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Artificial Intelligence as Disruptive Technology in Accounting: A Qualitative Study of Practitioner Perceptions on Automation, Judgment, and Decision Support

Anntoniette Bendal[1], Scarlet Alexandra Sabasa[2], Cherry Ann Marie Espelita, MBA[3]
Ramon George Atento, PhD[4]
[1]J&T Express, [2]United Siegen Philippines Corp, [3]University of Cabuyao, [4]LPU-Manila
Corresponding Author: *anntoinettebendal@gmail.com*

Abstract

This study investigates how practicing accounting professionals in the Philippines interpret the adoption, usefulness, constraints, and governance implications of artificial intelligence (AI) in accounting work. Using a qualitative descriptive case-oriented approach, semi-structured interviews were conducted with 45 practitioners across multiple sectors (e.g., manufacturing, services, retail, logistics, banking, and professional services) from September to December 2025. Interviews were audio-recorded, transcribed using AI-assisted transcription, translated to English where needed, and analyzed inductively through thematic analysis supported by NVivo. Findings indicate that AI is currently adopted most comfortably in low-risk assistive uses—particularly summarization, document clarification, and preliminary review of lengthy narratives—rather than as a stand-alone engine for core accounting decisions. Deeper integration into routine accounting processes (e.g., posting, classification, reconciliation, forecasting, and assurance) remains conditional and uneven due to limited top-management sponsorship, weak policy institutionalization, and significant data-readiness constraints. A central mechanism emerging from the data is verification overhead: where outputs lack traceability or auditability, AI can add an additional validation step, reducing net efficiency gains. External compliance realities—especially manual, template-bound regulatory reporting—further constrain end-to-end automation. Governance concerns (confidentiality, cybersecurity exposure, error opacity, and non-transferable professional liability) operate as decisive adoption barriers and reinforce boundary conditions in which AI may assist but cannot replace human judgment, contextual interpretation, and accountable sign-off. Participants anticipate workforce recomposition rather than immediate displacement, emphasizing upskilling in AI literacy, analytics/forecasting, cybersecurity awareness, and AI governance.

Keywords: *Artificial intelligence; accounting analytics; technology adoption; thematic analysis; governance and risk; human judgment; Philippines*

1. Introduction

Artificial intelligence (AI) has moved from a speculative frontier to an operational capability embedded in contemporary organizations through automation tools, learning algorithms, and data-driven systems that increasingly support routine processing, pattern detection, and prediction. Within management practice, AI is commonly understood not merely as a set of computational techniques but as an enabling infrastructure that reshapes workflows, reallocates tasks, and alters how information is produced and used in decision-making. This positioning situates AI within the broader logic of disruptive technologies—innovations that may reconfigure roles, performance expectations, and value creation mechanisms by enabling new efficiencies while rendering legacy routines less competitive.

Accounting work is particularly exposed to these dynamics because substantial components of financial operations are rule-governed, repetitive, and data-intensive. Transaction processing, reconciliations, document classification, routine reporting, and compliance checks are increasingly supported by digital systems that can accelerate throughput and reduce human error. As organizations scale and financial activities become more complex, decision-makers often seek tools that improve timeliness and reliability of financial information, strengthen internal controls, and enhance the detection of anomalies that may signal fraud, misstatement, or operational leakage. Consequently, AI is frequently framed as a capability that can elevate accounting from primarily clerical routines toward more analytical and interpretive functions, where accountants contribute through judgment, advisory work, and decision support.

At the same time, the diffusion of AI into accounting raises persistent concerns about displacement and professional identity. The same features that make accounting tasks amenable to automation—structured inputs, standardized procedures, and compliance-driven outputs—also create apprehension that routine roles may be reduced or redesigned. This tension is intensified by the growing expectation that finance functions should be agile and analytics-enabled, placing pressure on professionals to acquire new competencies in technology use, data interpretation, and governance. In this context, questions of readiness are not limited to technical skill; they extend to how professionals conceptualize the boundaries between machine-enabled computation and human judgment, particularly in high-stakes decisions where context, ethics, and organizational strategy shape the meaning and implications of financial information.

The practical implications of these issues are not confined to accounting as a profession in the abstract. Accounting systems underpin managerial control and performance measurement across industries, including resource-intensive service settings where accountability, cost containment, and risk governance are critical. Decisions regarding the adoption of AI-enabled tools therefore require evidence on how professionals understand AI's opportunities and limitations, and how they anticipate changes to work design, capability development, and decision quality. However, much of the public discourse on AI tends to oscillate between optimistic claims of efficiency and alarmist narratives of human replacement, while empirical accounts grounded in practitioner and decision-maker perspectives—especially within specific local and organizational contexts—remain comparatively limited.

Given these conditions, the present study examines the perceived impact of AI as a disruptive technology on accountancy practice through qualitative inquiry among accounting decision-makers and accounting professionals in Region IV-A (CALABARZON), Philippines. The study focuses on how participants characterize AI's role in accounting work, how they distinguish between automatable routines and judgment-based tasks, and what they infer about professional readiness and future work configurations. Specifically, the study aims to (1) describe participants' awareness and understanding of AI in relation to accounting practice, (2) determine perceived applicability of AI across accounting and assurance-related activities, and (3) generate emergent themes regarding AI's potential effects on decision support, control quality, workforce roles, and the continuing place of professional judgment.

2. Review of Related Literature

2.1 Awareness and Knowledge as Precursors to Adoption

Higher levels of AI awareness and knowledge among accounting professionals are strongly associated with greater acceptance and readiness to adopt AI in accounting practice. This foundational relationship was empirically observed in early qualitative research, which found that experienced professionals recognized AI's development and implications, emphasizing the necessity for accountants to embrace technology and specialization to enhance operational efficiency (Bendal et al., 2020). Subsequent studies confirm and quantify this link, showing that accountants who are knowledgeable about AI and actively engage with it tend to experience positive changes in accounting procedures and improved efficiency (Mgammal, 2024; Hashid & Almaqtari, 2024). However, research from adjacent fields cautions that general digital adoption does not automatically translate to deep AI integration.

A study on educational settings found a significant gap between the frequent use of digital platforms and the adoption of true AI-adaptive learning systems, with systemic barriers like cost, access inequity, and algorithmic bias concerns shaping perceived effectiveness and uptake (Rao et al., 2025). This underscores that while individual technological readiness—including digital literacy and innovation orientation—significantly influences favorable attitudes (Madan & Chawla, 2025), organizational and structural factors are equally critical.

Resistance to change remains a notable barrier, but increased AI awareness mediates more positive attitudes and openness to AI integration, as seen in both professional and student populations (Odonkor et al., 2024; Rawashdeh et al., 2025). The diffusion of innovations theory applied in emerging economies further supports that AI awareness and training are critical for overcoming adoption challenges and enhancing professional roles (Assidi et al., 2025).

Overall, the evidence suggests that enhancing AI knowledge and readiness among accounting professionals is a key, but not solitary, factor in fostering acceptance; successful adoption also requires addressing systemic implementation barriers (Mgammal, 2024; Madan & Chawla, 2025; Assidi et al., 2025; Rao et al., 2025).

2.2 AI-Driven Efficiency and Accuracy in Routine Tasks

AI-enabled automation significantly reduces processing time and human error in routine accounting tasks compared to manual or conventional workflows. Early professional insights identified AI's role in enhancing efficiency and accuracy in tasks such as auditing and financial reporting, automating repetitive work to yield cost and time savings (Bendal et al., 2020). Advanced machine learning algorithms and predictive models now provide empirical support, improving transaction classification, error detection, and anomaly identification, leading to higher accuracy and faster processing speeds in financial reporting (Mohammad et al., 2025; Goel & Mishra, 2025).

