history. Skills development captures capability. Organisational context captures the environment in which meaning and capability become enacted. None is sufficient independently. Together they create a research architecture capable of examining why similar technologies can be interpreted and integrated differently across organisations and professionals.

The framework is deliberately not presented as a conventional causal model. The arrows indicate analytical relationships rather than statistically testable paths. This preserves the interpretivist orientation while still providing conceptual structure. Future researchers may subsequently use findings generated through this framework to develop quantitative constructs or mixed-method models, but such operationalisation should follow empirical refinement rather than precede it.

The framework also incorporates an explicit interpretive process between antecedents and integration. This process includes meaning-making, sensemaking, trust formation, professional judgement, negotiation and adaptation. The addition is theoretically important because antecedents do not automatically produce behaviour. A training programme, for example, may increase knowledge without producing use if professionals distrust the technology. Management support may encourage experimentation without producing integration if infrastructure is inadequate. Interpretation is the mechanism through which conditions become meaningful in practice.

Finally, the framework introduces an emergent outcome dimension. AI integration may change reporting routines, professional roles, control processes and future perceptions. This allows the framework to support longitudinal research and process tracing rather than restricting inquiry to a single cross-sectional snapshot.

6 The Four Antecedent Constructs

6.1 Financial Professionals' Perceptions

Financial professionals' perceptions are conceptualised as situated interpretations of AI's meaning, value, risks and implications for professional work. The construct encompasses perceived usefulness, trust, perceived risk, professional identity, perceived threat or opportunity, and beliefs about the boundaries of human and machine judgement. It is informed by TAM and UTAUT but is not reduced to those constructs.

The interpretive distinction matters. Perceived usefulness can be understood as an evaluation emerging from work experience rather than as a stable attitude. A professional may find AI useful for data extraction but unsuitable for final judgement. Trust may be conditional rather than absolute: an accountant may trust AI for low-risk reconciliation but require human verification for unusual transactions. Perception therefore needs to be explored in relation to task, risk, prior experience and organisational accountability.

Interview questions should encourage participants to describe specific situations rather than offer abstract evaluations. Observation can reveal whether stated perceptions correspond with enacted practices. Documents can reveal how the organisation formally frames AI, including whether policies emphasise efficiency, innovation, risk or control.

6.2 Prior Experience with Traditional Systems

Prior experience refers to the accumulated history of professionals' interaction with traditional computer-based accounting and reporting systems. It includes ERP systems, accounting packages, spreadsheets, databases, reporting platforms and previous automation. The construct is temporal because present interpretations can be shaped by earlier technological episodes.

The framework treats technological biography as analytically important because professionals learn from system successes and failures. Previous experiences can create expectations about reliability, data quality, system support and organisational change. Such expectations can influence whether AI is interpreted as a logical extension of familiar digitalisation or as a qualitatively different technology requiring new forms of trust and control.

Researchers should therefore ask participants to reconstruct key technological transitions and identify turning points. Observation should focus on established routines and workarounds. Documents can help reconstruct the organisational history of system implementations and changes.

6.3 Professional Skills Development

Professional skills development refers to the processes through which financial professionals acquire, maintain and adapt capabilities relevant to AI-enabled reporting. It includes AI literacy, digital competence, data literacy, analytical skills, professional scepticism, ethical judgement, communication and the ability to validate AI outputs.

The construct is broader than training. Learning can occur through formal CPD, organisational workshops, peer learning, experimentation, self-directed learning and problem-solving. The framework therefore asks how professionals actually develop competence and how organisational conditions influence learning opportunities.

The relationship between skills and perception is recursive. Professionals with stronger capabilities may feel more confident evaluating AI, while confidence may encourage experimentation that generates further experience. Conversely, lack of skills may produce dependence on IT staff or avoidance of AI. The research design should therefore investigate these interactions rather than treating skills as a static demographic attribute.

6.4 Organisational Context

Organisational context includes management support, resources, infrastructure, data, organisational culture, governance, policies, system compatibility and relationships among finance, IT and management. It provides the environment within which professional interpretation becomes enacted.

