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Algorithmic Accountability and Audit Quality in AI-Assisted Auditing: The Mediating Role of Professional Judgment Quality and the Moderating Role of AI Competence

Tanvir Sajid Tanvir

tanveersajidbajwa@gmail.com

National Textile University

Research Article

Keywords: algorithmic accountability, audit quality, professional judgment, AI competence, AI-assisted auditing, moderated mediation, PLS-SEM

Posted Date: November 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11397635/v1

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Additional Declarations: No competing interests reported.

Abstract

As AI uses are rapidly adopted by audit practice, the question is: Does algorithmic accountability, which encompasses the transparency, explainability, traceability, and control of AI-based audit tools, lead to an improvement in audit quality? Based on the literature on algorithmic accountability and the audit quality literature, this paper constructs a conceptual model where algorithmic accountability (independent variable) affects audit quality (dependent variable) via a mediating mechanism, namely the quality of the auditor's professional judgment, and the auditor's competence in using AI is a moderator of both the direct and indirect effects. This conceptual model is then illustrated empirically, with the results showing that algorithmic accountability affects audit quality through the mediator variable professional judgment quality, with the moderator variable being the competence of the auditor in using AI. Drawing on the most recent theoretical and empirical research (2025–2026), the paper makes two key arguments: First, using AI in auditing can boost the quality of audit judgments made by auditors in interpreting AI-generated evidence, not just increase detection rates; and second, AI systems must be accountable to enhance the quality of these audit judgments. The validity of seven hypotheses that emerge from the model is evaluated with the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) on an illustrative dataset consisting of 625 simulated respondent profiles which are created to illustrate the analytical procedure. The measurement model had a high level of reliability, convergent validity, and discriminant validity for all four constructs. In line with the mediation hypotheses, there was a complementary partial mediation, as the quality of the professional judgment was an indirect effect of algorithmic accountability on audit quality (indirect $\beta = .187$, $p < .001$), and the direct effect was also significant ($\beta = .295$, $p < .001$) accounting for 38.8% of the total effect. Contrary to the moderation hypotheses, there was no significant moderation from AI competence to either pathway, although AI competence was a strong, independent predictor of both professional judgment quality and audit quality, in its own right. The paper ends by drawing out audit firm, standard-setting body and academic implications for the implementation of responsible AI-assisted audit, and for the replication of the illustrated model based on the primary data gathered from practicing auditors.

Introduction

AI is no longer a tool that will help you be more efficient, it is now a core part of today's audit. Industry surveys show that most firms are currently making time-saving decisions more important than ever with the rise of AI solutions enabled by chat assistants, transaction-scoring engines and generative documentation tools in the majority of their engagements, large audit firms are increasingly embracing AI (Journal of Accountancy, 2026).

Now, machine learning models are capable of accurately categorizing millions of financial documents with reported accuracy greater than 95%, natural language processing tools can detect anomalies in contracts and disclosures, and generative systems can create audit documentation and summaries of risk indicators (Abdo-Salloum & Chehade, 2026; Sundarasen et al., 2026). This change will future-proof auditing and move it from a sample-based verification activity to one that ensures that the entire

population is verified. However, the same bibliometric evidence that illuminates this transformation reveals that the intellectual agenda of the profession has evolved from, "Can AI enhance audit efficiency?" to, "Can AI be trusted, explained and held accountable without compromising the judgment that is at the heart of assurance services (Sundarasen et al., 2026)? Quality of audit performance has never been limited to only the number of calculations performed; it is dependent on auditor competence, independence, sufficient and appropriate audit evidence and, most importantly, the application of professional skepticism in the interpretation of such audit evidence.

The generation of a risk score, an anomaly flag or a draft conclusion by an opaque algorithm leaves the auditor with a judgement issue, rather than a calculation issue, regarding the weight to give to the output. The focus of the literature is, therefore, not about whether AI can identify misstatements but whether the accountability framework for AI, its transparency and explainability, and its governance, influence the auditor's judgment, and consequently the quality of the audit (Bracci, 2023; Libby & Witz, 2025). This is no idle worry. The results of empirical and field studies from 2025 and 2026 are conflicting regarding the impact of AI on audits. Some studies have found that AI can increase productivity and enhance fraud detection (Abdo-Salloum & Chehade, 2026; Saber et al., 2026), while others have indicated that implementing AI without skepticism and preparedness can negatively impact the auditor's performance (Puthukulam et al., 2021).

The practice side arrived at the same conclusion in industry-sponsored surveys, AI accelerates audit coverage and detects anomalies, but introduces a clear level of discomfort in the exercise of professional judgment, skepticism, and trust, which has been dubbed the “final frontier” of audit by professionals (AccountingWEB, 2026). Recognizing that the profession has a yet-to-be settled account of how the use of AI in governance translates or does not translate to audit quality, regulators and standard-setters have initiated the process of developing guidance on AI in the context of the profession. Auditors are cautioned that the true value of generative AI is in redirecting human judgment, not in its speed; and those companies will need to be careful not to let their own professional skepticism be subsumed by an authoritative sounding machine output (Journal of Accountancy, 2026). Despite this commonality of concern, no literature has yet articulated a parsimonious model relating the algorithm's accountability to the quality of the resulting audit in an explicit psychological or behavioral mechanism, nor have they explicitly identified conditions under which the mechanism works best, or worst.

Previous reviews also highlight that there is a lack of an integrative framework that connects the three loosely linked streams of adoption and readiness, technical capability and quality and governance for auditing with AI, and that these streams have fragmented research (Sundarasen et al., 2026). This paper aims to bridge the gap by theoretically proposing a conceptual model (CM) with four constructs, namely, the independent variable (IV) is algorithmic accountability, the dependent variable (DV) is audit quality, the mediator construct is professional judgment quality, and the moderating boundary condition is auditor AI competence.

The model presented here makes three related arguments. First, algorithmic accountability as the transparency, explainability, traceability, and governance of the AI tools used during an engagement is a necessary, but not sufficient, ingredient for audit quality; its impact on audit quality is not direct, but is mediated through the auditor's judgment process. Second, the process of converting accountable AI features to the area of the professional judgment's audit conclusions, which is the profession's own definition of “judgment integration” in AI-assisted audit work, is the last and most critical phase that creates audit evidence that is of a higher quality (CPA Journal, 2026). Third, this mediated pathway is thought to be dependent on the AI competence of the auditor, which is the fusion of technical AI literacy, algorithmic skepticism, and interpretive skill allowing an auditor to productively use an accountable AI feature without the tendency to either blindly defer to algorithms (automation bias) or reflexively discount them (algorithm aversion) (Dietvorst et al., 2015; Parasuraman & Riley, 1997).

The question is not just academic. The consequences of audit failures are significant, both in terms of their reputational impact, legal liability and systemic costs, and the social license enjoyed by the profession relies on the credibility of the assurance it can offer to capital markets (Power, 1999). As AI is used mainly as an efficiency tool, not yet given the same level of attention to accountability and competence, the profession is at risk of AI audits becoming more efficient (almost instant) and more information-rich, but also less substantive in empirical terms (Yin et al., 2026; Parasuraman & Riley, 1997; Dietvorst et al., 2015). But if algorithmic accountability and the ability of auditors are built side by side, AI can enhance, not diminish, the evidentiary basis of the auditor's opinion. Understanding how and under what conditions the two trajectories differ is thus directly relevant to the practice of auditing, to regulators, and to investors and other users of audited financial information.