AI-driven systems automate repetitive tasks such as reconciliations and ledger updates, enhancing operational efficiency and reducing manual intervention (Thanasas & Kampiotis, 2024). This automation creates capacity for value-adding activities, a principle reflected in strategic business frameworks that advocate using technology to "Raise" and "Create" new service dimensions while "Reducing" or "Eliminating" inefficient processes (Atento et al., 2025d). Natural language processing (NLP) further optimizes financial document processing by extracting and interpreting unstructured data, which supports real-time reporting and compliance while minimizing errors (Goel & Singh, 2025).

Empirical studies and case analyses report notable productivity gains, including reductions in manual activities and significant efficiency improvements, demonstrating AI's transformative impact on accounting workflows (Singh, 2025; Jejeniwa et al., 2024; Victoria et al., 2024). Overall, AI integration in accounting not only streamlines routine processes but also improves accuracy, timeliness, and decision-making quality, confirming its measurable benefits over traditional methods (Odonkor et al., 2024).

2.3 Enhanced Fraud Detection and Audit Quality

AI and machine-learning methods significantly improve fraud and anomaly detection performance in accounting and auditing compared with traditional approaches. This potential was acknowledged by practitioners who foresaw AI as a critical tool for improving fraud detection capabilities (Bendal et al., 2020).

Contemporary research validates this, showing that machine learning algorithms, including supervised and unsupervised models, effectively identify patterns and anomalies in large, complex financial datasets that traditional manual or sampling methods often miss (Adelakun et al., 2024; Bakumenko & Elragal, 2022; Antwi et al., 2024). Ensemble methods and deep learning models have demonstrated high accuracy and strong fraud detection capabilities, outperforming conventional statistical and rule-based techniques (Mahmoud & Kareem, 2025; Syahrudin et al., 2025; Bao et al., 2020).

Natural language processing (NLP) enhances detection by analyzing unstructured data such as emails and financial documents, uncovering hidden fraud signals (Wang et al., 2025). However, the integration of quantitative anomaly detection with qualitative, contextual understanding remains vital. Frameworks from other data-intensive fields, such as healthcare analytics, argue that the most robust insights come from synthesizing computational outputs with narrative, context-rich data, ensuring alerts are interpreted with necessary nuance (Atento et al., 2025c).

AI-driven systems enable continuous auditing and real-time anomaly detection, improving audit accuracy, timeliness, and risk management while reducing false negatives and increasing coverage (Waykole, 2025; Grissa & Abaoub, 2024). Despite challenges like data quality and model explainability, AI integration in auditing and internal controls is widely recognized as a transformative advancement that strengthens financial oversight and fraud prevention (Adelakun et al., 2024; Wang et al., 2025).

2.4 The Irreplaceable Role of Human Judgment

Human professional judgment remains essential for complex accounting and business decisions despite the availability of AI decision-support tools. This aligns with early findings where respondents consistently concluded that while AI improves efficiency, human intervention remains essential for decision-making, qualitative analysis, and exercising professional judgment (Bendal et al., 2020).

AI systems enhance efficiency and provide quantitative outputs but lack true agency, ethical reasoning, and contextual understanding required for nuanced, qualitative interpretation and accountability (Lehner et al., 2022; Joshi, 2025). This limitation is underscored in conceptual models like Narrative Health Analytics, which posit that interpretability, cultural context, and ethical mediation are non-negotiable layers when transforming raw data (including AI outputs) into actionable, human-centered insights (Atento et al., 2025c).

Hybrid human-AI decision-making platforms integrate human knowledge with AI capabilities to maintain regulatory compliance, ethical standards, and contextual judgment at critical decision points (Onalaja et al., 2025). Research highlights risks of overreliance on AI, cognitive biases, and the need for human intuition to appropriately override or complement AI outputs, especially in morally or ethically sensitive decisions (Chen et al., 2023; Nordiansyah et al., 2025; Hao et al., 2024).

Ethical challenges such as transparency, fairness, and accountability require shared responsibility between humans and AI, with governance and auditing processes adapted to support this collaboration (Lehner et al., 2022; Murikah et al., 2024). Overall, AI supports but does not substitute professional judgment, emphasizing a complementary relationship where human expertise guides and validates AI-driven insights in complex decision-making contexts (Leitner-Hanetseder et al., 2021; Li, 2025).

2.5 Transformation of Accounting Roles and Tasks

AI adoption in accounting primarily leads to task reallocation and upskilling rather than full replacement of accountants. This anticipated evolution was evident in earlier research, where respondents believed AI would affect the profession but viewed its integration as a means to enhance human capabilities rather than replace them, fostering a collaborative environment (Bendal et al., 2020). This mirrors transformations in other professions; for instance, global healthcare faces a parallel shift where demand for new competencies (digital health documentation, specialized care) requires a fundamental reorientation of training pipelines to address both domestic needs and global opportunities (Atento et al., 2025b).

In accounting, routine and clerical tasks are increasingly automated, allowing accountants to focus on higher-value activities such as analytical reasoning, decision-making, and strategic advisory roles (Leitner-Hanetseder et al., 2021; Singh, 2025; Reslan & Maalouf, 2024). Studies show that AI enhances efficiency and accuracy while increasing the demand for skills in data analytics, AI management, and cybersecurity (Assidi et al., 2025). The evolving roles require accountants to collaborate with AI technologies, emphasizing human–AI complementarity where professionals use AI as cognitive assistants rather than substitutes (Sentuti et al., 2025).

This shift can be viewed through a strategic lens akin to the "Blue Ocean" approach, where the profession moves beyond competing in traditional "red ocean" tasks (compliance, data entry) toward creating new value in advisory services, strategic interpretation, and ethical governance (Atento et al., 2025d). Despite concerns about job displacement, evidence suggests that AI drives specialization pressures and necessitates continuous upskilling to adapt to new digital workflows (Rawashdeh, 2023; Shaleh, 2024). AI transforms accounting work by reallocating tasks and upgrading skills, supporting accountants in more strategic and technology-enabled functions rather than replacing them entirely (Jejeniwa et al., 2024; Odonkor et al., 2024).

2.6 Synthesis of Literature

Across the reviewed scholarship, a coherent explanatory chain emerges linking (a) individual readiness and awareness, (b) operational value realization through automation and analytics, (c) control and assurance enhancement, and (d) enduring boundary conditions that preserve the primacy of professional judgment, culminating in (e) workforce and role reconfiguration rather than wholesale occupational substitution. In combination, these streams depict AI in accounting not as a monolithic replacement technology, but as a socio-technical capability whose organizational value depends on literacy, governance, and the redesign of work.

First, the literature converges on the proposition that awareness and knowledge are foundational precursors to adoption. Early qualitative evidence indicates that experienced professionals already recognized AI's trajectory and its implications for specialization and efficiency (Bendal et al., 2020). Subsequent empirical studies extend this relationship, suggesting that accountants with stronger AI knowledge and engagement report more favorable attitudes and perceive improvements in procedures and efficiency (Mgammal, 2024; Hashid & Almaqtari, 2024). Importantly, this association is not treated as sufficient on its own: parallel evidence from adjacent domains highlights that frequent use of digital platforms does not automatically translate to substantive AI integration, because adoption is shaped by structural constraints such as cost barriers, access inequities, and concerns about algorithmic bias (Rao et al., 2025). This nuance is reinforced by work emphasizing innovation orientation and digital literacy as individual-level drivers of favorable attitudes (Madan & Chawla, 2025), while also acknowledging that resistance to change and institutional conditions can inhibit uptake even when awareness is present (Odonkor et al., 2024; Rawashdeh et al., 2025; Assidi et al., 2025). The net implication is that awareness and knowledge function as necessary enabling conditions, while organizational readiness and systemic feasibility function as implementation gatekeepers.

