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ARTIFICIAL INTELLIGENCE ADOPTION IN ACCOUNTING: A THEORETICALL EXAMINATION OF OPPORTUNITIES, CHALLENGES AND IMPLICATION FOR THE FUTURE OF PROFESSIONAL ACCOUNTING PRACTICE

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Abstract

Artificial Intelligence (AI) is being adopted across the accounting profession at a pace that has outrun the profession's theoretical understanding of what that adoption actually involves. Much of the existing literature treats AI adoption as a technical event — a system installed, a tool switched on — rather than as the organizational and professional process it actually is. This paper offers a theoretical examination of that process, integrating adoption theory (the Technology–Organization–Environment framework, the Technology Acceptance Model, and the Unified Theory of Acceptance and Use of Technology) with recent empirical evidence from accounting, auditing, and professional services research. It argues that AI adoption in accounting should be understood as a socio-technical process operating simultaneously at three levels — organizational readiness, individual acceptance, and professional identity — each of which can independently stall adoption regardless of a technology's capability. The paper reviews the opportunities AI creates across audit quality, fraud detection, predictive analytics, and advisory work, and sets these against the governance, ethical, and workforce challenges that recent field evidence shows are just as consequential. It closes by considering what sustained AI adoption implies for the accountant's professional role, for accounting education, and for the standard-setting bodies that will eventually have to formalize expectations around AI-assisted professional judgement. The contribution is a theoretical account of adoption that treats capability and acceptance as genuinely separate problems, neither of which rersolves the other.

Keywords: Artificial Intelligence, accounting profession, technology adoption, TOE framework, technology acceptance model, professional judgement, auditing, accountitng education.

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Introduction:

The accounting profession has absorbed new technology before — computerized ledgers, enterprise resource planning systems, cloud accounting, robotic process automation — and each wave produced a familiar cycle of enthusiasm, resistance, gradual adoption, and eventual normalization. Artificial intelligence is frequently discussed as though it belongs to this same cycle, just faster and more capable. That framing understates what is actually happening. Earlier accounting technologies mostly automated defined, rule-based tasks; AI systems increasingly perform tasks that used to require professional judgement - flagging which transactions warrant scrutiny, drafting narrative disclosures, classifying ambiguous entries, and generating first-pass interpretations of financial data (Choi & Xie, 2026). That shift changes what "adoption" actually means for the profession, and the theoretical apparatus accounting researchers have historically used to study technology adoption needs to be examined against it rather than simply assumed to still apply.

The empirical picture developing around AI adoption in accounting is more differentiated than early commentary suggested. Abbas (2026), reviewing ninety-one studies on AI and digitalization in management accounting, finds a field that has moved past treating AI as a single undifferentiated technology and toward examining how specific applications reshape specific accounting activities. Choi and Xie (2026), in one of the first large-sample field studies of generative AI use inside actual accounting workflows, combine survey data from 277 professional accountants with transaction-level records from seventy-nine small and mid-sized firms and find genuine productivity gains — including a reallocation of roughly 8.5 percent of accountant time away from routine data entry and toward business communication and quality assurance — alongside a persistent pattern of accountants over-relying on AI-suggested classifications that turn out to be wrong. That combination, gains and new failure modes appearing together in the same dataset, is a useful corrective to adoption narratives that treat AI capability as the main story.

This paper works through AI adoption in accounting as a theoretical problem rather than a technology-readiness checklist. It draws on three complementary bodies of adoption theory — the Technology–Organization–Environment (TOE) framework (Tornatzky & Fleischer, 1990), the Technology Acceptance Model (TAM) (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) — and applies them to the accounting-specific evidence that has accumulated over the past several years. The central argument is that **AI adoption in accounting fails or succeeds at three separate levels that do not automatically move together: whether the organization is structurally ready, whether individual accountants actually trust and use the tools available to them, and whether the profession's own definition of professional judgement can accommodate AI-assisted work**. A firm can clear the first hurdle and still stall at the second or third. The paper reviews the opportunities and challenges the recent literature associates with AI adoption in accounting, and closes by considering what durable adoption implies for professional identity, accounting education, and the standard-setting infrastructure that governs the profession.

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Conceptualizing AI Adoption in the Accounting Profession

AI adoption in accounting is not a single event but a layered process, and the accounting-specific literature has begun to reflect that. Murphy et al. (2024), applying topic modelling to 930 peer-reviewed abstracts on accounting and AI, identify eleven distinct research clusters spanning efficiency, fraud detection, automation, and informational reliability — a spread that makes clear the field is not asking one question (“will AI replace accountants?”) but many overlapping ones about specific applications in specific accounting contexts. Yang et al. (2024), studying AI adoption across three auditing firms of varying size, find that the factors shaping adoption differ meaningfully by firm size and market position: larger firms operating in AI-saturated environments perceive AI mainly through an operating-efficiency lens, while smaller firms face a different problem — weaker organizational readiness that leaves them poorly positioned to manage the very constraints AI introduces.

