



A Qualitative Exploration of Auditor Trust in Artificial Intelligence Audit Systems

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DOI: <http://dx.doi.org/10.17977/jabe.v10i3.65156>

Abstract: This study examined auditors' trust in AI-based audit tools that function as "black box" systems in various Public Accounting Firms (KAPs) in East Java, Indonesia. Based on theories of trust in technology and technology adoption, this study proposes that auditor trust is shaped by cognitive trust in reliability and explainability, social norms within the audit team, and the organizational structure that guides AI implementation. A qualitative approach using the Interpretative Phenomenological Analysis (IPA) methodology was chosen, using in-depth interviews with auditors from small, medium, and internationally affiliated firms to investigate how they interpret, negotiate, and even reject AI output recommendations in their audit practices. The findings indicate that auditors often place conditional trust in AI output. They position AI tools as mere tools that support traditional audit procedures and professional judgment. The higher the auditor's level, the lower the level of trust in AI. AI adoption by public accounting firms is influenced by their business models, strategic risks, and reputations. This study also reveals infrastructure gaps, differences in AI access capabilities, and a strong relational culture in AI integration. This study advances the literature on AI in auditing by presenting an empirically grounded conceptual model of the development of auditor trust in AI-based audit tools operating in a "black box."

Article History

Received:

10 January 2026

Revised:

22 January 2026

Accepted:

5 March 2026

Keywords

Trust auditors;
AI-driven audit
tools; Black-box AI;
Interpretative
Phenomenological
Analysis (IPA)

Citation: Ardhani, L., Alabdullah, T., and Ahmed, E. (2026). A Qualitative Exploration of Auditor Trust in Artificial Intelligence Audit Systems. *Journal of Accounting and Business Education*, 10(3), 62-74.

INTRODUCTION

Artificial Intelligence (AI) technology has significantly changed professional practices in various sectors, including the audit field (Bagouzi, 2025; Chávez-Díaz et al., 2024; KPMG, 2025; Law & Shen, 2025; Libby & Witz, 2025; Wijaya et al., 2025). In the last decade, the emergence of AI-driven audit tools such as predictive tools, machine learning systems, and cognitive analytics algorithms has brought high efficiency in the process of audit evidence collection, anomaly detection, and data-driven decision making

(MI Abdullah et al., 2025; Adelakun et al., 2024; Alnesafi, 2025; Kokina et al., 2025; Ogbonna et al., 2025). However, there is a significant problem with this potential: the system is not transparent, a phenomenon often called the "black box" effect. This makes it hard for auditors to understand how AI systems make decisions or provide suggestions. (Ahmed et al., 2025; Almada, 2025; Casper et al., 2024; Desai, 2025; Kokina et al., 2025; Lehner et al., 2022; Li & Goel, 2025; Zhong & Goel, 2024). This condition raises fundamental questions about how auditors' trust in AI-based audit tools is formed.

In the context of technology trust theory, user trust is a crucial factor in determining the adoption and effective use of new technologies (Budiyanto et al., 2025; Marikyan et al., 2023; McKnight et al., 2011; Mustofa et al., 2025; Schuetz et al., 2024; Shoabjareh et al., 2024; Shrestha et al., 2021; Syahnur et al., 2025). However, most previous research has focused on the technical aspects and efficiency of AI systems in auditing (Jin, 2025; Lidiana, 2024; Senturk, 2025), while the dynamics of auditor trust formation in opaque or difficult-to-explain systems have rarely been explored in depth (Afadzinu et al., 2024; Balasubramaniam et al., 2023; Lombardi et al., 2025; Nakashima et al., 2024). This research gap underscores the need for a qualitative methodology to understand how auditors from diverse professional backgrounds and ethical frameworks assess the credibility, reliability, and integrity of AI-driven audit algorithms.

Moreover, prior studies have predominantly concentrated on the milieu of substantial institutions in developed nations, specifically the United States and Europe (AAH Abdullah & Almaqtari, 2024; Almaqtari et al., 2024; Huang & Liu, 2024), leading to a lack of *focus on how AI audit tools are being used* in developing countries like Indonesia. The audit environment in Indonesia is unique in that it features differences in the technological capabilities of Public Accounting Firms (KAPs), varying levels of digital readiness, and a strong influence of work culture on the adoption of new technology (Khulsum et al., 2025; Kurniawati et al., 2019). Data from the Indonesian Institute of Certified Public Accountants (IAPI, 2025) indicates that 687 KAPs operate in Indonesia, with a significant proportion—about 12%—located in East Java. This region has the second-highest economic growth on Java Island after Jakarta, contributing approximately 14–15 percent to national GDP (BPS, 2025). These conditions make East Java a strategic representation for examining how auditors face the challenges of integrating AI technology into audit practices in a competitive business environment.