Second, the evidence base substantiates AI's measurable operational value through efficiency gains and error reduction in routine tasks, aligning strongly with the automation thesis. Professional insights initially emphasized time and cost savings from automating repetitive work in reporting and audit-related tasks (Bendal et al., 2020). Later research provides stronger technological specificity and empirical grounding, emphasizing machine-learning-driven improvements in transaction classification, anomaly identification, reconciliations, and ledger processes, which reduce manual intervention and improve speed and accuracy (Mohammad et al., 2025; Goel & Mishra, 2025; Thanasas & Kampiotis, 2024). NLP-based approaches broaden the automation scope by enabling extraction and interpretation of unstructured financial texts to support real-time reporting and compliance (Goel & Singh, 2025). These operational improvements are consistently positioned as enabling a shift from routine clerical effort to higher-value activity and decision support, including through strategic frameworks that interpret technology as a mechanism for eliminating inefficiencies and creating higher-value service dimensions (Atento et al., 2025d). Collectively, this stream frames AI as an efficiency and quality amplifier whose strongest immediate benefits accrue in high-volume, standardized, rules-based tasks.

Third, AI's contribution is amplified in higher-stakes functions through fraud detection, continuous monitoring, and audit quality enhancement. Early practitioner expectations anticipated AI's capacity to improve fraud detection (Bendal et al., 2020), and contemporary work demonstrates that supervised, unsupervised, ensemble, and deep-learning models can identify complex anomaly patterns in large datasets beyond the reach of manual or sampling-based techniques (Adelakun et al., 2024; Bakumenko & Elragal, 2022; Antwi et al., 2024; Mahmoud & Kareem, 2025; Syahrudin et al., 2025; Bao et al., 2020). NLP further extends detection capabilities by analyzing unstructured sources (e.g., documents and communications) to identify latent fraud signals (Wang et al., 2025). At the same time, the literature cautions that robust insight requires interpretive integration: computational alerts must be evaluated using contextual and narrative understanding to avoid misinterpretation and to preserve decision relevance (Atento et al., 2025c). This logic is consistent with the broader view that AI strengthens oversight through continuous auditing and real-time detection, even as challenges such as data quality and explainability persist (Waykole, 2025; Grissa & Abaoub, 2024; Adelakun et al., 2024).

Fourth, a cross-cutting theme across all streams is the irreducible role of human judgment. Respondents in early qualitative work consistently argued that AI can improve efficiency and provide outputs, but human intervention remains essential for decision-making and qualitative assessment (Bendal et al., 2020). This position is strengthened by conceptual and empirical arguments that AI lacks ethical reasoning, agency, and context-sensitive understanding needed for accountability and nuanced interpretation (Lehner et al., 2022; Joshi, 2025). Complementarity is therefore conceptualized not as a vague reassurance but as a structural requirement: human–AI decision systems are needed to preserve compliance, ethical judgment, and contextual interpretation (Onalaja et al., 2025), while mitigating risks of overreliance and bias through human oversight and governance (Chen et al., 2023; Hao et al., 2024; Nordiansyah et al., 2025; Murikah et al., 2024). Narrative-oriented analytics perspectives reinforce that interpretability and ethical mediation are necessary layers in translating AI output into actionable insight (Atento et al., 2025c).

Finally, these dynamics converge in the literature on work transformation, which predominantly anticipates task reallocation and upskilling rather than replacement. Early perceptions already framed AI as capability enhancement rather than full displacement (Bendal et al., 2020). Empirical and conceptual works indicate that as routine tasks are automated, accountants are repositioned toward analytical reasoning, strategic advisory work, and decision support (Leitner-Hanetseder et al., 2021; Singh, 2025; Reslan & Maalouf, 2024). This shift raises skill demands in analytics, AI management, and cybersecurity, and implies continuous professional development as an adoption requirement (Assidi et al., 2025; Rawashdeh, 2023; Shaleh, 2024). Human–AI complementarity is further articulated as collaboration with AI as a cognitive assistant rather than a substitute (Sentuti et al., 2025), with strategic arguments suggesting the profession may differentiate by moving beyond traditional compliance-centric work toward higher-value interpretive and governance functions (Atento et al., 2025d). The synthesis thus supports a socio-

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technical transition in which AI catalyzes the redesign of accounting work around judgment, interpretation, and governance.

2.7 Research Gaps

Despite broad convergence on AI's efficiency and control benefits and the necessity of professional judgment, the literature reveals several limitations that motivate further inquiry.

Insufficient integration across the full adoption-to-outcomes pathway. Much of the literature addresses adoption readiness, operational efficiency, fraud detection, judgment boundaries, or workforce impacts as separate silos. Fewer studies explicitly connect these domains into a unified account of how awareness/readiness translates into workflow redesign, assurance enhancement, and role transformation under realistic organizational constraints (e.g., cost, resistance, bias concerns) (Rao et al., 2025; Assidi et al., 2025; Odonkor et al., 2024).

Limited qualitative evidence capturing boundary-setting in practice. While the irreplaceability of judgment is widely asserted (Bendal et al., 2020; Lehner et al., 2022; Joshi, 2025), fewer studies provide fine-grained qualitative accounts of how practitioners delineate what is delegable to AI versus what must remain under human accountability, especially in decision contexts that blend quantitative outputs and qualitative interpretation.

Governance, explainability, and ethical accountability remain under-contextualized. Research recognizes explainability and data quality challenges and ethical concerns (Lehner et al., 2022; Murikah et al., 2024; Grissa & Abaoub, 2024), yet evidence is thinner on how these concerns concretely shape adoption decisions and day-to-day use in organizations, including how oversight is operationalized to prevent overreliance and error amplification (Chen et al., 2023; Hao et al., 2024; Nordiansyah et al., 2025).

Need for localized, decision-maker-inclusive perspectives in emerging economy settings. Diffusion and adoption studies note the importance of awareness and training in emerging economies (Assidi et al., 2025), but there remains a relative scarcity of localized qualitative evidence incorporating both accounting decision-makers and practitioners, particularly regarding how resource constraints and institutional conditions influence perceived feasibility and role redesign.

Workforce transformation is often described at a high level, with limited role-differentiated detail. Although the literature predicts task reallocation and upskilling (Leitner-Hanetseder et al., 2021; Assidi et al., 2025; Sentuti et al., 2025), fewer studies distinguish between the implications for clerical, supervisory, assurance-related, and strategic finance roles, or clarify which competencies are perceived as most critical for maintaining value under AI-enabled workflows.

Taken together, these gaps justify qualitative inquiry that simultaneously examines (a) readiness and perceptions, (b) operational and assurance-related applicability, (c) practical boundary conditions for judgment and accountability, and (d) anticipated role redesign and upskilling within a specific organizational and regional context.

3. Methodology

3.1 Research Design

This study employed a qualitative descriptive design with an exploratory–explanatory logic. It was designed to elicit accounting practitioners' and accounting-related decision-makers' perceptions of artificial intelligence (AI), and to interpret these perceptions into data-driven themes that culminated in an emergent conceptual model (i.e., a thematic model derived from participant accounts rather than a statistical or predictive model). The unit of meaning was participants' articulated perceptions, interpreted within a context- and sector-informed lens based on the professional environments represented in the sample. The case was bounded to practitioner accounts of accounting work and AI adoption in Region IV-A (CALABARZON), Philippines, within the September–December 2025 fieldwork period.

3.2 Study Context and Participants

Participants were accounting practitioners and accounting-related decision personnel based in Region IV-A (CALABARZON), Philippines. The final sample comprised 45 participants (n = 45). Most were affiliated with private corporations, with representation from SMEs and manufacturing, and smaller representations from banking/financial services, academe, government, and healthcare/hospital settings.

The participant pool included CPAs, general accountants, auditors, controllers, and owner-practitioners (owners who also perform accounting functions). To maintain analytic relevance to accounting decision processes, clerical roles (e.g., accounting clerks) and roles limited to routine clerical processing were excluded. Professional experience ranged from approximately 3 to 30 years, reflecting early-career perspectives alongside senior practitioners and decision personnel.