This variation matters theoretically because it undercuts any account of AI adoption that treats the technology as the primary variable. Gold et al. (2026), examining robotic process automation adoption intentions among accounting professionals in an emerging-economy context, find that behavioural intention to adopt is shaped as much by organizational and environmental factors specific to that setting as by the technology's demonstrated capability — a finding broadly consistent with Zhang et al.'s (2025) interview evidence from forty-one companies, where institutional and individual factors together determined whether AI adoption in managerial accounting actually took hold. The working definition of AI adoption this paper uses, accordingly, is not “a firm begins using an AI tool” but the fuller and more demanding condition that the tool becomes durably integrated into professional workflow, trusted enough to inform judgement, and governed well enough that its outputs can be defended — a definition that treats adoption as an outcome to be explained rather than a starting assumption.

Theoretical Foundations of AI adoption in Accounting

The Technology-Organization-Environmental Framework

The TOE framework explains adoption as a function of three interacting contexts: the technology itself (its relative advantage, complexity, and compatibility with existing systems), the organization (its size, resources, structure, and readiness), and the environment (competitive pressure, regulation, and industry norms) (Tornatzky & Fleischer, 1990). Applied to accounting, TOE has proven durable precisely because AI systems rarely operate in isolation — they sit on top of existing accounting information systems, enterprise resource planning platforms, and data-governance arrangements, so a firm's technological readiness is inseparable from the state of infrastructure it already has. Yang et al. (2024) apply TOE directly to auditing firms and find regulatory environment and innovation-management capacity operating as the more binding constraints, ahead of the technology's raw capability. Saci et al. (2026), surveying 238 French accounting professionals, find IT infrastructure, financial readiness, and vendor support all functioning as organizational-level determinants of adoption intention — evidence that the TOE variables identified three decades ago for earlier enterprise technologies still carry real explanatory weight for AI specifically,

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The Technology Acceptance Model and UTAUT

Where the TOE operates at the organizational level, TAM and UTAUT explain adoption at the level of the individual professional deciding whether to actually use a tool that is available to them. TAM reduces that decision to two constructs — perceived usefulness and perceived ease of use (Davis, 1989) — and both constructs turn up repeatedly in the accounting-specific literature. Saci et al. (2026) find perceived usefulness and ease of use mediating the effect of nearly every organizational factor they examine, meaning that even strong infrastructure and vendor support influence adoption only through how usable and useful individual accountants perceive the resulting tool to be. UTAUT extends this model by adding performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), and accounting-specific applications of UTAUT have generally found perceived risk operating as a countervailing force against usefulness — Ross and Zhang (2025), surveying 136 accounting practitioners about ChatGPT use, find perceived risk significantly dampening adoption even where usefulness is clearly recognized, and notably find that trust itself does not independently predict use once risk and usefulness are accounted for. The theoretical implication is that usefulness alone is not a sufficient condition for adoption in accounting specifically, where the professional and legal consequences of a wrong output are unusually high.

Dynamic Capabilities and Human-AI Complimentarity

A third theoretical strand treats AI less as a discrete tool to be accepted or rejected and more as a capability that reshapes what the organization and the professional can jointly do — the dynamic capabilities perspective (Teece et al., 1997). Choi and Xie's (2026) field evidence gives this perspective concrete empirical viewpoint: they find accountants selectively intervening when AI confidence scores are low, a pattern consistent with genuine complementarity rather than either full delegation or outright rejection. Bou Reslan and Jabbour Al Maalouf (2024), analysing survey data from 454 accountants, reach a parallel conclusion — AI adoption is changing what accounting work involves and what skills it requires, rather than displacing the professional outright. Taken together, these three theoretical strands suggest that AI adoption in accounting is not adequately explained by any single level of analysis: organizational readiness (TOE) determines whether the infrastructure exists, individual acceptance (TAM/UTAUT) determines whether professionals actually use what is available, and capability reconfiguration (dynamic capabilities) determines whether the resulting human–AI arrangement produces genuinely better outcomes rather than simply faster ones.