Literature Review and Theoretical Background

Algorithmic Accountability in Auditing

The concept of algorithmic accountability was first developed as a concept in journalism studies and public administration research that is focused on the opacity of automated decision making processes that impact people's lives without offering a way for oversight or redress (Diakopoulos, 2015). Ananny and Crawford (2018) have since warned that “transparency” open-source access to an algorithm's code or data – does not provide accountability for a system, since meaningful accountability also means that users of a system should be able to understand how the outputs of that system are generated, and that responsibility for their consequences should be clearly held. Busuioc (2021) has abstracted this, and has structured it into multi-dimensional elements: answerability (the duty to account for and justify decisions), enforcement (the ability to punish or correct algorithmic failures), and the overall legitimacy of the human-machine relationship. In the field of accounting and public sector studies, Bracci (2023) took this agenda further by proposing ‘intelligent accountability’ as a model of accountability that leverages algorithmic systems in accountability infrastructures like audits to reinforce or undermine accountability mechanisms depending on the extent to which their results are contestable and traceable by human overseers.

This is directly reinforced more recently in the industry and technical arena in the context of auditing AI decision-making: In the audit-technology area, the guidance explicitly states that a defensible audit trail is not best practice, but rather a baseline requirement of having a traceability system in place, with layered evidence (decision output, environmental context, human oversight controls) and “proof bundles” that connect AI decisions to specific data inputs (mlflow.org, 2026). Algorithmic accountability, as applied to an audit, is the degree to which an AI tool utilized during an audit (a) communicates its purpose, scope, and limitations to the auditors who are utilizing it; (b) provides outputs that can be explained and traced back to identifiable inputs, weights, or decision rules; (c) is validated, monitored, and documented within a governance structure with clear ownership; and (d) enables the auditors to override, challenge, and correct the output, rather than accept it as final. This definition aligns with major firms' actual experience with their AI governance: transparency reporting highlights the need for human accountability, ownership of AI governance, and mandatory human review of AI-generated content, as well as the lack of consistency in disclosing the validation of AI-specific output and the capacity of an external reviewer to recreate how an AI output informed judgment (Journal of Accountancy, 2026; Sundarasen et al., 2026).

Artificial Intelligence can be a force to enhance data analysis and efficiency in auditing, however, auditors need to exercise professional skepticism to question the output of AI and ensure the final audit opinion is still on their shoulders (Van Nieuw & Schalck, 2026). It is in these areas – AI and data analytics in audit methodology, Public Company Accounting Oversight Board (PCAOB) proposals on audit and assurance-related technology, and the European Union's Artificial Intelligence Act – that regulatory activity has increased, with projects launched on AI and data analytics in audit methodology, and PCAOB proposals on audit and assurance-related technology (Sundarasen et al., 2026). Two other aspects of algorithmic accountability are important for this model. First, accountability is not inherent in the structure of an AI tool, a perfectly transparent model used without governance, documentation, and override capabilities, is not, in practice, accountable, as will be highlighted by practitioners when they speak about how AI is being used in audit, and how it is “a trust problem, not a speed problem” because each AI-assisted line in an audit file will need to be defensible to a regulator (DataSnipper, 2026).

Second, the accountability is not all-or-nothing: the aim of achieving full disclosure and operationalization of AI governance is not uniformly met by audit firms, with disclosure indices derived from Big Four reports on AI disclosures showing that while there has been a high level of disclosure of human oversight and training, there has been less and more variable disclosure of AI-specific validation and explainability (Sundarasen et al., 2026). This is exactly why algorithmic accountability is a valid independent variable that can be used to account for differences in downstream audit results.

Notably, algorithmic accountability as defined here is not the same as the related, but narrower, concept of explainable AI (XAI), which is a technical property of a model, namely its ability to provide explanations of the model's outputs that are comprehensible to people. Explainability is not the only part of accountability; it must be accompanied by other components, such as notifying the user of the model's limitations, documenting its validation, and retaining the ability for the auditor to override the

model, otherwise accountability from the sociotechnical perspective proposed here is low. This distinction is evident in the research by Zhong and Goel (2024) and summarized in recent reviews on XAI in auditing, which reveal that using XAI tools can enhance interpretability and help with the evidentiary aspects of auditing standards (e.g., ISA 500), but only in conjunction with governance arrangements that enable auditors to leverage interpretability and act upon it (Sundarasen et al., 2026). The concept of algorithmic accountability used in this paper is then best understood as being made up of explainability as one necessary element within a broader governance and disclosure framework.

Audit Quality in the AI-Assisted Audit Environment

While this definition links audit quality to auditor competence (detectability) and independence (willingness to report), audit quality has traditionally been conceptualized in this manner (DeAngelo, 1981). This construct has been further developed and expanded to include a number of other dimensions in the succeeding research, such as the sufficiency and appropriateness of audit evidence, the accuracy of risk assessment, the defensibility of the auditor's conclusions, compliance with auditing standards, and the overall credibility of the audit opinion to external users. The definition does not need to be replaced, but must be extended in the AI-assisted environment: AI will modify Evidentiary Gathering and Risk Assessment, but the overall requirements for quality, sufficiency, appropriateness, defensibility and independence of judgment will not be modified (Sundarasen et al., 2026).

The impact of AI on audit quality is highly varied and complex. While some of the advantages of implementing AI in auditing are that it enhances the quality and accuracy of audit judgments, and enables auditors to redirect their time from mundane tasks to more analytical and judgmental work, others are reported to be that AI can assist with full-population testing and manage risk detection and scoring. Some of the benefits of using AI in auditing are that it can help with full-population testing, risk detection and scoring, and enable auditors to reallocate their time from mundane tasks to more analytical and judgmental work; and others are that it can improve the precision and reliability of audit judgments. (CPA Journal, 2026; Journal of Accountancy, 2026) AI-driven automation, accuracy and cost-effectiveness are also positively correlated with audit-quality effectiveness, consistent with the productivity argument for adoption of AI, in a 2026 analytical study of AI-powered automation within U.S. organizations (Saber et al., 2026); and conference-based evidence from non-Big-Four accounting firms also confirms that structured AI adoption increases the likelihood of achieving more sustainable audit-quality outcomes when governance safeguards are present (Handoko et al., 2025).

The era of transition is even more complex now, as modern financial auditors are required to navigate the new age of agentic AI automation and intricate sustainability assurance frameworks while maintaining a solid base of professional judgment in their decision-making process (Deliu, 2026). The evidence in the field also suggests that the use of AI can help to mitigate the risk of auditor legal liability by lessening the connection between auditor-client closeness and auditor negligence, as the use of AI-supported procedures is perceived as more objective (Libby & Witz, 2025). Despite these positive effects, however, empirical survey research on practicing auditors conducted by Puthukulam et al.

(2021), using structural equation modeling, showed that the use of AI was directly negatively associated with auditor performance, which the authors believe is due to the excessive reliance of the user on AI outputs and a lack of technological readiness among auditors. Consistent with these findings, complementary findings from AI-expert-system research also warn that the benefits of AI in audit quality are not guaranteed, but vary based on the integration of AI into the existing review and control processes (Khayoon et al., 2025); and, in terms of broader applicability to audit efficiency, practice-oriented research literature highlighted the importance of firms linking AI tools with sufficient staff capability for the effectiveness gains associated with the use of AI to enhance audit efficiency to materialize (Hady & Fitria, 2025).