3.3 Sampling Strategy and Recruitment

A purposive sampling strategy was used, supplemented by snowball referrals. Eligibility required that participants: (a) were actively engaged in accounting- or audit-related work within an organizational setting, and (b) had at least three (3) years of relevant professional experience. CPA licensure was not a requirement. Participants were included if they were practicing in substantive accounting roles (e.g., accountant, auditor, controller) or held junior-to-senior managerial responsibility related to accounting oversight and decision processes.

Recruitment was conducted through professional and personal networks, including LinkedIn outreach, contacts through companies and professional associations, and a substantial portion through the researcher's school-based network, including alumni and professional contacts developed across institutions served over time. The sample size concluded at n = 45 primarily due to access and participant availability, rather than a pre-specified thematic saturation stopping rule.

3.4 Data Collection Procedures

Data collection occurred from September to December 2025. The primary mode was online interviewing using Google Meet, Zoom, and Microsoft Teams. One interview was conducted face-to-face. In addition, one small informal group discussion with three to four alumni participants was conducted in a naturalistic setting. This discussion served as a supplementary elicitation encounter and was incorporated into the qualitative corpus as supporting narrative data.

Interviews followed a semi-structured guide organized around four domains—awareness, knowledge, applicability, and potential—with additional prompts addressing participants' concerns and practical irritants regarding AI in accounting work. The guide contained approximately 12 core questions, with probes applied flexibly depending on participants' responses. Interviews typically lasted 60–90 minutes, with the shortest session approximately 30 minutes.

3.5 Recording, Transcription, Translation, and Data Preparation

All sessions were audio-recorded using platform-based recording functionalities (where applicable) and downloaded as audio files. Transcription was conducted using AI-enabled transcription tools to generate text for analysis. Interviews were conducted in English and Filipino (Taglish) based on participant preference and conversational flow; relevant segments were subsequently translated into English for analysis and reporting consistency. Participant identifiers and organizational references were removed during preparation, and participants were labeled using numeric codes (P1–P45).

3.6 Data Analysis and Conceptual Model Development

Data were analyzed using inductive thematic analysis (data-driven coding). The researcher served as the sole coder and followed a structured workflow: (1) familiarization with transcripts, (2) generation of initial codes, (3) development of candidate themes, (4) review and refinement of themes for internal coherence and distinctiveness, and (5) consolidation and naming of themes aligned to the study's organizing domains while preserving emergent content that extended beyond the initial guide.

Coding was initiated in Microsoft Word during early organization and memoing, and subsequently managed and refined using NVivo to support systematic code organization, retrieval, and theme development. The final thematic structure was then synthesized into an emergent conceptual model that mapped the perceived mechanisms through which AI affects accounting work (e.g., routine-task automation, control enhancement, decision-support contributions, boundary conditions of judgment, and implications for roles and skills).

Where analytically warranted, themes were examined for role- and function-informed contrasts (e.g., decision-oriented participants versus practitioner-only participants; auditors versus internal accounting roles). These contrasts were treated as interpretive patterns rather than statistical comparisons.

3.7 Trustworthiness and Rigor

Several credibility and trustworthiness practices were implemented:

a. Member checking: participants were provided summaries of key points and/or thematic interpretations for confirmation and clarification where feasible.

b. Peer debriefing: interpretations and thematic structures were discussed with peers to challenge assumptions and refine analytic coherence.

c. Triangulation: themes were assessed across variations in participant sector context and role, and across data-elicitation modes (online interviews, the face-to-face session, and the small group discussion) to check consistency and divergence in accounts.

d. Audit trail: analytic materials were retained to document the progression from raw transcripts to codes and themes (e.g., coded outputs, evolving theme definitions, and supporting notes).

3.8 Researcher Positionality and Reflexive Management

The researcher had prior relationships with some participants (e.g., former students, mentees, and professional contacts connected to alumni networks). This positionality was addressed by emphasizing voluntary participation, encouraging candid responses, using a semi-structured guide to reduce leading prompts, and relying on transcript-based coding to privilege participant language over presumed intent. Peer debriefing further served as a constraint against over-interpretation or familiarity bias.

3.9 Ethical Considerations and Data Governance

Informed consent was obtained through verbal consent recorded at the beginning of interviews using a standardized consent script. For some participants, consent terms were also communicated in advance in writing, indicating that participation and responses signified agreement to the conditions described. The study was conducted as an independent professional inquiry (outside classroom protocols), and no formal institutional ethics committee clearance was obtained.

Confidentiality was protected through anonymization (P1–P45), exclusion of personally identifying information from reporting, and removal of organizational identifiers. Audio files and transcripts were stored initially on a local external drive and then uploaded to a password-protected Google Drive for analysis; access was restricted to the researcher only.

4. Results and Discussion

Interviews were conducted from September to December 2025 using online platforms (Google Meet, Zoom, and MS Teams), with one face-to-face interview and one small informal group discussion. A semi-structured interview guide (approximately 12 core questions with flexible probes) elicited participants' perceptions of AI awareness, perceived usefulness, adoption constraints, risk concerns, and perceived impacts on accounting work. Sessions typically lasted 60–90 minutes (minimum ~30 minutes), were audio-recorded, and transcribed using AI-enabled transcription prior to cleaning and coding. The analysis followed an inductive thematic approach supported by NVivo, proceeding through familiarization, initial coding, theme development, and iterative refinement. To strengthen credibility, the researcher maintained an audit trail and conducted peer debriefing and participant summary checks where feasible; identities and organizations were anonymized using participant codes. For reporting consistency, Taglish excerpts were translated into English while retaining the original intent and emphasis.

4.1 AI Awareness, Meaning-Making, and Readiness: Assistive Intelligence Under Verification Norms

Across participants, "AI" was defined primarily in functional, task-oriented terms rather than as a distinct technical system integrated into core accounting workflows. AI was most commonly described as an assistive tool for summarizing lengthy documents, clarifying complex instructions, and accelerating initial comprehension in document-heavy tasks such as due diligence. One participant emphasized the value of AI for synthesizing long reports and clarifying head-office instructions, framing it as a high-utility aid rather than a substitute for professional analysis (P23). Another participant similarly described using AI to speed contract review by quickly filtering key details, while stressing that it functions as an assistant—not a "magic" solution that replaces human judgment (P9).

A second, closely linked pattern was the conceptual blurring of AI with existing automation and analytics tools, particularly Excel and ERP systems. Participants repeatedly indicated that trust hinges on traceability: outputs are acceptable only when the underlying logic and data sources can be inspected and verified. One participant emphasized that "AI" can be mistaken as automatically correct even when outputs are generated from conventional tools; consequently, results must be traced back to their source (P34). Another participant described vendor-branded "AI solutions" that functioned largely as automation macros, arguing that confidence comes from audit trails rather than technology labels (P17).

Awareness was described as socially visible but operationally weakly institutionalized. Several participants reported that workplace adoption remains limited and that exposure is often driven by social media and vendor marketing rather than by formal policies and workflow integration. One participant described AI exposure primarily through online content and vendor messaging, noting that AI is not yet deployed in a structured way in daily work (P12). Another participant similarly observed that awareness may be amplified in professional networks, but operational processes remain predominantly manual, limiting practical uptake (P41).

Readiness was commonly framed as openness to learning, paired with persistent anxiety about correctness and the expectation that verification remains unavoidable. One participant expressed willingness to learn but emphasized fear of incorrect outputs and the need for manual checking, which can create duplicated work (P6). Another participant described anxiety about incorrect financial insights as sufficiently high that re-checking becomes routine, weakening the promise of speed gains (P29).