The construct should be investigated as lived organisational context rather than a checklist. Researchers should ask how policies are enacted, how management support is experienced, how resources are allocated, how failures are handled and how professionals negotiate responsibility when AI produces uncertain results.

The organisational context can also create contradictions. An organisation may publicly support AI but provide limited training. It may invest in infrastructure but retain fragmented data. It may encourage innovation while imposing strict controls that discourage experimentation. These tensions are valuable interpretive evidence and should be incorporated into analysis rather than treated as noise.

7 Research Questions and Methodological Alignment

Because the paper is a methodological framework article, its questions are designed to guide inquiry rather than generate hypotheses for statistical testing.

- How do financial professionals interpret the role, usefulness, risks and implications of artificial intelligence in financial reporting?
- How does prior experience with traditional computer-based accounting and reporting systems shape professionals' interpretations of AI?
- How does professional skills development influence financial professionals' capacity and confidence to engage with AI-enabled financial reporting?
- How do organisational contextual factors enable or constrain the translation of professional interpretations and capabilities into AI integration?
- How do socio-professional and organisational-technical conditions interact to shape the process and outcomes of AI integration in financial reporting?

The fifth question is particularly important because it prevents the study from treating the four antecedents as independent themes. The methodological objective is to understand relationships among them. For example, the researcher should examine whether prior system experience shapes perceptions, whether perceptions influence engagement with training, whether training changes trust, and whether organisational context allows those changes to become embedded in practice.

8 Methodological Architecture

8.1 Research Philosophy and Qualitative Orientation

An interpretivist philosophy is appropriate because the study seeks to understand meanings and contextualised experiences. Qualitative methods are appropriate because the phenomenon involves processes, interactions and practices that cannot be adequately captured through predetermined response categories. Interpretive case study is a particularly suitable strategy where the researcher seeks to understand AI integration within bounded organisational settings. Multiple-case designs may be used where comparison across organisational contexts is required.

The framework does not prescribe one single qualitative strategy for every study. Instead, it establishes methodological compatibility. Researchers should select a strategy based on the research question, access, time horizon and desired contribution. A longitudinal case may be preferable for examining recursive change, whereas a multiple-case study may be preferable for comparing organisational contexts. What remains constant is the interpretive socio-technical logic and the use of complementary evidence sources.

8.2 Unit of Analysis

The primary unit of analysis is the socio-technical process of AI integration in financial-reporting work. Analysis can be nested across individual, professional, workflow, system, organisational and institutional levels. Researchers must avoid moving between levels without explanation. A participant's perception is evidence about that participant's interpretation, not automatically evidence about the organisation as a whole.

Table 1: Unit of Analysis

Level	Focus
Individual	Perceptions, trust, judgement, skills, experience and interpretation
Professional	Professional norms, identity, role expectations and competence
Workflow	Reporting routines, exceptions, human-AI interaction and workarounds
System	AIS/ERP, AI capabilities, data, interfaces and integration
Organisation	Culture, resources, management, governance and structure
Institutional	Regulation, standards, professional expectations and industry conditions

8.3 Sampling and Participants

Purposive sampling is recommended because participants should possess direct knowledge of financial reporting and relevant technology. Potential participants include accountants, financial reporting specialists, auditors, finance managers, internal-control professionals and relevant IT specialists. Maximum-variation sampling can capture differences in professional role, experience and organisational position. Sampling decisions should be documented and justified in terms of information richness and theoretical relevance rather than statistical representativeness.

8.4 Data Sources

The framework recommends three core sources: semi-structured interviews, observation and document analysis. The combination is intentional. Interviews access meaning and retrospective experience; observation accesses enacted practice; documents access formal organisational representations and historical evidence. Together they provide a stronger basis for examining the difference between what people say, what organisations formally prescribe and what occurs in practice.

9 Semi-Structured Interview Protocol

Semi-structured interviews are the primary method for accessing participants' meanings, technological biographies and professional interpretations. The interview guide should be organised around the four antecedent domains but should remain open to emergent issues. The researcher should use probes to move from general opinion to specific experience.