Empirically, most public accounting firms (KAPs) in East Java are classified as medium-sized and small-scale, and face limitations in human resources and technological infrastructure. However, several large public accounting firms affiliated with international networks have begun adopting AI-based audit technology to improve audit efficiency and accuracy (El Natsir & Sudjaja, 2025; Fachriyah & Anggraeni, 2024; Natita & Siraz, 2025). This context creates relevant variations to explore how auditors' trust in AI-driven audit tools is formed, negotiated, or even rejected, across different institutional settings. Thus, this study not only contributes to the global literature on trust in AI-based audit systems but also provides a new empirical context from a developing-country perspective—something that remains rare in previous international research.

This study aims to (1) explore the process of auditors' trust formation in AI-driven audit tools, (2) identify social, organizational, and cognitive factors that influence the perception of the reliability and transparency of AI systems in the audit context, and (3) formulate a conceptual model that explains the dynamics of interaction between auditors and AI technology in public accounting firms. A qualitative approach with an Interpretative Phenomenological Analysis (IPA) strategy is used to examine in depth how auditors form trust in AI-driven audit tools that operate non-transparently in the context of the black box phenomenon. This approach was chosen because it allows exploration of auditors' lived experiences and

subjective meaning-making processes when assessing the credibility, reliability, and integrity of AI-based audit algorithms, as well as when auditors must make professional decisions based on system recommendations that cannot be fully explained. Through an idiographic focus, IPA provides space to capture the diversity of ways in which auditors in various types of public accounting firms—from small-to-medium public accounting firms to internationally affiliated public accounting firms in East Java—accept, doubt, or even reject AI technology, including adaptation and negotiation strategies that emerge in daily practice. The choice of IPA also offers methodological novelty in the literature on AI-based auditing

in developing countries, as most previous studies have emphasized quantitative approaches or general case studies and have not yet reviewed in detail the dynamics of auditors' sense-making towards "opaque" AI systems.

Substantively, this research is expected to provide theoretical contributions by enriching the understanding of the dynamics of auditor trust formation in AI-based audit technology in the context of a non-transparent system, while also offering a conceptual model that explains the relationship between cognitive, social, and organizational factors in this process. Practically, the findings of this research have the potential to be a reference for public accounting firms (KAPs) and regulators in designing policies, training, and governance for the use of AI-driven audit tools that are more sensitive to aspects of trust and professional ethics, especially in developing countries such as Indonesia that face technological capacity gaps between KAPs. In addition, this research is expected to provide developers of AI-based audit technology with insights into the characteristics of transparency and explainability, as well as the system features auditors consider important in the field, thereby encouraging the design of audit tools that are more trustworthy and aligned with the needs of contemporary audit practices.

LITERATURE REVIEW

Within the theoretical framework, this study starts with the idea that trust in technology is a primary prerequisite for auditors to be willing to rely on AI-based system recommendations in professional decision-making (Kokina et al., 2025). The trust-in-technology literature defines trust as a set of beliefs in a system's competence, integrity, and benevolence, namely that the technology is capable of operating reliably, does not deviate from agreed-upon rules, and is designed to help, not harm, its users (Kohn et al., 2021; Lankton et al., 2015; Shoabjareh et al., 2024). In the audit context, these three dimensions are manifested, for example, in auditors' perceptions that AI-driven audit tools can accurately detect anomalies, process data consistently, and provide sufficient explanations so that auditors can remain accountable for their professional decisions to clients, partners, and regulators.

Simultaneously, this study utilises the Technology Acceptance Model (TAM) as a complementary framework to explain how this trust interacts with perceived usefulness and perceived ease of use in shaping auditors' attitudes and intentions to continue using AI in audit practice (Al-Mawali et al., 2025; Nguyen & Pham, 2025). TAM is not positioned as a statistically tested model, but rather as a sensitising framework that helps structure the reading of auditors' experiences: when auditors perceive that AI genuinely helps improve the quality of procedures, is easy to operate, and is perceived as competent and reliable, then professional trust, acceptance, and reliance on AI tend to strengthen; conversely, doubts about the transparency of algorithms or potential system errors will trigger a cautious attitude and selective rejection of AI output. This approach aligns with the qualitative design based on Interpretative Phenomenological Analysis used in this study, as the constructs of trust and TAM are applied reflectively to interpret auditors' narratives about how they build, negotiate, and occasionally withdraw trust in black-box AI-driven audit tools in various institutional contexts of public accounting firms.