This directly suggests that the impact of AI on quality-relevant performance is not a technological fixed but depends on how auditor's process and act on the AI output exactly the quality judgment mediated competence moderated structure proposed in this paper. Another nuance in the recent literature is that efficiency benefits of AI may be achieved at the expense of the affective and ethical nature of the audit vigilance. In a three-wave longitudinal study of accounting and auditing professionals, it was established that AI-related work pressure was linked to a “numb efficiency paradox” whereas professionals began to do more of the same, they became less affectively capable of spotting warning signs, potentially leading to a decline in ethical vigilance and professional skepticism over time (Yin et al., 2026). In a directly related study, sponsored by the industry, 2026 practitioners surveyed indicated that they felt AI enabled them to get through much more ground and identify more anomalies, but at the same time they felt a bit uneasy because of the loss of real-world judgment and skepticism that this efficiency gain entails (AccountingWEB, 2026). The results confirm that audit quality in the age of AI is not solely a function of efficiencies or detection rates; it is grounded in the psychological and judgmental underpinning that leads to valid conclusions, and this is another call for professional judgment quality as a more immediate result to examine.

A related subtlety is the difference between audit efficiency and audit quality, the latter often being confused with the former in the recent literature. Productivity metrics like engagement turnaround time or hours saved are more easily measured and communicated than others—such as surveys from industry groups, which report that businesses are “overwhelmingly prioritizing time saving” in their decisions to deploy AI (Journal of Accountancy, 2026). Quality of audit, on the other hand, is a latent characteristic that can be imperfectly captured by inspection results, restatement frequency or peer-review outcomes, all of which suffer from a significant time delay and are confounded by other factors that are not related to the use of AI. This measurement asymmetry has potentially led to an inflation of the benefits of AI; while efficiency gains are observed, quality gains are not, which highlights the importance of a model like that proposed here in which audit quality and its immediate (judgement-based) determinants are outcomes of primary theoretical interest, rather than efficiency as a proxy for quality.

Professional Judgment Quality as a Mediating Mechanism

In auditing, professional judgment is the application of relevant audit training, knowledge and experience to make informed decisions regarding the actions to take during an audit engagement based on the circumstances of the engagement and the audit context (Nelson, 2009). Judgement quality is typically evaluated by how accurate and consistent risk and materiality assessments are the suitability of evidence used, the level of professional skepticism applied to any evidence including the machine generated signals and the reasonableness of the process used to link evidence to the judgement. Professional skepticism, a skeptical mind, an evaluation of information, and a critical assessment of evidence, along with a tendency to not make conclusions until there is enough evidence is a long-standing component of the behavioral aspects of the quality of judgment (Hurtt et al., 2013; Nelson, 2009).

The practitioner and academic literature from 2025 and 2026 share a perspective on justice that is both reorganization and not elimination of the task of judgment. The CPA Journal defines the last stage of the model of AI-assisted audit planning as “auditor judgment integration,” where the auditor interprets the AI output, validates it against professional standards and adds their own context of the client and the industry, and outlines the use of AI as an assistant to, not a substitute for, professional skepticism (CPA Journal, 2026). Likewise, industry experts remind us that the primary risk that generative and analytic AI brings to audit is “automation bias,” the tendency to rely on technology outputs without taking the time to properly analyze or question them, which is already emphasized in auditors' code of ethics (Journal of Accountancy, 2026). But more recently, audit technology vendors have offered commentary on workflow design in the same vein: AI workflows that are connected and context-rich are valuable because they allow review effort to focus on “the areas where judgment delivers the greatest value” and not because they remove judgment from the process (Wolters Kluwer Tax and Accounting, 2026).

On the formal governance level, evidence from practice demonstrates that audit firms explicitly maintain human responsibility for AI-assisted conclusions, and explicitly state that AI is used in support, but not in place of, judgment (Sundarasen et al., 2026). To grasp the impact of AI on judgment quality, two phenomena from the human-automation literature stand out. Two phenomena from the human-automation literature have been pivotal in understanding the impact of AI on judgment quality. Automation bias refers to the tendency to gamble on relying heavily on automated cues, especially those that come across as authoritative, thereby decreasing attention to disconfirming information (Parasuraman & Riley, 1997). The opposite failure mode is algorithm aversion, when after a few errors, decision makers lose trust in an algorithm and reject its output more than is statistically justified, even when it is superior to the unaided human decision maker (Dietvorst et al., 2015). Both phenomena shift quality of judgment away from evidence-based ideal, and both are argued in recent literature to be influenced by the accountability of the underlying AI system: if an AI system's output is explainable, and its governance is transparent, auditors will be better equipped to meaningfully calibrate trust, rather than sliding into either blind trust or reflexive distrust (Sundarasen et al., 2026).

This process of calibration is exactly the kind of process that professional judgment quality is claimed to capture and is the means by which algorithmic accountability is expected to impact on audit quality. Last

but not least, under AI-induced work pressure, affective and motivational dynamics are also threats to judgment quality, in addition to cognitive biases. As mentioned above, the numb efficiency paradox records a pathway through which pressure from AI related activities undermines ethical vigilance or skepticism even as external efficiency is maintained, and complementary qualitative evidence indicates that experienced auditors who feel their own skills are being undermined by AI can respond in a defensive way to pressure, for example, by dismissing the AI supported advice as a “coping mechanism” rather than as a reasoned evidentiary opinion (a phenomenon different from, but related to, algorithm aversion). Together, these results support the judgment quality as a multiply-determined construct that is sensitive to the accountability of the AI system, the auditors' competence, and the psychological context of the audit.

AI Competence as a Boundary Condition

In this model, AI competence refers to an auditor's technical literacy, interpretive ability, and tempered skepticism about AI tools, or a combination of these, his or her ability to understand what AI can and cannot do, to question its results, to know when it is likely to be wrong, and to combine its results with his or her own judgment. It is a construct that is not just about software skills at the end of the day, as the literature makes clear that it is not about the willingness to use AI tools, but about the ability to use them in ways that maintain the quality of the audit (Munoko et al., 2020; Sundarasen et al., 2026), and that the audit skill-set of the future will be complemented by the development of “algorithmic literacy” in addition to technical skills, as described by professional bodies (Sundarasen et al., 2026). Empirical evidence backs up the notion of the moderating effect of AI competence.

The results revealed that continuous learning (which proxies building AI competence over time) had a significant moderating effect on the positive influence of psychological readiness and PS on auditor performance, in addition to significantly reducing the negative influence of AI use, consistent with a moderation pattern of changing the slope rather than the level of the relationship between AI and performance-relevant outcomes (Puthukulam et al., 2021). Qualitative complementary evidence shows that, when facing the same piece of AI advice from a different type of audit, auditors who feel threatened by the required new skills are more likely to dismiss the AI system as being inappropriate or unaccountable, whereas those who feel affirmed are more likely to act on the advice, suggesting that the same AI inputs result in different psychological effects on processing the same AI outputs. Similar to the rules and standard-setters, regulators and standard-setters have also started to recommend new auditor competency rules tailored to AI use as a governance lever, in addition to the rules set for the AI systems themselves (Sundarasen et al., 2026).

This evidence, all taken together, is sufficient to model the competence of an AI as a moderator that can either help or hinder the ability of the system's accountability features to translate into improvements in the quality of the judgment. All this evidence, taken together, is sufficient to model the competence of an AI as a moderator that can either help or hinder the ability of the system's accountability features to translate into improvements in the quality of the judgment.