A recommended sequence begins with professional background and technological history, then moves to perceptions of AI, skills development, organisational context and expected or observed integration. The sequence is deliberate: asking about prior experience before asking about AI can reduce the risk that participants interpret every question solely through the immediate AI discourse. It also allows the researcher to understand the historical resources through which participants construct meanings.

Table 2: Semi-Structured Interview Protocol

Domain	Core questions	Probes	Evidence sought
Perceptions	How do you understand AI in financial reporting? What benefits and risks do you see?	Trust? usefulness? risk? judgement? professional identity?	Meanings, evaluations, concerns
Prior experience	What systems have you used and how did you experience previous changes?	Successes? failures? workarounds? data problems?	Technological biography
Skills	What skills are needed and what training have you received?	CPD? AI literacy? data literacy? gaps?	Capability and learning
Organisation	How does your organisation support or constrain AI?	Management? resources? culture? infrastructure? governance?	Lived organisational context
Integration	What would meaningful AI integration look like?	Tasks? workflow? controls? human intervention?	Process and outcomes

Interviewing should be iterative. Early interviews can reveal concepts or vocabulary that improve later questions. If participants repeatedly mention prior system failures, subsequent interviews can probe the relationship between system history and trust. If participants identify governance as more important than training, later interviews can explore how governance affects professional capability. Such iteration is consistent with interpretive inquiry and with the hermeneutic movement between parts and whole described by Klein and Myers (1999).

10 Observation Protocol

Observation boundaries. Observation should be treated as feasible and proportionate rather than mandatory access to live financial transactions. Where direct observation of confidential reporting work is restricted, researchers may observe demonstrations, de-identified workflow episodes, training sessions, system walkthroughs, meetings or controlled process simulations. The study design should document what was observable, what was inaccessible and how those access constraints affected interpretation.

Observation is used to examine how socio-technical relationships become enacted. The researcher should observe reporting workflows, system interactions, human review, exception handling, finance-IT communication, use of workarounds and governance practices. The objective is not to evaluate employee performance but to understand how technology and professional practice interact.

Particular attention should be given to episodes in which a technical output requires professional interpretation. For example, an AI system may classify a transaction or flag an anomaly. The researcher can document what happens next: Does the professional accept the result? Check it against source documents? Consult a colleague? Override the system? Escalate the issue? Such episodes provide rich evidence about trust, skills, prior experience and governance.

Table 3: Observation Protocol

Observation area	Indicators	Interpretive question
Workflow	Task sequence, system use, manual intervention	How is formal process enacted?
Human-AI interaction	Acceptance, checking, questioning, override	How is trust negotiated?
Workarounds	Spreadsheets, parallel systems, manual corrections	Where does the formal system fail to fit practice?
Finance-IT interaction	Consultation, troubleshooting, responsibility	How are social and technical problems coordinated?
Governance	Approval, audit trail, access, exception handling	How is accountability enacted?
Learning	Peer assistance, experimentation, problem-solving	How is capability developed in practice?

Field notes should distinguish description from interpretation. A descriptive note might record that an accountant opened a spreadsheet after an AI-generated reconciliation produced an exception. An interpretive note might suggest that the spreadsheet represents a workaround caused by distrust. The distinction should be maintained so that later analysis can revisit the interpretation rather than treating it as an observation fact.

11 Document Analysis Protocol

Documents provide evidence of formal organisational arrangements and representations. Relevant materials include accounting procedures, ICT policies, AI policies, strategic plans, system manuals, implementation reports, training records, competency frameworks, governance documents, audit reports and internal-control documentation. Regulatory and professional documents can provide institutional context.

Document analysis should consider provenance, purpose, audience, date and organisational authority. A policy statement should not be assumed to describe actual practice. Instead, it should be compared with interviews and observations. Divergence between formal policy and lived practice is analytically important because it can reveal implementation gaps, contested meanings or institutional pressures.