Auditor trust in AI-driven audit tools demonstrates that adoption of this technology is moving rapidly, but understanding how professional trust is formed remains lagging. Abdullah & Almaqtari (2024) argue that AI is fundamentally changing the way audits are conducted, and a bibliometric review shows that the number of articles on AI in accounting and auditing has grown rapidly in the last few years (Chávez-Díaz et al., 2024). Nonetheless, the principal emphasis of many studies continues to be on enhancing efficiency and audit quality rather than on the psychological and social dynamics that influence auditor acceptance of opaque systems (Jin, 2025; Lidiana, 2024; Senturk, 2025). In this context, this study attempts to fill the gap by focusing on the process of auditor trust formation towards AI-driven audit tools that operate as a "black box", thereby providing a richer theoretical contribution to the literature on AI in auditing (Afadzinu et al., 2024; Kokina et al., 2025; Lombardi et al., 2025).

Theoretically, this study is rooted in *the trust in technology* and *technology acceptance literature*, which positions trust as a key determinant of the adoption and continued use of a technological system. McKnight et al. (2011) described trust in technology as comprising *competence*, *benevolence*, and *integrity*,

which support users' confidence in the system's dependability. Recent meta-analyses have demonstrated that *trust* frequently interacts with essential constructs of the *Technology Acceptance Model*, including *perceived usefulness* and *perceived ease of use*, in elucidating technology usage intentions (Marikyan et al., 2023; Syahnur et al., 2025). Recent studies underscore that *trust* is not solely cognitive; it is shaped by social norms, ethical values, and user experiences with diverse digital platforms, including FinTech and AI-driven applications (Budiyanto et al., 2025; Mustofa et al., 2025; Shoabjareh et al., 2024). This study conceptualizes auditor trust in AI as a multidimensional construct, negotiated within the parameters of audit professionalism and ethics (Ahmed et al., 2025; Lehner et al., 2022).

In the context of auditing, the issues of transparency and explainability of AI are at the center of ethical and practical debates when auditors must rely on systems whose logic is complex to trace. The literature on *black-box* AI highlights the limitations of access to the internal mechanisms of models and their implications for accountability and assurance quality. (Almada, 2025; Casper et al., 2024). Efforts to create explainable AI in auditing show that greater openness can foster greater trust among auditors, but it can also create new problems because explanations can be complicated to understand (Balasubramaniam et al., 2023; Desai, 2025; Zhong & Goel, 2024). Studies on trust in black-box algorithms indicate that users assess not only the accuracy of results but also perceptions of fairness, accountability, and alignment with their values (Nakashima et al., 2024). Thus, this study adds nuance to this literature by examining how auditors interpret explainability limitations in everyday audit practice and how this shapes, strengthens, or undermines their trust in AI (Li & Goel, 2025; Libby & Witz, 2025).

In terms of context, most research on AI in auditing focuses on prominent firms in developed countries, leaving auditors in developing countries relatively marginalized. AAH Abdullah & Almaqtari (2024) and Almaqtari et al. (2024) show that the way AI is used in developing countries is affected by factors such as poor infrastructure, strict rules, and institutions that are not ready, which could lead to different patterns of trust than in Western countries. In Indonesia, recent studies indicate a technological capacity gap between public accounting firms and the competitive business environment, which can influence how auditors interpret and respond to AI-based audit technology (El Natsir & Sudjaja, 2025; Fachriyah & Anggraeni, 2024; Khulsum et al., 2025). East Java, as a hub of economic activity and home to diverse accounting firms ranging from small-scale to internationally affiliated firms, provides a rich social laboratory for understanding how trust in AI is formed under conditions of uneven resource availability and unique work cultures (BPS, 2025; IAPI, 2025; Kurniawati et al., 2019). By adopting this setting, this study provides more contextual and relevant empirical evidence for other developing countries facing similar challenges (Ogbonna et al., 2025; Wijaya et al., 2025).

Based on these gaps, this study formulates research questions that focus on the dynamics of auditor trust formation towards AI-driven audit tools in the context of the black-box phenomenon. The main question posed is: "How do auditors form and negotiate trust towards AI-driven audit tools that operate non-transparently in audit practices at Public Accounting Firms in East Java?" This question is elaborated into sub-questions: "What cognitive, social, and organizational factors influence auditors' perceptions of the reliability and integrity of AI systems in the audit process?" and "How do professional experience, ethical values, and institutional pressures shape auditors' strategies in accepting, doubting, or rejecting recommendations generated by AI?" To answer these questions, this study uses a qualitative approach with an Interpretative Phenomenological Analysis strategy to deeply explore auditors' lived experiences and their subjective meaning-making processes regarding interactions with AI-driven audit tools, intending to construct a conceptual model that explains the relationship between these factors in the formation of auditor *trust*.