4.2 Adoption Drivers and Implementation Barriers: Institutional Non-Commitment and Data-Readiness Constraints

Participants framed AI adoption as constrained less by personal resistance and more by an institutionalization gap—limited top-management sponsorship translating into weak policy direction and low organizational urgency. One participant argued that adoption does not progress when AI is absent from the vocabulary and routine practices of senior leaders; without top-down urgency, policy and structured implementation do not materialize (P5). Another participant echoed this, noting that decision-makers are not yet convinced of AI's day-to-day strategic value, resulting in a lack of clear policy and limited workflow integration (P19).

Barriers were described as structural, centered on data readiness and trustworthiness. Participants repeatedly emphasized that the key constraint is not the subscription price of tools but the cost of making internal data clean, consistent, and integrated. One participant noted that internal data quality must be addressed before AI can be applied meaningfully and that this preparatory work is itself substantial (P31). Another participant similarly argued that the "true cost" is the organizational work required to make data trustworthy; without that, AI cannot generate reliable value (P14).

A broader "not ready" narrative emerged regarding the local data ecosystem. One participant described distrust toward some local datasets due to inconsistency or delays, making AI-dependent analytics difficult to justify (P27). Another participant framed the problem as a feasibility trap: high-quality external data are expensive, while free sources are viewed with skepticism, producing a "data poverty" cycle that blocks AI adoption before it begins (P2).

Finally, adoption was constrained by a pragmatic "if it isn't broken" lock-in. Participants described ERP and Excel workflows as adequate for client expectations and regulatory requirements, reducing perceived urgency for standalone AI integration. One participant questioned why firms should invest in AI when stakeholders are satisfied with ERP/Excel-based outputs and no clear pain point exists (P38). Another participant emphasized that the issue is not resistance to change, but resistance to disruptive change without clear incremental value; organizations seek "evolution" from existing workflows rather than vendor-promoted "revolution" (P22).

4.3 Routine-Task Automation: Conditional Efficiency, Verification Overhead, and Regulatory Workflow Friction

Participants broadly recognized that AI-enabled automation could improve efficiency in routine accounting processes—particularly repetitive posting, reconciliation, and classification. However, automation was consistently framed as conditional: speed gains were valued only when accuracy and traceability were assured. One participant stated that repetitive posting can be automated, but blind trust is unacceptable; correctness is prioritized over speed because speed without accuracy produces professional liability (P37). Another participant supported automation for reconciliation, but conditioned acceptance on transparency regarding how discrepancies were flagged; otherwise, verification expands workload and can create "double work" (P11).

A recurring concern was verification overhead, in which automation adds a validation layer rather than removing work. One participant described trial use of AI-assisted expense classification that required full human review due to logic errors, increasing steps rather than reducing workload (P26). Another participant similarly expressed concern about "black box" report generation, arguing that outputs still require re-auditing to ensure reliability (P3).

These concerns were grounded in domain logic and professional judgment. One participant emphasized that correct posting requires accounting expertise; even a capable system still needs trained professionals as the last line of defense (P40). Another participant noted that complex transactions (e.g., accruals and intercompany items) require contextual reasoning that is difficult to standardize (P15).

External institutional constraints further limited end-to-end automation. Participants described regulatory reporting requirements as manual and template-bound, often forcing rework even when internal processes are automated. One participant emphasized that reporting templates are often not machine-readable, breaking the "end-to-end" automation promise and forcing manual reformatting (P29). Another participant described manual submissions to regulators as a persistent bottleneck that absorbs time savings generated internally (P7).

Deviant cases indicated that end-to-end automation becomes feasible under conditions of data maturity, co-designed accounting logic, and supportive infrastructure. One participant described fully automated bank reconciliation and posting with minimal double-checking once rules are configured (P18). Another reported that routine classifications could be treated as authoritative when logic is co-developed with CPAs and embedded into controlled workflows, reducing verification overhead (P42). A further deviant case described middleware integration that enabled automation of government-report submission, suggesting that regulatory friction can be mitigated where organizations invest in the necessary technical architecture (P4).

4.4 Analytics-Enabled Decision Support: Embedded Intelligence and Traceability-Driven Forecasting Practices

Participants described decision support as present in existing BI infrastructures (dashboards, scorecards, trend reporting), but AI was often not salient as a distinct practice. One participant explained that "AI for analytics" is often interpreted as the organization's BI tools (e.g., Power BI), yet it is perceived as a built-in feature rather than a standalone AI adoption decision (P21). Another participant described decision-making as anchored in scorecards and dashboards using established tools, emphasizing the absence of a standalone "AI advisor" for decisions (P33).

Forecasting remained largely human-led due to traceability and accountability requirements. One participant emphasized that forecasts must be defensible and explainable; AI may provide a number, but cannot justify assumptions in the way expected in executive settings (P8). Another participant similarly described forecasting as a collaborative, cross-functional process where accountability remains human even if tools provide analytic suggestions (P16).

A deviant case illustrated conditions under which AI becomes explicit in decision support. One participant described using a standalone AI tool for sales forecasting and inventory decisions that ingests real-time data streams beyond what their team can process using conventional methods, and reported frequent reliance on its recommendations (P39).

4.5 Fraud Prevention and Audit Quality: Controls-by-Design, Human Skepticism, and Conditional AI-Forward Assurance

Fraud prevention and audit quality were predominantly framed as outcomes of platform design and control configuration rather than as standalone AI practices. Participants emphasized "controls-by-design" features—audit trails, approval workflows, segregation of duties, and role-based access—as core mechanisms for minimizing fraud opportunities. One participant stated that the strongest controls are already embedded in ERP design, enabling traceability of anomalous transactions through system logs without requiring AI overlays (P13). Another participant similarly described fraud prevention as anchored in ERP control architecture, with the operational priority being correct configuration and enforcement (P6).

Participants argued that widely used platforms can be sufficient in SME settings, while recognizing that some fraud vectors originate outside system logic (e.g., fabricated documents). One participant noted that built-in controls reduce opportunities for fraud within the system, while documentary fraud can bypass controls and therefore still requires procedural verification (P27).

Fraud detection was frequently described as investigative and rooted in professional skepticism and traditional audit routines. One participant emphasized manual processes such as vendor master file review and risk-based sampling, framing fraud detection as an investigative function rather than an AI alert system (P44). Another participant emphasized reliance on traditional physical and procedural checks (e.g., cash counts, inventory checks, and reconciliations) as methods most likely to detect ground-level irregularities (P19).

Continuous monitoring was commonly described as automated exception reports and log generation paired with human review. One participant described continuous monitoring as the production of exception logs that a person reviews on a routine cadence, positioning automation as an aid rather than a replacement for judgment (P32). Another participant similarly described monitoring as automated reporting of logs where "intelligence" remains human interpretation (P9).

Deviant cases demonstrated contexts where AI-forward assurance becomes operationally central. One participant described using a machine-learning anomaly detection platform to flag subtle real-time patterns that humans may not readily detect, making it a core part of the audit plan (P37). Another participant described continuous auditing models that score transactions for fraud risk using extensive behavioral and data features, where analytics teams tune models and auditors investigate alerts (P22).

4.6 Governance and Risk Constraints: Confidentiality, Cybersecurity Exposure, Error Opacity, and Non-Transferable Liability

Participants articulated governance concerns that materially constrained professional AI use, expressed as practical risk calculations about information governance, operational cybersecurity, and liability.

A dominant barrier involved confidentiality and uncertainty over data custody once financial data are submitted to AI tools. One participant described privacy as the primary concern, questioning where financial data reside and rejecting generic vendor assurances as insufficient for confidentiality-dependent work (P14). Another participant stated discomfort uploading client data—even anonymized—to public AI platforms due to unresolved uncertainty about data destination and use, which was framed as incompatible with professional ethics (P29).

Cybersecurity concerns were operationalized as increased exposure through vendor dependencies and integration points. One participant described AI tools as expanding the attack surface and adding vendor-side vulnerability to existing threats (P8). Another participant argued that platform compromise could expose financial and customer information through vendor failure rather than internal lapses, and judged the risk disproportionate to efficiency gains (P17).