Table 4: Document Analysis Protocol

Document type	Potential evidence	Primary construct
AI/ICT policy	Strategic orientation, acceptable use, governance	Organisational context
Accounting procedures	Formal reporting workflows and controls	Integration/context
Training and CPD records	Skills development and capability-building	Professional skills
System manuals	Functionality, historical configuration	Prior experience/context
Implementation reports	Change history, problems, lessons	Prior experience/context
Audit/internal-control reports	Control weaknesses, risks, accountability	Organisational context
Strategic plans	Management priorities and resources	Organisational context
Job descriptions	Expected technology and professional competencies	Skills development

12 Triangulation and Cross-Source Interpretation

Triangulation is central because the socio-technical phenomenon has multiple forms of evidence. Interviews reveal what participants say and mean; observations reveal what happens in practice; documents reveal formal organisational representations. The researcher should not expect these sources to agree perfectly.

Convergence strengthens credibility. Complementarity adds different forms of understanding. Contradiction can reveal tensions between formal policy and lived experience. Expansion occurs when one source identifies an issue that another method can explore more deeply. For example, interviews may reveal concern about AI reliability; observation can examine how that concern affects checking behaviour; documents can show whether the organisation has formal validation procedures.

Cross-source matrices can be used to compare evidence for each construct. The objective is not mechanical counting but systematic interpretation. Researchers should preserve contradictory cases and negative evidence rather than removing them. Contradiction may indicate that a construct operates conditionally rather than uniformly.

13 Interpretive Data Analysis and the Analytical Cycle

To reduce confirmation bias, sensitising concepts should not be used as a closed coding template. Researchers should maintain an emergent-code register, record disconfirming evidence, compare cases or participant groups where possible, and document instances where the data do not fit the proposed four-domain architecture. The framework should be allowed to fail or require modification in empirical use; otherwise, its methodological status would be reduced to confirmation of its own assumptions.

The framework recommends thematic analysis informed by interpretive principles. Coding should begin with broad sensitising concepts but remain open to emergent meanings. The four antecedent domains provide initial orientation rather than predetermined final themes.

Phase 1 involves familiarisation with transcripts, field notes and documents. Phase 2 identifies initial meanings, experiences, events and interactions. Phase 3 applies sensitising codes relating to perceptions, prior experience, skills and organisational context. Phase 4 examines relationships among codes. Phase 5 develops higher-order socio-technical themes. Phase 6 produces an integrated interpretive account that connects meanings, practices and context.

A central analytical cycle is proposed: Experience → Interpretation → Interaction → Organisational response → Adaptation → New experience. This cycle operationalises the recursive logic of the framework. For example, a previous system failure may produce distrust; distrust may cause intensive checking of AI outputs; checking may slow implementation; management may introduce additional training; training may change confidence; and subsequent successful use may alter the original perception of AI.

The researcher should also use negative-case analysis. If two professionals with similar technological histories interpret AI differently, the difference should be investigated. Perhaps their organisational roles differ, or their accountability differs, or one has received more relevant training. Negative cases can therefore help refine the framework and prevent premature generalisation.

The hermeneutic relationship between part and whole is also important. A participant's statement about AI should be interpreted in relation to their professional role, organisational context and technological history. Conversely, the emerging understanding of the organisation should be tested against individual accounts and specific episodes. This iterative movement supports deeper interpretation and aligns with Klein and Myers' (1999) principles.

14 Quality, Credibility and Reflexivity

Interpretive research requires quality criteria compatible with its philosophical assumptions. The framework therefore emphasises contextual richness, transparency, credibility, reflexivity, methodological coherence, triangulation and theoretically informed interpretation. It does not treat statistical reliability as the principal criterion of quality.

Klein and Myers (1999) provide an important foundation for evaluating interpretive field research. Their principles include attention to the social and historical context, the hermeneutic circle, the interaction between researchers and subjects, abstraction and generalisation, dialogical reasoning, multiple interpretations and suspicion. These principles can be operationalised in the present framework through case description, iterative interviewing, cross-source comparison, reflexive notes and explicit treatment of contradictory evidence.

Reflexivity is particularly important in AI research because AI is frequently discussed in terms of progress, disruption or risk. Researchers may enter fieldwork with strong assumptions about the inevitability or desirability of AI. Such assumptions can influence interview questions, interpretation and attention. Researchers should therefore maintain reflexive journals documenting expectations, methodological decisions, surprising evidence and alternative interpretations.