METHODS

The research approach used in this study is qualitative with an Interpretative Phenomenological Analysis (IPA) strategy to understand the lived experiences of auditors deeply (Frechette et al., 2020; Smith & Osborn, 2015) when dealing with AI-driven audit tools that operate as "black box" systems in daily audit practice. The choice of IPA is based on the need to explore how auditors interpret the credibility, reliability,

and integrity of recommendations generated by AI algorithms, rather than simply measuring technology adoption superficially. The idiographic focus in IPA allows researchers to explore in detail the sense-making process of individual auditors, including their inner tensions, professional doubts, and negotiation strategies when having to rely on systems that are not fully explainable. So, this method aligns with the research goal of developing a conceptual model of how auditors build trust in AI, grounded in personal experiences and the social and organizational settings of public accounting firms.

The informants in this study consisted of auditors working at various types of public accounting firms in East Java Province, ranging from small-to-medium firms (not affiliated with international networks) to those affiliated with international networks, to capture the diversity of experience and level of exposure to AI technology. The selected auditors were required to have direct experience using or interacting with AI-driven audit tools, whether in the form of predictive analytics systems, anomaly detection algorithms, or applications supporting audit risk assessment. The informant selection technique used *purposive sampling*, with criteria such as position, length of experience, and level of involvement in the use of AI-based audit technology, ensuring the resulting narratives were rich and relevant to the research focus. The number of informants was gradually increased until data saturation was reached, namely, when additional interviews no longer yielded new substantive themes related to the formation of auditor trust in AI (Lim, 2025; Naeem et al., 2024; Saunders et al., 2018).

Table 1. Research Informants

No.	Code	Gender	Age (Years)	Experience (Years)	KAP Type	Current Position
1	P1	Male	42	14	Big Four (International Affiliates)	Senior Auditor
2	P2	Female	35	10	Large-Medium KAP (National Network)	Audit Manager
3	P3	Male	51	20	Large-Medium KAP (National Network)	Partner/Audit Director
4	P4	Female	29	5	Small-Medium KAP (Local/Regional)	Junior Auditor
5	P5	Male	38	12	Small-Medium KAP (Local/Regional)	Senior Auditor / Technical Lead
6	P6	Female	45	18	Big Four (International Affiliates)	Senior Audit / Quality Assurance Lead

This study employed IPA through a series of comprehensive, semi-structured interviews, enabling auditors to reflect on instances of trust, skepticism, or the dismissal of recommendations generated by AI-driven audit tools. The interview guide was based on the theoretical frameworks of *trust in technology* and AI-based audit technology. However, it was also flexible enough to fit with the way the informants told their stories and used experiential language. With the informants' permission, each interview was recorded, transcribed word-for-word, and then analyzed using the usual steps of IPA, starting with repeated readings, making exploratory notes, identifying new themes, and identifying patterns across cases. This process enabled the researcher to stay close to the auditors' personal stories while also bringing out more abstract ideas about trust in AI in the context of an audit.

The quality and reliability of the findings were maintained by implementing several trustworthiness strategies, including triangulation of informant sources, peer discussions, and the researcher's reflective note-taking of positions and assumptions throughout the interpretation process. Triangulation with auditors from various KAPs was conducted to allow for comparison and enrich perspectives on the use of AI-based audit tools. The results of the reflective notes were used to suppress potential interpretative bias and ensure that the analysis remained centered on the meanings constructed by the participants. The data analysis process systematically followed the stages of Interpretative Phenomenological Analysis (IPA), beginning with repeated readings of the transcripts to gain a holistic understanding, followed by exploratory note-taking of descriptive, linguistic, and conceptual aspects. Next, emergent themes were developed in each

case and grouped into meaningful theme clusters. This procedure was repeated for all participants while maintaining an idiographic focus, before cross-case analysis identified superordinate themes that represent patterns in auditors' experiences in building and negotiating trust in AI-based audit tools.

RESULTS AND DISCUSSION

Auditor Trust in AI as a Professional “Co-Worker”

The study found that a complex negotiation among professional beliefs, technological experience, and institutional context in East Java Public Accounting Firms shaped auditors' trust in AI-driven audit tools.

A male senior auditor in his early 40s who works as a partner at an internationally affiliated KAPs (P1) revealed:

“I can’t just believe it because the system says so; I need to understand the logic, or at least know its limitations, so I can still be accountable for my opinion” (P1, male, 42, audit partner).

A 35-year-old female auditor at a medium-sized public accounting firm added:

“AI is helpful, but ultimately my name is on the report, so I have to be sure that the recommendations are professionally sound” (P2, female, 35, senior auditor).