Participants also highlighted error opacity and the risk of "confident wrong outputs." One participant described AI as capable of producing plausible analyses based on misinterpreted data, generating false positives that consume effort (P2). Another participant contrasted spreadsheet traceability with AI opacity, arguing that AI errors are harder to inspect and defend in governance settings (P23).

The decisive constraint concerned non-transferable accountability and liability. One participant emphasized that regulatory responsibility attaches to the signer; an algorithm cannot be blamed, and liability cannot be automated away (P41). Another participant similarly stated that undetected AI errors expose the firm's reputation and professional standing, while the tool itself bears no sanction (P5).

A deviant case indicated that these risks can be mitigated where AI is deployed as secured enterprise infrastructure. One participant described using a private, on-premise language model with strict data-loss prevention, ensuring data remain inside the firewall and framing risk as manageable through controlled inputs, ownership of outputs, and systematic review (P31).

4.7 Boundary Conditions: Human Judgment, Context, and the Non-Substitutability of Decision Accountability

A stable boundary condition emerged: AI was viewed as assistive rather than substitutive because accounting work is embedded in local regulation, organizational discretion, and accountable sign-off. Participants emphasized that AI does not reliably capture Philippine-specific regulatory details and that outputs depend heavily on the framing of appropriate inputs. One participant noted that AI cannot consistently grasp local context such as updates to local tax ordinances and BIR issuances, and that improper framing reintroduces "garbage in, garbage out" risks (P11). Another participant framed regulatory heterogeneity as a barrier, emphasizing that compliance treatments can differ across regulatory regimes (e.g., SEC versus PEZA) and that generalized AI training may miss agency-specific nuance (P28).

Participants also located final authority in human judgment. One participant stated that AI can suggest, but final approval of journal entries remains human because professional discretion to override suspicious outputs cannot be delegated (P17).

Another participant reinforced this boundary in higher-stakes decisions (e.g., provisioning and complex valuation), noting that while algorithms can generate ranges, executives sign off and remain responsible (P3).

Boundary reasoning extended to managerial sensemaking and implementation. One participant argued that AI cannot participate in board-level explanations of forecast variance because the "why" often includes contextual realities such as politics, weather delays, and supplier issues, which require human synthesis and defense (P40). Another participant similarly stated that implementation and buy-in are decisive; even strong recommendations fail without operational acceptance, and a key role is translating analytics into actionable business sense (P32).

Participants expressed skepticism toward replacement narratives. One participant described AI replacement claims as exaggerated marketing, comparing them to earlier anxieties surrounding Excel and ERP where tools changed but the need for judgment remained (P19). Finally, a relational constraint was noted in client-facing contexts: one participant described that many clients—especially older ones—prefer human discussion for delicate matters such as taxes and financial distress, where relational trust is critical (P7).

4.8 Role Transformation and Skills: Task Reallocation, Upskilling Imperatives, and the "Left Behind" Anxiety

Participants framed AI's impact primarily as role redesign and task reallocation rather than immediate replacement. Routine work is expected to shrink, shifting effort toward interpretation, validation, exception handling, and analysis. One participant described the shift "from data gatherer to data interpreter," arguing that junior staff must learn to analyze AI outputs and manage exceptions rather than focus on data entry (P23). Another participant similarly predicted that automation will reshape job descriptions by reallocating time from reconciliation tasks to validation and strategic analysis, with repetitive work decreasing but new work emerging around verification and interpretation (P9).

Upskilling was framed as broader than tool usage, emphasizing AI literacy and governance competence. One participant argued that professionals must learn how to interpret, validate, and govern AI outputs, and that cybersecurity knowledge becomes increasingly critical as systems become more connected (P34). Another participant emphasized forecasting and analytics as emerging core skills, including the ability to ask high-quality questions and critique model outputs, positioning advanced spreadsheet skill as baseline rather than differentiating competence (P16). A further participant extended this into governance, emphasizing the need to audit AI-enabled processes and manage model risk as a new layer of control responsibility (P41).

Participants identified implications for education and professional development. One participant argued that accounting curricula should integrate data analytics, basic data governance, and ethical AI use into core subjects rather than treating them as peripheral (P30). Another participant noted that CPD remains heavily concentrated on tax updates and should include mandatory units for digital fluency and AI oversight, describing continuing education as lagging behind practice expectations (P12).

Replacement anxiety was expressed in nuanced terms, often framed as fear of irrelevance rather than direct substitution. One participant stated that the dominant fear is being left behind and that upskilling preserves professional relevance and may enable higher-value roles (P37). Another participant described anxiety among mid-career practitioners whose expertise is concentrated in manual tasks, emphasizing the difficulty of shifting competencies for those who are less technologically confident (P5). Overall, the pattern supports a view of workforce change as recomposition: fewer purely routine roles, greater demand for analytics- and governance-capable accounting professionals, and closer collaboration with IT/data functions.

Closing synthesis of Themes 1–8

Across Themes 1–8, the results depict AI as an emerging capability that is presently adopted most comfortably in low-risk support functions (summarization and document clarification), while integration into core accounting workflows remains bounded by institutional non-commitment, data readiness constraints, verification overhead, and governance risk. In many settings, analytics and controls are perceived as already embedded in ERP/BI systems, reducing AI salience as a distinct adoption decision; forecasting and assurance remain anchored in traceability, contextual justification, and accountable sign-off. Deviant cases indicate that deeper AI integration becomes viable when organizations have mature data environments, codevelop AI logic with accounting expertise, and deploy enterprise-grade controls that mitigate privacy and cybersecurity risks. Themes 7–8 further clarify that adoption is bounded by human-centered judgment and accountability, while professional trajectories are expected to shift toward upskilling in AI literacy, analytics, and governance rather than immediate wholesale displacement.

4.9. Discussion of Findings

Integrative interpretation of the results

The findings portray AI adoption in accounting as a bounded transition rather than a linear diffusion of a superior technology. Across Themes 1–8, AI was treated as valuable but narrowly "safe" when used for low-risk cognitive support (e.g., summarization, document clarification), while its integration into core accounting workflows remained constrained by (a) institutional non-commitment, (b) data readiness deficits, (c) verification overhead, and (d) governance risk (confidentiality, cybersecurity exposure, and non-transferable liability). This pattern is consistent with the argument that adoption is not determined solely by perceived usefulness; it also depends on organizational readiness, policy sponsorship, and the extent to which technology can be aligned with professional accountability structures.

Importantly, the results show two parallel realities. In mainstream organizational contexts, AI is often conceptually collapsed into existing tools (ERP, Excel, BI platforms), reducing its salience as a distinct "adoption decision." In contrast, deviant cases illustrate that where data maturity is high and AI is deployed as controlled infrastructure (e.g., anomaly detection platforms, continuous auditing models, on-premise LLMs, or end-to-end workflow middleware), AI becomes a distinct operational capability rather than a peripheral assistant. The discussion below maps these findings to the RRL domains (2.1–2.5) and clarifies the mechanisms implied by the qualitative evidence.

Awareness and knowledge as precursors to adoption

The evidence supports the literature's claim that awareness and knowledge are foundational precursors to adoption, but also reinforces a key qualification: awareness does not equal organizational uptake. Participants demonstrated awareness of AI largely through social exposure (vendors, online discourse) and personal experimentation, yet many reported limited workplace implementation. This aligns with prior work suggesting that technological readiness shapes attitudes but does not guarantee deep AI integration when structural barriers—policy, access, equity, organizational systems—remain unaddressed (Madan & Chawla, 2025; Rao et al., 2025).

The present findings refine that relationship by highlighting a "verification norm" in accounting: as AI awareness increases, so does recognition that AI outputs must be validated. Thus, awareness may increase interest, but it simultaneously foregrounds professional risk and reinforces the need for auditability and traceability. This offers an explanation for conditional acceptance: practitioners can acknowledge AI's relevance while resisting "aggressive" integration into decision-critical workflows. The implication is that adoption is not simply a function of awareness/knowledge; it is mediated by whether AI can be made compatible with professional control requirements (Assidi et al., 2025; Odonkor et al., 2024).