An audit trail should document the development of the interview protocol, sampling decisions, coding changes, theme development and theoretical conclusions. Peer debriefing can provide opportunities for alternative interpretations. Participant engagement may be used selectively to clarify factual matters or interpretations, while recognising that participants' own interpretations may change and need not be treated as an absolute validation of the researcher's account.

Transferability should be supported through thick description. Rather than claiming statistical generalisability, researchers should explain the organisational, technological and professional context sufficiently for readers to judge whether findings may be relevant elsewhere.

15 Ethical Considerations

Research on AI-enabled financial reporting can involve commercially sensitive information, professional reputation, confidential financial data and potentially sensitive system information. Ethical design should therefore address informed consent, confidentiality, secure data storage, controlled access and careful anonymisation.

Observation requires particular care because system screens, reports and transaction records may contain confidential information. Researchers should minimise collection of personally identifiable or commercially sensitive information and should establish boundaries concerning what can be observed, recorded and reproduced.

Interviews can also create employment-related risks. Professionals may hesitate to criticise AI systems, management or organisational readiness if they fear consequences. Interview protocols should therefore emphasise voluntary participation and confidentiality, and reporting should avoid unnecessary identification of individuals or organisations. Where organisational documents are used, permission and data-protection requirements should be followed.

Ethics should also encompass the researcher’s responsibility to avoid technologically deterministic interpretations. If AI is presented as inherently superior or inherently harmful, participants' accounts may be distorted. Ethical interpretive research requires representing complexity and preserving legitimate disagreement.

16 Methodological Principles of the Framework

Table 5: Methodological Principles of the Framework

Principle	Meaning	Methodological implication
Contextuality	AI integration is situated in professional, organisational and institutional settings.	Provide thick description of the case context.
Interpretive meaning	Actors construct meanings around AI through interaction and experience.	Use open-ended questions and contextual analysis.
Historical experience	Prior technologies shape current interpretation.	Reconstruct technological biographies.
Socio-technical interdependence	Social and technical elements are mutually implicated.	Analyse people, systems and practices together.
Practice orientation	Reported beliefs and enacted behaviour may differ.	Combine interviews and observation.
Triangulation	Different sources provide different forms of evidence.	Integrate interviews, observation and documents.
Reflexivity	Researcher interpretation influences knowledge production.	Maintain reflexive notes and an audit trail.
Emergence	Integration can change the conditions that produced it.	Consider recursive and longitudinal relationships.

These principles translate the theoretical foundation into research practice. They also provide criteria by which future empirical applications of the framework can be evaluated. A study that measures only perceptions through a survey, for example, would not fully instantiate the framework because it would not capture historical experience, enacted practice or documentary context. A study using interviews, observation and documents but treating participants' statements as objective facts would also depart from the interpretivist foundation.

17 Sensitising Propositions

The following propositions guide inquiry without imposing deterministic causal assumptions. They are intended to sensitise researchers to relationships that may emerge in empirical settings.

- SP1. Financial professionals' interpretations of AI are shaped by their professional and technological histories.
- SP2. Prior experience with traditional computer-based accounting and reporting systems influences how professionals interpret the opportunities, risks and trustworthiness of AI-enabled financial reporting.
- SP3. Professional skills development shapes professionals' capacity to interpret, evaluate and engage with AI-enabled financial reporting.
- SP4. Organisational context shapes the conditions under which professional interpretations and capabilities can be translated into AI-enabled financial-reporting practice.
- SP5. The interaction between socio-professional antecedents and organisational-technical conditions shapes the character and extent of AI integration.
- SP6. AI integration can recursively reshape professionals' perceptions, technological experience, skills and organisational practices.

The sixth proposition is particularly important because it prevents the framework from becoming another linear antecedent model. If AI integration changes professional roles, it can change skills requirements. If AI failures occur, they can reshape perceptions and governance. If implementation succeeds, professionals may develop new experience that changes future interpretations. AI integration therefore becomes both an outcome and a source of subsequent conditions.