Theoretical Lenses: Accountability Theory and the Audit Quality Framework

This paper brings together two streams of thinking. As outlined above, algorithmic governance literature builds on accountability theory, which posits that accountability is achieved when a system is made transparent, answerable, and enforceable, and that these features rely on beliefs and behaviors of the people who use the system, not on its output. (Ananny & Crawford, 2018; Busuioc, 2021; Diakopoulos, 2015). In the context of auditing, this tradition suggests that algorithmic accountability should influence, and not directly determine, the actions of auditors, particularly in their interpretation and use of AI outputs.

This is the theoretical foundation for including professional judgment quality as a mediator instead of assuming that algorithmic accountability has a direct influence on audit quality. The second lens is the audit quality production framework originally developed by DeAngelo (1981) and developed in subsequent competence-and-independence based models of audit quality, which suggests that audit quality is a function of the auditor's competence in detecting misstatements and of the auditor's willingness and ability to be independent and report such misstatements.

This framework provides the dependent variable and makes the process of the mediation through judgment, not just through detection capacity more clear: detection capacity can be increased artificially, but the transition from detection to opinion on quality audit goes through judgment – and this judgment must be corroborated by the reporting and human evaluation. Lastly, the human-automation interaction research literature (Dietvorst et al., 2015; Parasuraman & Riley, 1997) provides the psychological micro-foundations for the mediation of the pathway between AI-competence and the effect of the mediated pathway, as both over-trust and under-trust in automation is a competence-dependent phenomenon. Taken together, the three literatures warrant the specific mediation-centered design of the conceptual model developed in the next section, and are also directly in line with the mediation-methodology literature used in other aspects of accounting research such as recent PLS-SEM studies that include economic pressure and audit environment as explicit mediating mechanisms between antecedent conditions and audit-quality outcomes (Dao, 2025), which supports the appropriateness of the present conceptual model design using mediation rather than a direct-effects design.

Conceptual Model and Hypotheses Development

The proposed model posits that algorithmic accountability (IV) has a direct effect on audit quality (DV) which is mediated by professional judgment quality (Med) and that moderates the direct effect of algorithmic accountability on professional judgment quality (Mod) and the direct effect of professional judgment quality on audit quality (Mod). The model is thus a first-stage moderated mediation model in which the indirect effect of algorithmic accountability on audit quality, through professional judgment quality, is conditional on the level of auditor AI competence.

Algorithmic Accountability and Audit Quality

In theory, systems that rely on AI to generate evidence should enhance audit quality given their transparency regarding scope and limitations, their capacity to explain and track evidence created by AI, and the inclusion of a documented governance framework, and because their results are subject to auditor override rights (Bracci, 2023; Busuioc, 2021). Research indicating that the use of AI, when done well and with proper accountability, is associated with decreased perceived independence risk (Libby & Witz, 2025) and more objective risk assessment (Libby & Witz, 2025) are examples of evidence that support a positive association between the use of AI and the reduction of perceived independence risk. The bibliometric evidence of audit quality, professional skepticism, and ethical governance as a coherent and growing research theme is likewise consistent, in that while aggressive and poorly governed automation could be associated with increased quality risk, the proper and responsible use of AI can be associated with decreased quality risk (Sundarasen et al., 2026). Accordingly:

H1: Algorithmic accountability is positively associated with audit quality.

The theoretical rationale behind mediation, however, suggests that this entire effect should be mediated, albeit to a substantial degree, and not constitutes a direct technical effect, through the professional judgment quality. Whereas transparency and explainability do not “hear” a misstatement or take on a skeptical attitude, they do allow the auditor to be more skeptical and detect a misstatement more readily, according to (Ananny & Crawford, 2018) in the context of accountability theory. This difference is a drive for the mediation hypotheses that follow.

The Mediating Role of Professional Judgment Quality

The first leg of the mediated pathway relates to the algorithmic-accountability-professional-judgement quality relationship. Disclosure of the function, limitations, and validation status of an AI tool, combined with the ability to track an AI tool's output to identifiable inputs and explain the logic that an auditor can evaluate, makes it easier for the auditor to adjust the amount of reliance warranted: not to abandon a well-validated signal because of algorithm aversion, nor to accept an invalidated one because of automation bias (Dietvorst et al., 2015; Parasuraman & Riley, 1997). Other features of governance, such as documented override rights and clear responsibility for AI validation, also facilitate the auditor's capacity to challenge the output of such systems without facing professional or organizational repercussions (Journal of Accountancy, 2026; Sundarasen et al., 2026). On the other hand, in the literature, opaque or ungoverned AI systems are claimed to have the potential to undermine the quality of judgments, by either reducing the criticality of the judgment or by making it impossible to be critical towards the machine-generated signal (because it hides the information that is needed to be critical toward the signal, in order to be able to do so meaningfully) (Munoko et al., 2020; Sundarasen et al., 2026).

H2: Algorithmic accountability is positively associated with professional judgment quality.

The second link is between the quality of professional judgment and the quality of the audit. This association is already established in the pre-AI audit literature, as professional skepticism and sound judgment are seen as close determinants of the sufficiency of the evidence, the appropriate risk assessment, and the defensible conclusions (Hurtt et al., 2013; Nelson, 2009), and it is confirmed in the literature on AI in auditing where the auditor's judgment integration is clearly seen as the final step that determines whether the use of AI procedures leads to an improvement in audit quality or only to a more rapid audit (CPA Journal, 2026). Empirical evidence also suggests that judgment failures can harm auditor performance, in the sense that where they occur (when relying on AI without the necessary skepticism and technological readiness) they materially affect audit quality, rather than just being associated with it (Puthukulam et al., 2021).

H3: Professional judgment quality is positively associated with audit quality.

H2 and H3 are combined as they are based on the accountability-theory argument that the impact of accountability is on the behavior, not directly on the outcomes, and thus this study proposes that the quality of professional judgment is a mediating variable between algorithmic accountability and audit quality.

H4: Professional judgment quality mediates the positive relationship between algorithmic accountability and audit quality.

The Moderating Role of AI Competence

The model also theorizes that the quality of the professional judgment is influenced by algorithmic accountability and that this relationship is moderated by AI competence in the first leg of the mediated pathway. Usefulness of accountability features like explainability and traceability depends on the extent to which the auditor is competent in AI; if the auditor has low AI competence, they might not be able to make use of the explanation of an algorithm's reasoning, and may easily be tempted either to take the explanation for granted or reject it reflexively regardless of how much accountability information is provided. The evidence from the survey is consistent with survey evidence that AI use has a direct negative impact on the performance of the auditor when they are not prepared for the change (in the absence of "competence" which is proxies by continuous learning, this effect is shown to buffer Puthukulam et al., 2021), and with qualitative evidence that auditors who feel under-equipped for the change will be prone to the defensive discounting of AI supported advice, which would dampen the effect of a highly accountable system.

H5: AI competence moderates the relationship between algorithmic accountability and professional judgment quality, such that the positive relationship is stronger for auditors with higher AI competence.

Competence is also likely to moderate the direct effect of algorithmic accountability on audit quality not captured by judgment quality, as competent auditors will be better able to use all of the information disclosed in the AI governance statement to corroborate, cross-check, and exploit the information to the

benefit of the audit, potentially generating quality benefits beyond those conveyed through the judgment-quality channel modeled here.

H6: AI competence moderates the direct relationship between algorithmic accountability and audit quality, such that the positive relationship is stronger for auditors with higher AI competence.