Efficiency and automation: benefits constrained by verification overhead

Consistent with the RRL, participants generally recognized AI's potential to improve efficiency and reduce time in routine tasks (Bendal et al., 2020; Thanasas & Kampiotis, 2024; Singh, 2025). However, the findings complicate the "efficiency" narrative by documenting verification overhead—the tendency for automation to add an additional layer of checking rather than reduce effort. This is not merely resistance to change; it reflects a rational response to risk. In accounting, "speed" is not unambiguously valuable if it increases exposure to misclassification, compliance error, or reputational consequences. The results therefore suggest that the realized efficiency of AI depends on whether organizations can (a) improve upstream data quality, (b) make model logic transparent enough for review, and (c) redesign workflows so that validation is targeted (exception-based) rather than universal.

An additional constraint observed in the data is institutional and regulatory friction—especially where reporting remains template-driven and manual. Even if internal processes are optimized, external compliance systems can reintroduce manual work, which reduces the net advantage of end-to-end automation. This resembles the RRL's caution that implementation barriers can prevent "readiness" from translating into actual adoption (Rao et al., 2025). The deviant cases (e.g., middleware automation and co-developed classification logic) show that these frictions are not inevitable; rather, they require deliberate systems engineering and governance alignment.

Fraud detection and audit quality: why "AI-forward" assurance remains uneven

The RRL emphasizes that AI and machine learning can enhance fraud detection and auditing,

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especially in high-volume, complex datasets (Adelakun et al., 2024; Grissa & Abaoub, 2024; Mahmoud & Kareem, 2025). The present findings partially support this promise but explain why it remains uneven in practice. Many participants described fraud control as already embedded in ERP systems via "controls-by-design" (roles, audit trails, approval workflows). In such contexts, AI is not perceived as adding decisive marginal value, especially when the organization's fraud risks are believed to be manageable through established controls and human professional skepticism.

Deviant cases provide an important boundary condition: AI-forward assurance appears most plausible where (a) transaction volume is high, (b) behavioral data is rich, and (c) continuous monitoring requires pattern recognition beyond human scale. In these environments, dedicated anomaly detection and risk-scoring models can serve as core audit infrastructure. This bifurcation suggests that AI's fraud-detection advantage is contingent on data richness and operational scale, and that in smaller or lower-complexity environments, ERP controls plus human investigation may remain dominant.

A further implication is that the value proposition of AI in auditing is not only technical accuracy; it is also institutional trust. Models must be defensible, explainable, and auditable in governance contexts. This ties directly to Theme 6's governance constraints and Theme 7's boundary condition around accountable sign-off.

The irreplaceable role of human judgment: adoption boundaries as professional governance

The evidence strongly corroborates the RRL's position that AI does not substitute for human professional judgment, particularly where decisions are interpretive, ethical, and accountability-bearing (Bendal et al., 2020; Lehner et al., 2022; Joshi, 2025). The contribution of the present study is to specify why judgment remains central: accounting professionals operate in a regime of non-transferable liability. Even if an AI tool provides an analysis, the practitioner retains responsibility for correctness, compliance, and defensibility. This creates a structural boundary: AI can assist cognition but cannot absorb accountability.

Participants also emphasized the contextual specificity of regulation and organizational realities. Local regulatory heterogeneity (e.g., differing treatments under multiple agencies) and board-level explanatory demands (the need to defend forecasts and decisions with context such as operational disruptions) reinforce the limits of "generic" AI outputs. The results therefore support a hybrid governance logic: AI may be useful as decision support, but decision authority remains human because the professional must interpret, justify, and assume consequences (Onalaja et al., 2025; Chen et al., 2023).

This aligns with broader arguments that robust decision quality arises when computational outputs are integrated with contextual interpretation and ethical mediation (Atento et al., 2025c). In practical terms, "human-in-the-loop" is not simply a preference—it is an accountability requirement embedded in professional practice.

Transformation of accounting roles and skills: recomposition rather than replacement

The findings align with the RRL's claim that AI adoption transforms accounting roles through task reallocation and upskilling, rather than full replacement (Leitner-Hanetseder et al., 2021; Reslan & Maalouf, 2024; Sentuti et al., 2025). Participants expected routine tasks to shrink and new work to emerge around interpretation, exception handling, validation, governance, and cybersecurity-aware practice. Notably, the study adds nuance by identifying the dominant anxiety as "being left behind" rather than being replaced—suggesting that perceived occupational risk is stratified by capability and adaptability.

The education and CPD implications were explicit: respondents viewed existing professional development as lagging behind tool expectations and argued for earlier integration of analytics, data governance, and ethical AI use into core accounting training. This echoes diffusion-oriented arguments that awareness and training reduce adoption barriers (Assidi et al., 2025), but the present findings suggest that training must extend beyond operational tool use to include governance competence—how AI is validated, audited, and controlled.

An emergent explanatory model from the qualitative evidence

Synthesizing the eight themes yields a practical model of AI adoption in accounting:

a. Awareness and Assistive Use (Low Risk): AI is used for summarization/clarification where consequences are limited.

b. Institutional Gatekeeping: Adoption stalls without management sponsorship, policy, and workflow integration.

c. Data Readiness Filter: Poor data integration/trustworthiness blocks meaningful AI application.

d. Verification Overhead Mechanism: In high-accountability settings, AI can create extra review work unless workflows are redesigned for exception-based validation.

e. Governance Risk Constraint: Confidentiality, cyber risk, and error opacity suppress use of public/third-party AI for sensitive work.

f. Accountability Boundary: Final authority remains human because liability and contextual defense are non-transferable.

g. Recomposition Outcome: Roles shift toward interpretation, governance, analytics literacy, and cybersecurity-aware practice.

h. Deviant Pathway: Where data maturity and enterprise controls exist, AI becomes distinct infrastructure (continuous auditing, anomaly detection, end-to-end automation), reducing overhead and enabling deeper integration.

This model clarifies why adoption is uneven and why the same technology can be experienced as "mere assistant" in one setting and as core infrastructure in another.

Practical implications for organizations and decision-oriented analytics

For practice, the findings suggest that AI initiatives in accounting should be evaluated less as software procurement and more as governance redesign:

1. Policy and governance first: Adoption requires explicit rules on allowable data, approved tools, documentation standards, review procedures, and accountability allocation.

2. Data readiness as the primary investment: Tool cost is secondary to data cleaning, integration, and trust-building.

3. Exception-based validation: To avoid verification overhead, workflows should be designed so AI automates routine tasks while humans focus on exceptions and high-risk items.

4. Enterprise-grade deployment for sensitive use: If AI will touch regulated or confidential data, private or controlled deployments (with DLP, access controls, logging) reduce adoption friction.

5. Capability-building: Upskilling must include AI literacy (interpretation/validation), governance (model risk thinking), and baseline cybersecurity.

4.10 Limitations

Several limitations should be considered when interpreting the findings. First, the study uses a qualitative design with purposive and snowball recruitment, which strengthens depth and contextual richness but limits statistical generalizability. The sample reflects a diverse set of sectors and roles, yet it remains shaped by professional networks and availability, and the stopping point (n = 45) was driven by feasibility rather than a formally documented saturation threshold. As a result, the thematic structure should be interpreted as an empirically grounded account of patterns within this participant set rather than a population estimate of national practice.

Second, much of the evidence is based on self-reported perceptions and narrated experiences, which can be influenced by recall bias, selective emphasis, and social desirability (especially when discussing competence, compliance, or risk). Moreover, the study did not independently audit organizational AI policies, system configurations, or actual workflow logs. Therefore, the results reflect how practitioners understand and justify AI use and non-use, rather than a direct measurement of implementation maturity.