Opportunities Presented by AI Adoption in Accounting

Automation and Efficiency Gains

The most immediate and best-documented opportunity remains efficiency. Interview evidence from Big Four accounting firms shows robotic process automation implemented across a wide range of accounting processes with substantial reductions in processing time (Cooper et al., 2019), and a follow-up study of the same firms finds both firm leadership and lower-level staff generally viewing RPA's effect on the profession positively (Cooper et al., 2022). Choi and Xie

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(2026) extend this picture into generative AI specifically, documenting a 12 percent increase in general-ledger granularity and a 7.5-day reduction in monthly close time associated with AI adoption in their field sample — concrete, quantified evidence that efficiency gains from AI extend beyond the transactional-processing tasks that earlier automation technologies targeted. These findings echo an argument Appelbaum et al. (2017) made earlier, before generative AI entered common use: that the real efficiency payoff from analytics in accounting comes from embedding it directly into existing performance-measurement structures rather than running it as a separate, IT-owned initiative bolted onto conventional reporting.

Enhanced Analytical and Predictive Capability

Beyond efficiency, AI expands what accounting information can be used to predict rather than merely report. Ranta et al. (2023) identify predictive analytics, the use of textual and unstructured data, and explainable-AI techniques as the areas where machine learning contributes most directly to accounting research and practice, while Rikhardsson and Yigitbasioglu (2018) find in their review of business intelligence and analytics research that empirical coverage of how these tools actually change day-to-day accounting tasks remains comparatively thin despite strong practitioner interest — a gap the more recent field studies discussed below have begun to close. Ding et al. (2020) supply a concrete empirical demonstration: machine-learning estimates of insurance loss reserves outperformed the managerial estimates firms actually reported in four of five insurance lines examined, a specific and well-defined example of AI improving on human judgement in an accounting estimation task. Bertomeu et al. (2021) show a related capability on the diagnostic side, using machine learning across accounting, audit, and market variables to detect patterns associated with financial misstatements — with the finding that accounting data alone predicts misstatements poorly, and becomes useful only in combination with audit and market information, a result that complicates any simple story about AI substituting for the full range of professional judgement involved in financial statement review. Yoshioka and Ishii (2025) extend this analytical opportunity toward generative AI specifically, proposing a framework that integrates generative AI with data-science techniques to support simulation, scenario analysis, and real-time forecasting in ways a conventional, historically oriented reporting cycle cannot easily replicate.

Improved Audit Quality and Fraud Detection

Auditing has been an early and well-studied site of AI adoption specifically because audit work already involves large volumes of structured and semi-structured data suited to machine processing. Kokina and Davenport (2017) trace the early stages of this shift, arguing that automation was beginning to change what auditors actually spend their time on well before generative AI entered common use. More recent field evidence from Kokina et al. (2025), drawn from interviews with professionals working with AI in accounting and assurance settings, documents genuine gains in anomaly detection and testing coverage, while identifying transparency, explainability, and the risk of professional overreliance as the conditions that determine whether those gains actually translate into better audit quality rather than a false sense of assurance.

Advisory and Strategic Value Creation

A less-examined but increasingly documented opportunity concerns the accountant's advisory role. aci et al.(2026), find AI adoption among French accounting professionals concentrated not only in routine-task automation but also in the strengthening of strategic advisory work — real-time data analysis feeding directly into client-facing advice rather than staying confined to back-office processing. Choi and Xie's (2026) finding that AI-adopting accountants reallocate time toward business communication rather than simply working faster on the same tasks points in the same direction: the efficiency gained from automating routine work appears to be getting redirected toward exactly the advisory and interpretive activities that the literature consistently identifies as the profession's more durable long-term contribution.

Challenges Confronting AI Adoption in Accounting

Governance, Explainability and Trust

The same field evidence documenting AI's benefits documents governance problems just as clearly. Choi and Xie (2026) find accountants over-relying on inaccurate AI-suggested classifications in a meaningful share of cases — an error pathway the authors note becomes more consequential as AI outputs grow more fluent and more difficult to distinguish from genuinely reliable work. Kokina et al. (2025) identify transparency, explainability, and algorithmic bias as unresolved problems in AI-enabled auditing specifically, not peripheral concerns but central obstacles to trusting AI output enough to actually act on it. Eulerich et al. (2024a), examining robotic process automation risks specifically, find that automation is frequently deployed as a quick fix for underlying process weaknesses rather than a genuine solution, and that its governance is considerably more difficult than firms typically anticipate at the point of adoption — a companion paper from the same authors proposes internal-control principles built specifically for RPA environments on the reasoning that governance frameworks designed for manual processes simply do not ttransfer (Eulerich et al, 2024b)

Ethical and Data-Privacy Concerns

Zhang et al. (2023), examining the ethical dimensions of AI in managerial accounting, identify data security, privacy, misuse, accountability, and transparency as recurring concerns that automation and analytics projects tend to treat as secondary rather than central design considerations. These concerns intensify with generative AI specifically, where outputs are probabilistic and their provenance is often opaque even to the accountants using them — Dong et al. (2024), reviewing the broader ChatGPT-and-LLM literature in accounting and finance, note that questions about accountability and auditability for LLM-generated outputs remain only partly answered even as adoption of these tools accelerates in practice.