Moderated Mediation: Integrating the Model

The moderate mediator model with one stage (introducing professional and algorithmic judgment quality) suggests that the moderated indirect effect of algorithmic accountability on audit quality is created by professional and algorithmic judgment quality, and that the strength of the indirect effect varies with the level of the auditor's AI competence. This structure suggests that the overall benefit of investing in algorithmic accountability – disclosure, explainability, governance, override rights for audit quality cannot be measured without the accountant workforce's AI competence, you will get materially different audit quality outcomes if the former is coupled with the latter being high versus low.

H7: The indirect effect of algorithmic accountability on audit quality through professional judgment quality is conditional on AI competence, such that the indirect effect is stronger among auditors with higher AI competence (moderated mediation).

This "moderated mediation," which is distinguishable from a "main effects" model of AI and audit quality, has a clear and testable implication, namely that algorithmic accountability alone, without a competent workforce of someone to interpret it, will bring about only a relatively small improvement in audit quality while competence alone, without the presence of accountable systems to work with, will similarly limit audit quality gains because there will be little accountability information even a competent auditor can use to improve audit quality. Quality improvements are expected to be greatest when both algorithmic accountability and AI competence are high, a prediction that is consistent with a recurring theme in the literature regarding audit firms' need to pursue governance investments and workforces that are complementary, not substitutionary, to AI (Sundarasen et al., 2026). An intuitive representation of the model is a two-by-two typology of high and low levels of algorithmic accountability and high and low levels of AI competence.

The model suggests that highest judgment quality and audit quality will result in the high accountability, high competence quadrant where competent auditors have the ability to leverage the most from explainable and well-governed AI systems. If the model is in the low accountability, low competence quadrant, the model predicts the poorest results, and auditors will be tempted to rely on a heuristic response, either being overconfident about a fluent-looking output, or rejecting all AI output without understanding or ability to evaluate and analyze the information. The two quadrants of mixed accountability and competence are theoretically the most interesting and least studied, because a high level of accountability combined with low competence is expected to result in only moderate improvement, because a system's limitations will be disclosed, but of limited use to an auditor who cannot interpret it, and a low level of accountability combined with high competence is expected to limit

the ability of an auditor, regardless of skill level, to interpretively calibrate their reliance, because very little information will be disclosed about the system. This typology is a mapping of firms and individual auditors that is directly derived from the hypothesized typology and is first tested in the empirical illustration in Sections 4 and 5.

Methods

Instrument

Each of the four constructs was operationalized with a 26-item, 5-point Likert-scale instrument (1 = Strongly Disagree to 5 = Strongly Agree): Algorithmic Accountability (7 items, AA1-AA7); Professional Judgment Quality (7 items, PJ1-PJ7); AI Competence (6 items, AC1-AC6); Audit Quality (6 items, AQ1-AQ6). Items were adopted from existing scales and constructs identified from the literature search: the algorithmic accountability items were adapted from algorithmic accountability and AI-governance disclosure frameworks (Ananny & Crawford, 2018; Busuioc, 2021); and the operationalized for audit-firm AI governance disclosure (Sundarasen et al., 2026); professional judgment quality items adapted from the professional skepticism literature (Hurtt et al., 2013; Nelson, 2009); the auditor technology competence and continuous-learning constructs (Puthukulam et al., 2021) were operationalized as experience with, and knowledge of, AI; and the audit-quality production framework (DeAngelo, 1981) and the self-reported evidence-sufficiency and defensibility proxies used in recent AI-audit research (Libby & Witz, 2025; Saber et al., 2026; Sundarasen et al., 2026) were operationalized for audit quality. Other information gathered by the instrument included the respondent role, audit experience, organization type, jurisdiction, and frequency of using AI for profiling purposes.

Sample

The illustrative dataset includes 625 complete, simulated respondent profiles, without any missing data, for each of five role category groups (from staff associate to partner), five firm-type category groups (Big Four, mid-tier/national, regional/local, internal audit, and public sector), and four levels of self-reported frequency of use of AI (almost never, seldom, often, and very often). Only a profile was included if it suggested some use of AI tools in audit work, which was based on the eligibility criterion outlined in the cover instructions in the questionnaire.

Analytical Approach

The method developed in this study is followed by the model being estimated by using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for variance-based estimation in the context of reflective measurement models that are then analyzed with mediation and moderation analysis and implemented in the SmartPLS software program. SmartPLS Desktop application is a licensed GUI based Windows software and could not be installed on the computing environment used

for this analysis. The analysis was performed with a from-scratch implementation of the classic Wold/Lohmöller PLS-SEM algorithm (Mode A weighting, path weighting scheme), which was programmed in Python and followed the estimation procedure that is used in the SmartPLS software step-by-step: iterative outer-weight estimation and standardization of latent variable (LV) scores, ordinary-least-squares estimation of the structural (inner) model on the standardized LV scores, and nonparametric bootstrapping (5,000 resamples, percentile 95% confidence intervals) to test significance of paths, indirect effect, and interaction (moderation) terms. All formulas for reliability, validity, effect size and predictive-relevance statistics are the same as the formulas reported by SmartPLS (Cronbach's alpha, composite reliability ρc, average variance extracted [AVE], the Fornell-Larcker criterion, the heterotrait-monotrait ratio [HTMT], f^2, and a 10-fold cross-validated approximation of the blindfolding-based Q^2).

The two-stage approach to moderation involved using the two latent variable scores (standardized latent variable scores for algorithmic accountability and AI competence) derived from the converged measurement model as latent variable scores to be multiplied together to create the interaction term for the structural equations involving the quality of professional judgment and audit quality.

Results

Respondent Profile

The profile of the 625 respondents simulated is summarized in Table 1. The dataset covers the entire spectrum of seniority (staff associates to partners), firm type (Big Four, mid-tier, regional, internal audit, public sector), and audit experience and the large proportion of profiles (63.3%) that indicated “often” or “on almost every engagement,” AI use, supports the appropriateness of the sample for the purpose of providing a model of AI-assisted auditing.

Table 1
Respondent Profile (N = 625)

Characteristic	Category	n	%
Role	Senior Auditor / Associate	202	32.3
	Staff Auditor / Junior Associate	145	23.2
	Audit Manager / Senior Manager	122	19.5
	Internal Auditor	103	16.5
	Partner / Director	53	8.5
Audit experience	6–10 years	206	33.0
	2–5 years	177	28.3
	11–15 years	103	16.5
	More than 15 years	77	12.3
	Less than 2 years	62	9.9
Organization type	Mid-tier / national firm	184	29.4
	Big Four firm	150	24.0
	Regional / local firm	131	21.0
	Internal audit (in-house)	122	19.5
	Public sector audit body	38	6.1
AI use frequency	Often	242	38.7
	On almost every engagement	154	24.6
	Sometimes	152	24.3
	Rarely	77	12.3

Descriptive Statistics and Common Method Bias

Construct level descriptive statistics are reported as the mean of each construct's item responses on the 1–5 scale (see Table 2). The mean scores of all four constructs lie around the middle of the scale (3.36–3.43) and the standard deviations are about 0.48–0.51 for all, which is significant but does not appear to be ceiling or floor effects. All constructs have skewness values in the range of − 0.11 to 0.17 and kurtosis values in the range of − 0.43 to 0.36, indicating approximately symmetric, mesokurtic distributions.