Third, the data indicate uneven exposure to AI across organizations; many accounts refer to AI as embedded within ERP/BI platforms or encountered through vendor discourse rather than as stand-alone systems used in core accounting workflows. This heterogeneity is analytically valuable, but it constrains the ability to compare "AI adopters versus non-adopters" in a controlled way. Relatedly, while subgroup contrasts were considered (e.g., decision-makers versus practitioners; audit versus accounting functions), qualitative comparisons remain interpretive and may be sensitive to differences in organizational scale, data maturity, and risk tolerance.

Fourth, the research context includes prior relationships between the researcher and some participants (e.g., former students or mentees). While this may increase openness and candor, it may also influence how participants frame responses (e.g., aligning answers with perceived expectations).

Although anonymity procedures were applied, the possibility of role-based impression management cannot be fully eliminated.

Finally, the regulatory and institutional environment described in the interviews is time-bound. AI tools, governance norms, and regulatory digitization can shift rapidly. The findings thus represent a snapshot of practice perceptions in late 2025 and should be interpreted with caution when extrapolating to future adoption trajectories or to regions with substantially different compliance infrastructures.

4.11 Future Research Directions

Future work can extend the present findings along four high-value lines of inquiry.

First, mixed-method validation and prevalence estimation. A natural next step is to translate the eight themes into a structured survey instrument and test them at scale (e.g., across sectors, firm sizes, and professional roles). This would allow estimation of the prevalence of key constructs identified here—verification overhead, governance risk sensitivity, institutional non-commitment, and "left behind" anxiety—and enable hypothesis testing (e.g., whether data maturity moderates the relationship between AI awareness and adoption depth).

Second, comparative case studies of "deviant pathway" organizations. The deviant cases suggest that deeper AI integration becomes viable when organizations have mature data environments and enterprise-grade governance (e.g., private deployments, anomaly detection platforms, workflow middleware). Future research should develop matched case studies comparing organizations with similar sectoral profiles but different AI governance architectures, focusing on operational outcomes (cycle time, error rates, audit findings, compliance exceptions) and on how accountability is formally allocated in AI-supported decisions.

Third, workflow-level evaluation of verification overhead and control effectiveness. A key mechanism emerging from the data is that AI can increase work when verification becomes universal rather than exception-based. Future studies should measure verification overhead directly through process mining, time-and-motion analysis, or audit-log analytics. This would clarify when AI reduces total workload and when it merely shifts effort from production to validation. Such studies can also test the effectiveness of specific design strategies (e.g., exception routing, confidence thresholds, human review gates, and audit-trail requirements).

Fourth, regulatory and professional governance research. Given the strong boundary-condition theme around non-transferable liability and local regulatory nuance, future research should examine how regulators, professional associations, and CPD systems can evolve to support responsible AI use. Topics include: (a) standards for auditability and explainability of AI-assisted accounting outputs; (b) guidance on acceptable use of third-party AI platforms for confidential data; (c) competency frameworks for AI literacy and model risk governance in accounting; and (d) curriculum reforms and licensure/CPD alignment with analytics and AI oversight capabilities.

Collectively, these research directions would strengthen the empirical foundation for decision-oriented AI governance in accounting, moving from perception-based accounts toward measurable implementation models and evidence-based policy and training interventions.

5. Conclusions and Recommendations

5.1 Conclusions

This qualitative study examined how practicing accounting professionals interpret the adoption, usefulness, constraints, and governance implications of AI in accounting work. The findings indicate that AI is presently adopted most comfortably in low-risk assistive applications, particularly summarization, document clarification, and initial review of lengthy narratives. In contrast, adoption into core accounting workflows (e.g., transaction classification, posting, reconciliation, forecasting, and assurance) remains conditional and uneven, shaped by organizational readiness rather than individual enthusiasm alone.

Across participants, the primary inhibitors of deeper adoption are (a) institutional non-commitment (limited top-management sponsorship and weak policy direction), (b) data readiness constraints (integration, cleanliness, and trustworthiness of internal data), and (c) verification overhead, wherein AI-enabled automation may add an additional validation step rather than reduce work when outputs are not sufficiently transparent or auditable. These adoption barriers are reinforced by the external environment, particularly manual and template-bound regulatory processes, which can reintroduce rework even when internal workflows are optimized.

Governance concerns emerged as decisive constraints on professional AI use. Participants highlighted uncertainty about confidentiality and data custody, heightened cybersecurity exposure through third-party tools, the difficulty of detecting “confident wrong” outputs due to opacity, and the non-transferability of accountability and liability in regulated professional practice. As a result, respondents consistently framed AI as an instrument that can assist analysis but cannot substitute for human decision authority, contextual interpretation, and defensible sign-off responsibility.

Finally, the findings suggest that AI’s workforce impact in accounting is best understood as recomposition rather than replacement. Participants anticipate shrinking routine tasks and increasing emphasis on interpretation, exception handling, governance competence, analytics literacy, and cybersecurity-aware practice. Anxiety was expressed more often as fear of being left behind than as certainty of direct replacement, implying that professional vulnerability is likely to be stratified by adaptability and access to relevant upskilling.

5.2 Recommendations

Recommendations for organizations and accounting leaders

Institutionalize AI through policy and governance. Establish clear guidelines on approved tools, allowable data classes, documentation standards, review gates, and responsibility allocation for AI-assisted work—especially for compliance-linked outputs.

Prioritize data readiness as the core investment. Before expanding AI use, invest in data integration, master data quality, standardized chart-of-accounts mapping, and reliable audit trails; treat tool subscription as secondary to data trust.

Design workflows to minimize verification overhead. Shift from universal checking to exception-based review using confidence thresholds, routing rules, and risk-tiered validation procedures so automation reduces total work rather than adding steps.

Use enterprise-grade deployments for sensitive contexts. For confidential or regulated data, prefer secured deployments (e.g., controlled environments, DLP controls, access management, logging, and vendor due diligence) rather than public AI tools.

Embed AI governance into internal controls. Update internal audit plans and control matrices to include AI-specific controls (model change control, prompt/output logging, bias/error monitoring where relevant, and incident response).

Recommendations for educators and training providers

Integrate AI literacy into core accounting education. Include interpretive competence (how to critique outputs), validation logic, and governance principles—not only “how to use tools.”

Strengthen analytics and forecasting capability. Add practical training in forecasting, scenario analysis, and decision analytics aligned with accounting use cases, emphasizing interpretability and defensibility.

Include cybersecurity and data governance fundamentals. Embed baseline privacy, security, and data stewardship competencies as part of professional readiness.

Recommendations for professional bodies and regulators

Modernize CPD requirements. Allocate mandatory CPD units for digital fluency, AI oversight, and data governance, balancing traditional tax updates with emerging competency needs.

Issue guidance on acceptable AI use in professional practice. Provide standards for confidential data handling, documentation, auditability, and accountability in AI-assisted outputs.

Support digitization and machine-readable compliance processes. Where feasible, promote regulatory submission pathways that reduce manual rework and enable more consistent end-to-end automation.

5.3 Implications

Implications for theory and research

The findings support the view that AI adoption in accounting is not explained solely by perceived usefulness; it is mediated by institutional readiness, governance risk, and accountability structures. The mechanism of verification overhead offers a practical theoretical refinement: in high-accountability domains, automation can paradoxically increase work unless workflows and controls are redesigned. Future research can formalize and test this mechanism across organizational contexts.

Implications for practice and decision analytics

For decision-oriented analytics, AI's value depends on whether outputs can be traced, defended, and governed. Organizations that treat AI as a governance redesign problem—rather than a standalone tool purchase—are more likely to realize productivity gains without increasing risk. The deviant cases indicate that deeper adoption becomes feasible when AI is implemented as controlled infrastructure, supported by clean data, co-developed accounting logic, and enterprise-grade controls.

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