Professional Skill Gaps and Workforce Disruption

The adoption of Artificial Intelligence is changing what Accounting tasks requires in a practical manner and the evidence on how well the workforce is adapting to that change is mixed. Bou Reslan and Jabbour Al Maalouf (2024) find AI adoption altering required skills across their sample of 454 accountants, and Ross and Zhang (2025) find that accounting practitioners, at the time of their survey, had relatively limited hands-on experience with generative AI and were using it predominantly for administrative tasks rather than the more analytically demanding applications the technology is theoretically capable of supporting — a gap between technological capability and workforce readiness that adoption theory alone does not fully explain, since it persists even where usefulness is recognized. Moll and Yigitbasioglu (2019) frame this as a legitimacy problem for the profession more broadly: as AI absorbs more of the accountant's traditional task list, the profession has to actively demonstrate what its distinctive human contribution now is, rather than assume that the contribution is self-evident.

Organizational and Implementation Barriers

Finally, a range of more mundae mundane organizational barriers shapes whether AI adoption actually sticks once initial enthusiasm fades. Saci et al. (2026) find perceived cost acting as a significant barrier to adoption intention even where usefulness and ease of use are both rated highly, and Yang et al. (2024) find smaller accounting firms specifically disadvantaged by weaker AI readiness relative to larger competitors operating in more AI-saturated environments — a finding with real implications for competitive structure within the profession, since it suggests AI adoption may widen rather than narrow the resource gap between large and small practices.

Implications for the Future of Professional Accounting Practices

Redefining Professional Roles and Identity

The cumulative evidence reviewed above points toward augmentation rather than replacement, but augmentation of a specific and demanding kind. Choi and Xie's (2026) finding that accountants selectively intervene when AI confidence is low is evidence of a genuinely new professional skill — knowing when to trust a system and when not to — that did not exist as a distinct competency before AI-generated outputs became a routine part of accounting workflow. As routine processing and first-pass analysis increasingly move to AI systems, what remains distinctively human concentrates around exactly the activities the literature keeps returning to: contextual interpretation, professional scepticism, ethical judgement, and the ability to communicate what an AI-generated output actually means to the people who have to act on it (Kokina et al., 2025; Bou Reslan & Jabbour Al Maalouf, 2024). That is not a smaller professional role than the one it replaces; if anything, the evidence on overreliance and misclassification suggests it is a more demanding one, since the accountant now bears responsibility for catching errors produced by a system that is frequently correct and therefore easy to trust by default.

Accounting Education and Continuing Professional Development

This shift carries direct implications for how accountants are trained. Traditional accounting education does not become less necessary because AI exists — sound knowledge of accounting principles and professional standards remains the basis on which an accountant can actually evaluate whether an AI-generated output is defensible — but it increasingly needs to be paired with AI literacy specifically aimed at knowing how these systems fail, not simply how they work. Ross and Zhang's (2025) finding that perceived risk, not availability, is what

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actually limits practitioner adoption of generative AI suggests that training curricula should address trust calibration and risk assessment directly, rather than assuming that exposure to a tool is sufficient preparation for using it responsibly. Moll and Yigitbasioglu (2019) make a related point about curriculum design: as automatable tasks shrink, accounting education has to more deliberately cultivate the judgement-intensive skills that remain distinctively valuable, rather than continuing to organize training primarily around tasks that AI is increasingly capable of performing on its own.

Regulatory and Standard-Setting Implications

Perhaps the least resolved area concerns what professional standard-setting bodies should actually require of AI-assisted accounting and audit work. The governance gaps documented by Eulerich et al. (2024a, 2024b) and Kokina et al. (2025) exist partly because control and governance frameworks were designed for manual and rule-based automated processes, not for probabilistic systems whose outputs vary in confidence and whose failure modes are not always visible to the professional relying on them. The evidence that accountants sometimes over-rely on incorrect AI classifications (Choi & Xie, 2026) suggests that professional standards will eventually need to specify not just that AI tools may be used, but how their outputs should be verified, documented, and challenged — something closer to the documented-scepticism requirements already familiar from auditing standards than to a simple technology-use disclosure. Firm-level and professional-body guidance is beginning to move in this direction, but the pace of AI capability development at present appears to be outrunning the pace at which formal standards are being written to govern its use.