18 Relationship to Established Theories

The framework is positioned as complementary to established technology-adoption and capability theories. TAM, UTAUT, TOE and RBV answer important questions, but none alone provides the methodological architecture proposed here.

Table 6: Relationship to Established Theories

Theory	Primary concern	Relationship to present framework
TAM	Perceived usefulness, ease of use and acceptance	Provides sensitising concepts for perception but does not exhaust interpretive meaning.
UTAUT	Behavioural intention and use	Highlights social influence and facilitating conditions; present framework investigates how these are experienced.
TOE	Technological, organisational and environmental adoption conditions	Useful for organisational context; present framework explores contextual meaning and enactment.
RBV	Resources and capabilities	Supports attention to skills and organisational resources; present framework examines how capabilities are developed and used.
STS	Interaction of social and technical systems	Provides the central theoretical architecture.
Interpretivism	Meaning, context and situated interpretation	Provides the philosophical and methodological orientation.

The distinction is important for publication because the framework should not claim novelty by simply relabelling existing constructs. Its contribution lies in methodological integration. It connects established theories to an interpretive research process that can reveal how antecedents interact in actual financial-reporting work.

This positioning also allows future empirical researchers to combine the framework with established theories without compromising its interpretive orientation. For example, TOE can inform an initial mapping of organisational conditions while interviews explore how those conditions are experienced. TAM can inform questions about perceived usefulness, while interpretive analysis examines how usefulness is constructed through task, risk and prior experience. RBV can inform analysis of capabilities, while observation examines how capabilities are enacted in practice.

19 Integrated Research Framework Matrix

Table 7: Integrated Research Framework Matrix

Domain	Core question	Interview evidence	Observation evidence	Document evidence	Analytical focus
Perceptions	How do professionals interpret AI?	Usefulness, trust, risk, identity, judgement	Checking, acceptance, override, consultation	AI policies, training materials, communications	Meaning and sensemaking
Prior experience	How does traditional-system history shape AI interpretation?	System transitions, failures, workarounds	Established routines, parallel systems	System manuals, implementation records	Technological biography
Skills development	How are capabilities developed?	Training, CPD, confidence, gaps	Learning-in-practice, peer support	Training records, competency frameworks	Capability and learning
Organisational context	How does context enable or constrain integration?	Management, resources, culture, governance	Workflows, finance-IT interaction, controls	Policies, plans, audit/governance documents	Enactment and constraint
Integration	How do the domains interact?	Accounts of change and adaptation	Human-AI episodes and workflow change	Implementation and outcome records	Emergence and recursivity

20 Implications for Future Empirical Research

The framework can support a range of empirical designs. A single-case interpretive study can examine AI integration within one organisation in depth. A multiple-case study can compare organisations with different technological and organisational conditions. A longitudinal design can follow professionals before, during and after implementation to examine changes in perceptions, experience and skills. Process tracing can reconstruct implementation episodes and identify how organisational responses emerge from particular interactions.

The framework can also support mixed-method research. Qualitative findings can generate constructs for later survey development, while quantitative findings can identify cases requiring deeper qualitative explanation. Importantly, the framework recommends that operationalisation follow qualitative conceptual development rather than assuming that existing adoption scales capture the phenomenon adequately.

The framework may be particularly useful in emerging AI environments where legacy systems remain important. In such settings, professionals' prior experience can be a major source of meaning and resistance or, alternatively, a resource for adaptation. Organisational resources may be uneven, and formal AI policies may lag behind actual use. Such contexts make the distinction between adoption and integration particularly visible.

For accounting education and professional development, the framework suggests that AI readiness should not be reduced to software training. Professional programmes may need to develop the capacity to interrogate AI outputs, understand limitations, maintain professional scepticism, manage data and participate in human–AI collaboration. For organisations, the framework suggests that technology investments should be accompanied by organisational and professional interventions rather than treated as stand-alone technology projects.

21 Limitations and Boundaries

Terminological boundary. The word 'antecedents' is retained because the framework directs attention to conditions that precede, accompany or shape AI integration. In an interpretivist design, however, antecedent does not imply an independently measurable causal variable. The preferred interpretation is temporally and analytically prior condition: something that becomes consequential through actors' interpretation and interaction. This distinction should be preserved in subsequent empirical studies.