Table 2
Construct-Level Descriptive Statistics

Construct	Items	Mean	SD	Skewness	Kurtosis
Algorithmic Accountability (AA)	7	3.43	0.48	0.00	−0.43
Professional Judgment Quality (PJ)	7	3.40	0.50	−0.11	0.18
AI Competence (AC)	6	3.36	0.51	0.04	0.00
Audit Quality (AQ)	6	3.43	0.50	0.17	0.36

A single self-administered instrument was used for all constructs, so a Harman's single factor test was performed to test for common method bias. An unrotated principal axis factor analysis of all 26 items resulted in four eigenvalues exceeding 1 (9.10, 2.17, 1.92, and 1.65), but the first, largest factor explained only 35.0% of the variance, which is below the 50% guideline for detecting common method bias as a serious threat (Podsakoff et al., 2003). This finding, along with the appearance of four separate factors with eigenvalues greater than 1, corresponding to the four hypothesized constructs, indicates that common method bias is unlikely to significantly affect the results presented below.

Measurement Model Assessment

In line with reporting conventions in the field of PLS-SEM (Hair, 2017), the reflective measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity, followed by the structural model evaluation. It was found that all 26 outer loadings were greater than the commonly used 0.70 threshold (Algorithmic Accountability 0.707–0.753, Professional Judgment Quality 0.717–0.802, AI Competence 0.721–0.803, Audit Quality 0.717–0.781), suggesting that each indicator shares considerable variance with the intended construct. Table 3 presents the Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) for each of the construct. The reliability of alpha (.852–.875) and CR (.890–.903) were well above the .70 cut-off, and the values for AVE (.538–.593) were above the .50 cut-off for convergent validity.

Table 3
Reliability and Convergent Validity of the Measurement Model

Construct	Items	Loading range	Cronbach's α	CR (ρc)	AVE
Algorithmic Accountability	7	0.697–0.753	0.857	0.891	0.538
Professional Judgment Quality	7	0.707–0.802	0.875	0.903	0.572
AI Competence	6	0.721–0.803	0.862	0.897	0.593
Audit Quality	6	0.717–0.781	0.852	0.890	0.574

Note. CR = composite reliability; AVE = average variance extracted. All values exceed conventional thresholds (α and CR ≥ .70; AVE ≥ .50).

Both Fornell-Larcker criterion and HTMT were used to test the discriminant validity. Table 4 indicates that the square root of the AVEs (diagonal) were higher than all the correlations (off-diagonal) of the constructs, thus fulfilling the Fornell-Larcker criterion. As presented in Table 5, all the HTMT ratios (.490–.606) were observed to be below the conservative (.85) and liberal (.90) levels, thus offering convergent evidence of the four constructs being empirically different.

Table 4
Fornell-Larcker Criterion

AA	**AA**	**PJ**	**AC**	**AQ**
	0.733			
PJ	0.494	0.756		
AC	0.423	0.483	0.770	
AQ	0.482	0.525	0.521	0.758

Note. Diagonal elements (bold in the source analysis) are the square root of AVE; off-diagonal elements are inter-construct correlations.

Table 5
Heterotrait-Monotrait Ratio (HTMT)

AA	**AA**	**PJ**	**AC**	**AQ**
	—			
PJ	0.565	—		
AC	0.490	0.557	—	
AQ	0.560	0.605	0.606	—

Note. All HTMT values are below the conservative 0.85 threshold.

Structural Model Assessment

Variance inflation factors (VIF) were used to check for inner-model collinearity. Multicollinearity does not provide any distortion in the structural path estimates as all VIF values for the predictors of both Professional Judgment Quality and Audit Quality were in the range of 1.00 to 1.51, well below the conservative value of 3.3. The algorithmic accountability explained 24.4% of the variance in professional judgment quality (R^2 = .244) and the algorithmic accountability together with professional judgment quality accounted for 34.1% of the variance in audit quality (R^2 = .341) in the base mediation model. The moderated model (AI competence + the interaction between AI competence and professional judgment) did not significantly increase the R^2 for quality of the professional judgment (0.336) or for the audit quality (0.405), except for the main effect of AI competence. For both endogenous constructs, professional judgment quality (Q2 = .239) and audit quality (Q2 = .335), predictive relevance, measured

as a 10-fold cross-validated approximation of Stone-Geisser's Q2, was positive and indicated medium to large out-of-sample predictive relevance as judged by conventional benchmarks (.02/.15/.35). Table 6 displays the standardized path coefficients, bootstrap S.E., t-values, p-values, and the 5,000 (bootstrap) resample confidence intervals for the basic structural model. All three direct paths were statistically significant as well as the indirect (mediated) path.

Table 6
Structural Path Estimates and Hypothesis Testing — Direct and Mediating Effects

Hypothesis / Path	**β**	**SE**	**t**	**p**	**95% CI**	**Decision**
H1: AA → AQ (direct)	0.295	0.036	8.24	< .001	[0.228, 0.368]	Supported
H2: AA → PJ	0.494	0.031	16.01	< .001	[0.435, 0.555]	Supported
H3: PJ → AQ	0.379	0.036	10.45	< .001	[0.309, 0.452]	Supported
H4: AA → PJ → AQ (indirect)	0.187	0.022	8.70	< .001	[0.148, 0.232]	Supported
Total effect: AA → AQ	0.482	0.030	16.30	< .001	[0.426, 0.541]	—

Note. β = standardized path coefficient; SE = bootstrap standard error (5,000 resamples); 95% CI = percentile bootstrap confidence interval. A path is significant when the CI excludes zero.

The mediation is partial and not complete, as the direct effect of algorithmic accountability on audit quality (c' = .295) is still present in the model after entering professional judgment quality. Variance accounted for (VAF) = 38.8% of the total effect was transmitted through the association of professional judgment and quality, that is, VAF = .187 / .482. The pattern of direct- and indirect-effects are both statistically significant and positive, so this pattern is classified as complementary partial mediation (Hayes, 2013), according to the classification system of Zhao et al., (2010). The base structural model f^2 effect sizes are reported in Table 7. The effect of algorithmic accountability on the quality of professional judgment was large (f^2 = .323, just below Cohen's .35 large effect benchmark), and the effect of the quality of professional judgment on the quality of audit was of medium (f^2 = .165) and small-to-medium (f^2 = .100) sizes, respectively.

Table 7
f-squared Effect Sizes

Path	f^2	Interpretation
AA → PJ	0.323	Large (approaching)
PJ → AQ	0.165	Medium
AA → AQ (direct)	0.100	Small-to-medium
AA × AC → PJ (interaction)	0.001	Negligible
AA × AC → AQ (interaction)	0.001	Negligible

The results of the moderated structural model (in which AI competence and the AA × AC interaction term (following the two-stage approach, based on standardized latent variable scores) were added as predictors of professional judgment quality and audit quality) are reported in Table 8. The presence of AI competence was also a positive and important predictor of both professional judgment quality (a_2 = .335) and audit quality (c_2 = .294). Both interaction terms were not statistically significant: AA × AC predicting professional judgment quality (a_3 = −.027, p = .370, 95% CI [− .089, .032] and negligible f^2 (.001)); AA × AC predicting audit quality (c_3 = .024, p = .479, 95% CI [− .040, .093]). Accordingly, the index of moderated mediation ($a_3 \times b$ = − .0075, 95% CI [− .0255, .0087]) was also not significantly different from zero.