Toward an Integrated View: AI Adoption as a Socio-Technical Process

Bringing the theoretical and empirical strands together, AI adoption in accounting is best understood as a socio-technical process operating across three levels that do not automatically move in step with one another. At the organizational level, TOE-derived evidence shows that infrastructure, resources, and regulatory environment determine whether the conditions for adoption exist at all (Yang et al., 2024; Saci et al., 2026; Gold et al., 2026). At the individual level, TAM- and UTAUT-derived evidence shows that usefulness, ease of use, and perceived risk determine whether accountants who have access to AI tools actually use them, and use them well (Ross & Zhang, 2025; Saci et al., 2026). And at the professional level, evidence on task reallocation, selective intervention, and skill change shows that durable adoption ultimately depends on whether the profession's conception of what counts as sound professional judgement can expand to include working productively alongside probabilistic systems (Choi & Xie, 2026; Bou Reslan & Jabbour Al Maalouf, 2024).

This layered view has a practical implication that the existing literature has not stated as directly as it might: interventions aimed at only one level are unlikely to produce durable adoption on their own. A firm can invest heavily in AI infrastructure and still see limited actual use if individual accountants perceive the tools as risky or poorly suited to their judgement-intensive work; conversely, individually enthusiastic early adopters cannot sustain firm-wide adoption if organizational governance and control structures are not built to support it. The opportunities reviewed in this paper — efficiency, analytical capability, audit quality, advisory value — are all real and increasingly well documented. But they are conditional opportunities, realized only where organizational readiness, individual acceptance, and professional-identity change change happen together rather than in isolation.

Directions for Future Research

Several gaps follow directly from the theoretical account developed above. First, adoption research in accounting has relied heavily on cross-sectional surveys capturing intention rather than sustained use; Choi and Xie's (2026) combination of survey and longitudinal transaction-level data is a useful model, but comparable field evidence outside large technology-enabled platforms remains scarce, particularly for small and mid-sized practices, which Yang et al. (2024) and Saci et al. (2026) both suggest face a distinct and under-studied set of constraints.

Second, the interaction between the three adoption levels identified in this paper — organizational, individual, and professional — has rarely been studied jointly. Most existing studies apply TOE, TAM, or UTAUT separately rather than modelling how a weakness at one level constrains outcomes at another; longitudinal, mixed-methods designs that track a single firm through organizational investment, individual uptake, and professional-identity change over time would test the layered account this paper proposes more directly than the largely cross-sectional evidence currently available.

Third, the overreliance problem documented by Choi and Xie (2026) and the explainability gap documented by Kokina et al. (2025) both deserve dedicated attention as accounting-specific phenomena rather than being treated as instances of a generic AI-trust problem imported from computer science. The professional and legal consequences of an accountant relying on an incorrect AI-generated classification differ meaningfully from the consequences of a consumer relying on an incorrect recommendation, and accounting research is well positioned to study that difference directly.

Finally, almost none of the empirical literature reviewed here addresses how professional standard-setting bodies should formalize expectations around AI-assisted judgement, even though the governance gaps identified by Eulerich et al. (2024a, 2024b) and Zhang et al. (2023) point directly toward that need. Comparative research examining how different professional bodies and regulatory regimes are beginning to address this question — and with what effect on actual practice — would meaningfully advance a literature that, at present, is considerably better at documenting AI's capabilities than at specifying how the profession should govern them.

Conclusion

Artificial Intelligence is not just the next entry in accounting's long history of adopting new technology; the evidence reviewed in this paper suggests it is qualitatively different, because it performs tasks that increasingly resemble professional judgement rather than merely accelerating rule-based processing. Understood through the combined lens of TOE, TAM, UTAUT, and dynamic-capabilities theory, AI adoption in accounting emerges as a genuinely

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layered process — organizational, individual, and professional — in which capability at one level does not guarantee success at another. The opportunities are substantial and increasingly well evidenced: efficiency gains, expanded analytical and predictive capability, improved audit quality, and a strengthened advisory role for the accountant. The challenges are equally well evidenced and, on the current evidence, no less consequential: governance gaps, ethical exposure, workforce skill deficits, and organizational barriers that appear to fall more heavily on smaller firms. The future of professional accounting practice implied by this evidence is not one in which accountants are displaced by AI, but one in which the profession's core competency shifts — from producing accounting information to judging the reliability of AI-produced accounting information — and in which education, firm governance, and professional standards all have unfinished work to do in catching up with a shift that, on the evidence reviewed here, is already well underway.

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