The framework is conceptual and methodological and therefore requires empirical validation. Its four antecedent domains are not claimed to be exhaustive. Institutional pressure, vendor relationships, regulatory uncertainty, data governance and economic conditions may be important in particular contexts. Researchers should therefore treat the framework as an adaptable architecture rather than a closed list of variables.

The framework also gives substantial attention to financial professionals. Other actors, including senior executives, IT specialists, software vendors, regulators, external auditors and professional associations, may shape AI integration and should be included where relevant. Future research can extend the framework into a broader actor-network perspective while retaining its interpretivist socio-technical foundation.

Interpretive research also produces contextually situated findings. The objective is transferability through analytical insight rather than statistical generalisation. Researchers should provide sufficient context for readers to judge relevance elsewhere. Finally, the recursive dimension of the framework may be difficult to capture in a purely cross-sectional design. Longitudinal research is therefore encouraged where feasible.

22 Publication Positioning and Contribution

The paper's contribution is deliberately bounded. It does not claim to introduce STS to AI research, to discover perceptions or organisational factors for the first time, or to establish a validated causal model. Its contribution is the construction of a domain-specific interpretive research architecture for AI-enabled financial reporting. The architecture makes four moves that are useful in combination: it treats prior technological experience as a temporal interpretive resource; treats skills development as enacted capability rather than training volume; treats organisational context as lived and negotiated rather than merely structural; and links these domains to interviews, observation and documentary evidence through an explicitly recursive analytical cycle. This combination provides a practical basis for empirical testing and refinement.

23 Conclusion

This paper has developed an interpretivist socio-technical research framework for investigating antecedents of artificial intelligence integration in financial reporting. The framework responds to a methodological limitation identified in the literature reviewed here: the tendency for AI integration to be examined primarily through adoption, acceptance, implementation or technology-specific outcomes, with less explicit guidance on how interpretive and historical processes can be investigated across professional and organisational levels. Adoption theories remain valuable, but understanding AI-enabled financial reporting also requires attention to the meanings, histories, capabilities and organisational conditions through which technology becomes embedded in professional practice.

The framework combines Interpretivism and Socio-Technical Systems Theory and organises inquiry around four antecedent domains: financial professionals' perceptions, prior experience with traditional computer-based accounting and reporting systems, professional skills development, and organisational contextual factors. These domains are treated as interconnected rather than independent predictors. Perceptions provide meaning; prior experience provides historical interpretation; skills provide capability; and organisational context provides the environment in which these elements are enacted.

Methodologically, the framework translates these concepts into a research protocol involving semi-structured interviews, observation and document analysis. Interviews provide access to meaning and technological biography. Observation reveals enacted practice and human–AI interaction. Documents reveal formal organisational structures and representations. Triangulation allows researchers to investigate convergence, complementarity and contradiction across these forms of evidence.

The framework's central methodological proposition is that AI integration can be investigated as a process of experience, interpretation, interaction, organisational response and adaptation. Financial professionals interpret AI through their histories; skills shape their capacity to engage with technology; organisational context enables or constrains their actions; and resulting interactions can reshape perceptions, skills and organisational arrangements. Integration is therefore recursive and emergent rather than purely linear.

The paper does not claim that perceptions, prior experience, skills or organisational factors have not been studied previously. Rather, it contributes a domain-specific methodological architecture for investigating how these antecedents are interpreted and mutually constituted in the practice of AI-enabled financial reporting. In doing so, it builds on established interpretive IS methodology and STS theory while responding to the rapidly developing AI-accounting research agenda.

Future empirical research should test, refine and potentially extend the framework across organisational and institutional settings. Its strongest contribution will arise when researchers use it not as a checklist but as a sensitising architecture that encourages attention to context, history, interaction, contradiction and emergence. Such an approach can deepen understanding of why the same AI capability may produce different professional and organisational consequences and can help move AI-accounting research beyond the question of whether organisations adopt technology towards the more consequential question of how technology becomes integrated into accounting work.

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