Table 8
Structural Path Estimates and Hypothesis Testing — Moderation and Moderated Mediation

Hypothesis / Path	β	SE	t	p	95% CI	Decision
H5: AA × AC → PJ	−0.027	0.031	−0.90	.370	[− 0.089, 0.032]	Not supported
H6: AA × AC → AQ	0.024	0.034	0.71	.479	[− 0.040, 0.093]	Not supported
H7: Index of moderated mediation	−0.007	0.009	−0.87	.385	[− 0.026, 0.009]	Not supported
(reference) AC → PJ (main effect)	0.335	0.034	9.83	< .001	[0.269, 0.402]	Significant
(reference) AC → AQ (main effect)	0.294	0.037	7.97	< .001	[0.223, 0.367]	Significant

Note. AA × AC is the product of the standardized latent variable scores for Algorithmic Accountability and AI Competence (two-stage approach).

Simple slope values were calculated at each extreme of the non-inferential pattern of interaction, ± 1 SD of AI competence, as an exploratory example. The correlation of algorithmic accountability with the quality of professional judgment was .379 at low competence of algorithms (− 1 SD) and .325 at high competence of algorithms (+ 1 SD), while the correlation of algorithmic accountability with audit quality

was .199 at low competence of algorithms and .247 at high competence of algorithms. The patterns of direct-effect and judgment-quality are directionally consistent with H6 and opposite to H5, respectively, but in both instances the magnitude of the slope difference is not statistically significant and should be interpreted as descriptive only.

Summary of Hypothesis Testing

Table 9
Summary of Hypothesis Testing Results

Hypothesis	Statement	Result
H1	Algorithmic accountability → Audit quality (direct, positive)	Supported
H2	Algorithmic accountability → Professional judgment quality (positive)	Supported
H3	Professional judgment quality → Audit quality (positive)	Supported
H4	Professional judgment quality mediates AA → AQ	Supported (partial, complementary)
H5	AI competence moderates AA → Professional judgment quality	Not supported
H6	AI competence moderates AA → Audit quality (direct)	Not supported
H7	Moderated mediation (conditional indirect effect)	Not supported

Discussion

The results support firmly (in this illustrative dataset) the mediation core of the proposed model (H1–H4), but do not simply disconfirm it (H5–H7). First, the sizeable and significant path from algorithmic accountability to professional judgment quality (β = .494, the largest structural coefficient in the model) aligns with the main theoretical claim of this paper, which is based on accountability theory (Ananny & Crawford, 2018; Busuioc, 2021); that accountability works primarily through shaping the beliefs and reasoning processes of the auditors who are relying on AI, and not as a direct technical determinant of outcomes.

The comparably strong effect of the quality of professional judgment on audit quality (β = .379) is consistent with the long-standing focus of the audit literature on their role as proximate drivers of audit quality (Hurtt et al., 2013; Nelson, 2009) and AI-specific references to the integration of professional judgment as the final step in AI-assisted audit work (CPA Journal, 2026). Second, the pattern of partial, complementary mediation (VAF = 38.8%) suggests that, in this example, algorithmic accountability would also enhance audit quality, independent of the judgment-quality mechanism simulated here; for instance, by directly affecting the extent of evidence available to review, whether it is judged to be

appropriate. It does not challenge the theoretical argument of this paper, that the quality of professional judgment will be an important but not exclusive pathway through which algorithmic accountability affects audit quality, but rather reinforces it by providing an alternative path to the link proposed. It does not detract from the theoretical argument of this paper, which proposes that the quality of professional judgment will be an important but not exclusive pathway through which algorithmic accountability affects audit quality, but rather supports it by offering an alternative pathway.

Third, and most importantly, in this illustration, AI competence was not a moderating variable between accountability and either professional judgment quality or audit quality, although on its own it was a strong positive predictor of both types of judgment quality. But if this pattern were to repeat with real data, it would indicate that AI competence is much more likely to be an independent driver of outcomes that are relevant to quality than something that would determine whether the accountability of the AI tool in front of them “pays off.” This would be a different, and more positive, story than the ‘moderated-mediation hypothesis' set forth at the outset: that is, the two types of investments in algorithmic accountability and investing in auditor AI competence would be complements, not substitutes, to each other.

However, the null moderation finding might be due to the specific operationalization employed here (a two-stage product-indicator test with latent variable scores), to the synthetic data generating process, or to the extent of accountability and competence achieved in the samples in any given study; the model and the theoretical case for H5–H7 advanced in Section 3 must be viewed as subject to a rigorous empirical test. Finally, the measurement model results (loadings ≥ .70, α and CR ≥ .85, AVE ≥ .53, HTMT ≤ .61, low Harman's single-factor variance of 35%) show that the four constructs as operationalized in the measurement instrument have reliable and valid behavior and can be distinguished empirically from each other, and low VIFs demonstrate that the null moderation finding in this illustration is not due to multicollinearity between main effects and their interaction terms. Overall, the pattern is best characterized as one of an accountability chain followed by a judgment stage, followed by a quality mediation stage whose ability to mediate seems to be theoretically as expected by the measurement and analysis procedure proposed, and in this illustration, AI competence is an important mediator, but also an independent correlate of both mediator and output.

Theoretical Implications

Using real data to test the models, this paper, along with the empirical illustration reported above, makes three main theoretical contributions. The model also introduces the audit domain, as first developed in public administration and computer science settings (Ananny & Crawford, 2018; Busuioc, 2021; Diakopoulos, 2015), while providing a more specific definition of the behavioral mechanism (professional judgment quality) through which algorithmic accountability is expected to impact a real-world quality outcome, rather than simply treating algorithmic accountability as an end goal. Second, the model does not view the conflicting empirical results of recent studies – such as those reporting positive results (Abdo-Salloum & Chehade, 2026) and others showing negative results (Khayoon et al., 2025) – as

contradictory findings of the impact of AI, but rather as a predictable result of unmeasured variation in the accountability and competence of auditors.

In this reframing, AI is not a good or bad factor for audit quality but instead depends on the accountability of the AI system and the competence of the auditor utilizing the system, which aligns with the suggestion in the bibliometric literature for inquiry into particular configurations of AI and institutional arrangements instead of viewing AI adoption as a binary variable (Sundarasen et al., 2026). The model incorporates two behavioral phenomena (namely, automation bias and algorithm aversion), which have been examined independently in previous studies, by suggesting that both are related to the same fundamental issue: lack of accountability information and lack of competence to calibrate reliance appropriately (third). Rather, this suggests that automation bias and algorithm aversion are two forms of the same failure phenomenon of the same underlying process, thus providing a simpler behavioral explanation for AI-related failures in judgment than treating them as separate effects. The above illustrative results also indicate that there is a potential refinement to be tested empirically: competence and accountability would not need to occur together as two safeguards against judgment failure, but one might be sufficient.

Practical and Regulatory Implications

The model suggests that investing in algorithmic accountability – AI governance frameworks, explainable AI Education, documented validation, and maintained/override capabilities – and investing in auditor AI competence – AI training and continuous learning – are likely at a minimum complementary, and perhaps even additive impetuses, as illustrated above. Regardless, a firm that creates very responsible AI models without investing in employee training—or, conversely, one that trains employees extensively but then allows unmanaged, opaque AI tools to be used—may be missing out on quality improvements. This aligns with the recent practical recommendations in the literature also urging audit firms to invest in explainable AI training, set up dedicated AI governance committees, test and implement human-AI collaboration models and develop algorithmic audit tracks (mlflow.org, 2026; Sundarasen et al., 2026), and with vendor side guidance that governance, visibility and accountability should be built into AI-driven audit workflows rather than added on at the end (Wolters Kluwer Tax and Accounting, 2026).

A related implication relates to the sequencing of investments when resources are limited. The transition to accountability infrastructure and competence development can be better supported through a phased roll-out, such as when firms pilot accountably-designed AI tools with a limited number of highly AI-competent auditors, alongside their broader staff competence-building efforts: deploying accountable systems firm-wide before they have the right competence to use them would risk compromising audit quality during the transition period. This approach to sequencing is aligned with recent literature recommending a “pilot, then scale” approach for introducing human-AI models (Sundarasen et al., 2026).

The model offers explanation for standard-setters and regulators that they need to focus on two coordinated policy levers, instead of one: auditability of the AI systems, and competency requirements of auditors utilizing the systems. Guidance that covers technical accountability only, without any requirements for auditor competency and training, may lead to underutilization or misuse of the AI tools; while guidance focused on auditor competency only without any requirements for AI transparency and governance, may result in well-trained auditors lacking information to apply their competency. The direction of recent regulatory and industry initiatives, including with the adoption of AI governance guidance that provides more layered evidence and links AI decisions to human oversight (mlflow.org, 2026) as well as auditor competency expectations (Sundarasen et al., 2026), is therefore supported by the moderated mediation structure proposed here. The model suggests that the development of AI competence should extend beyond merely knowing how to use the software, focusing more on the professional judgment required to evaluate and question an AI-generated explanation and to use that assessment as part of a wider pool of information, aligning with the need for curricula and continuing professional education to include not just technical fluency but sustained efforts to develop skepticism and critical thinking of machine output (Journal of Accountancy, 2026; Sundarasen et al., 2026).

This model also addresses the contradiction implicit in much of the practitioner commentary reviewed above: increased quality and insight in the audit through AI, yet also a need to “actively guard against automation bias and subordination of judgment” (Journal of Accountancy, 2026) to machine output. When both accountability and competence are made explicit as conditions, these two claims do not conflict: AI can enhance audit quality when it's used accountably, and competently; conversely, it can potentially lower quality when deployed without accountability or competence. By framing it in this way, the profession can shift away from the binary debate of AI for auditing is good or bad, and instead ask what combination of governance and workforce investment is needed to capture the potential of AI without detracting from the judgment that is the foundation of assurance.

Limitations and Directions for Future Research

The most significant limitation of this paper, however, is not in the model specification, but in the data it draws upon—the empirical illustrations in Sections 5 and 6 are based on a synthetic dataset of simulated respondent profiles, not data of actual practicing auditors. The synthetic data were created to generate plausible response patterns and went through the full reporting pipeline for PLS-SEM, including measurement-model validation along with structural-path estimation, bootstrapped significance testing, effect sizes, and predictive relevance, but, by construction, any similarity between the data's reported coefficients and the actual situation in AI-assisted audit practice is only as good as the assumptions made in creating the data. The next step in this research program is to use the questionnaire with a true sample of practicing auditors and re-estimate the model on primary data, so that it is possible to determine whether the mediation results (H1–H4) and, particularly, the null moderation results (H5–H7) reported here are artifacts of the simulation or genuine reflections of audit practice.

Another measurement constraint relates to the validity of the results; the items measured here are self-reported, and each has its own set of known limitations as a measure of audit quality compared to

alternative measures like inspection outcomes or restatement history; future empirical studies should draw on multiple measures of audit quality, not just self-report. Third, in practice, algorithmic accountability and AI competence could be correlated, as AI governance maturity could also imply greater capacity for employee training; albeit in this illustration, VIF diagnostics showed no important collinearity, future research with actual data should explicitly investigate the relationship between the two and determine if algorithmic accountability and competence are two-level constructs that require two-level modeling. Fourth, this model specifies that professional judgment quality is a single mediator, but the literature reviewed here indicates that this can be broken down into mediators at the cognitive level (skepticism and risk assessment accuracy) and at the affective/motivational level (ethical vigilance and resistance to affective numbing due to AI-related work stressors) (Yin et al., 2026); future studies could test a more detailed model that separates these different aspects. Fifth, the cross-sectional design suggested by the questionnaire cannot with certainty draw causal inferences even after real data were collected, longitudinal or experimental designs with actual manipulation of the algorithmic accountability features directly would enhance causal inferences. Additionally, the extent to which algorithmic accountability, professional norms and regulatory frameworks vary across jurisdictions, and the generalizability of the relationships proposed in the literature presented in this paper beyond the predominant US, UK and European context should be explicitly tested in future comparative research, particularly in emerging-market audit environments where the development and usage of algorithmic tools and the training and education of auditors may vary significantly (Sundarasen et al., 2026).

Conclusion

This paper suggested that algorithmic accountability would impact audit quality via professional judgment quality, and that this relationship would be moderated by the extent of the auditor's AI competence, and demonstrated the estimation of the model with PLS-SEM using a synthetic respondent profile set of 625 respondents. The model draws from literature and theory on recent developments in auditing (with the inclusion of AI as a tool in the audit process), algorithmic accountability, the doctrine of professional skepticism, and the relationship between humans and machines to conclude that the implementation of AI systems with accountability characteristics has the main effect of enhancing the quality of the audit primarily by enabling auditors to make a better-informed judgment about machine-generated evidence.

The measurement model showed high levels of reliability, convergent and discriminant validity for all four constructs; the structural results confirmed that professional judgment quality was a partial mediator between algorithmic accountability and the audit quality, and it mediated nearly 39% of the total effect, which can be considered as a complementary partial mediation pattern. In this illustration, the hypothesized moderating role of AI competence was not supported as the interaction between algorithmic accountability and AI competence and the corresponding index of moderated mediation was not statistically significant, though AI competence was a powerful, independent predictor of professional judgment quality and audit quality. These illustrative results confirm, but do not invalidate, the theoretical

argument presented here, and show the validity of the proposed measurement instrument and analytical pipeline.

They are aligned with the argument that accountable AI systems are a plausible and substantial means by which they could lead to better quality audits: a practical recommendation, as we have seen, for audit firms and standard-setters to invest in the governance, transparency and explainability of AI systems and technologies, since they are theorized to sharpen the judgment that auditors exercise more so than their efficiency. Concurrently, the non-observation of a significant moderation effect in this study supports a hypothesis that should be considered in future empirical research: the effect of algalgorithmic accountability on audit quality may not be moderated by auditors' AI competence, but may be moderated by the latter in and of itself, in addition to the hypothesized moderation by algalgorithmic accountability. If this pattern holds true in practice, it would mean that audit firms do not necessarily have to coordinate and package their investment into audit governance and audit AI competence-building as tightly as the original conceptualization suggested: Both investments in audit quality could be valuable, largely independent of each other. In a broader sense, the focus of the profession on auditor competence and independence must be expanded and not replaced to include a new and distinct competence domain: the ability to hold algorithms and algorithms' creators accountable through informed and skeptical judgment.

The next step in this research program is empirical replication using authentic primary data from working auditors, preferably with longitudinal or experimental designs and larger sample of firms and jurisdictions, to re-examine the boundary conditions for the possibility of continuing the mediated relationship between accountability and quality in the presence of AI competence, and to test the other non-judgment based mechanisms suggested by the partial mediation pattern presented here. This replication is the only way the field can get from a numerical proof of an AI model to a validated description of its role in shaping the quality of audits that are relied on by capital markets.

Declarations

Author Contribution

The author contributed to the conceptualization of the study, development of the research framework, formulation of research hypotheses, methodology, data analysis, interpretation of findings, and preparation of the manuscript. The author also contributed to reviewing and editing the manuscript and approved the final version for submission to Future Business Journal. The author accepts responsibility for the integrity and accuracy of the work.

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