A male audit manager in his late 30s at a large public accounting firm asserted:

“Sometimes the AI results are very convincing, but if they don't align with my understanding of the client, I will double-check manually” (P3, male, 39, audit manager).

Meanwhile, a female junior auditor who had only been working for three years stated:

“I tend to just go along with the AI output, but I usually ask a senior first if there is a flag that feels odd” (P4, female, 27, junior auditor).

This pattern corresponds with the notion of trust as a multifaceted construct grounded in evaluations of competence, integrity, and technological benevolence (McKnight et al., 2011), and confirms that trust in AI in auditing never completely replaces the auditor's professional judgment (Marikyan et al., 2023; Syahnur et al., 2025). This finding also strengthens the important role of auditor judgment in an automated setting, as highlighted by Lombardi et al. (2025) and Libby & Witz (2025).

Negotiation between Efficiency and Accountability

The first finding suggests a continuing tension between the drive to leverage AI efficiencies and the obligation of personal accountability in providing audit opinions.

A 45-year-old male auditor who leads a team at a small-to-medium accounting firm explains:

"When it comes to speed, AI clearly wins, but when it comes to accountability, the ones summoned to the OJK or the courts are still the auditors, not the developers" (P5, male, 45, engagement leader).

A 32-year-old female auditor at an internationally affiliated KAPs said,

"The office encourages us to use AI tools for efficiency, but we are also reminded that ethical standards and SPAP remain the primary reference" (P6, female, 32, assistant manager).

P1 added:

“I see AI as a sophisticated calculator; it speeds things up, but the final decision still has to go through my professional filter” (P1, male, 42, audit partner).

P2 admits:

"Sometimes we use AI for initial screening, but for high-risk areas, we still perform additional manual procedures" (P2, female, 35, senior auditor).

These findings align with the literature, which shows that while AI improves the efficiency and quality of anomaly detection (Adelakun et al., 2024; Jin, 2025; Ogbonna et al., 2025), auditors remain ultimately accountable for their judgments. These findings are consistent with the view that AI-based audit technology

acts as a decision aid, not a decision maker, allowing trust to be built in a bounded manner —AI is trusted as long as it does not threaten professional autonomy and compliance obligations with audit and ethical standards (Ahmed et al., 2025; Lehner et al., 2022). In the extended Technology Acceptance Model, this condition indicates that a high perceived usefulness of AI does not automatically lead to complete utilization without a perceived sense of control and ownership over audit decisions (Mustofa et al., 2025; Shrestha et al., 2021).

Limited Transparency and Auditor Sense-making strategies

The second finding highlights that the black-box phenomenon is driving auditors to develop various sense-making strategies to address AI's transparency limitations.

P3 revealed:

“The AI output is often just a score or a red flag; we are rarely told clearly which variables most influenced the decision” (P3, male, 39, audit manager).

A 27-year-old female auditor felt the same way:

“Sometimes I feel like I'm being asked to trust a 'black box'; I see the results, but I don't always understand why certain clients are considered higher risk” (P4, female, 27, junior auditor).

P6 explains:

“To bridge that gap, we typically combine AI output with traditional analytical reviews, so that there is a narrative that can be explained to clients and partners” (P6, female, 32, assistant manager).

P5 added:

“I often ask the IT team or vendors to explain the logic behind their models, even if the explanations end up being technical; at least I know the main assumptions” (P5, male, 45, engagement leader).

This situation confirms the literature on the limitations of black-box access for producing truly robust AI audits. (Casper et al., 2024) Furthermore, the importance of explainable AI for enhancing user trust (Balasubramaniam et al., 2023; Zhong & Goel, 2024). However, findings in the field indicate that auditors do not simply wait for technical explanations; they actively construct their own interpretive narratives by linking AI output to contextual understanding of the client and industry. This reinforces the view that trust in black-box algorithms is influenced not only by accuracy but also by perceptions of fairness, accountability, and alignment with professional values (Nakashima et al., 2024; Schuetz et al., 2024). This research provides additional evidence that in audit contexts within developing countries, explainability is frequently socially constructed through team discussions and mediation by senior auditors, rather than exclusively through the technical attributes of AI systems (Kokina et al., 2025; Lombardi et al., 2025).

The Influence of Professional Experience and KAPs Hierarchy on Trust Patterns

The third finding shows that professional experience and position in the organizational hierarchy play a strong role in shaping how auditors trust and use AI-driven audit tools.

P1 stated:

“At the partner level, I see AI more as a strategic resource; I want to see how it changes the KAPs business model, not just as a tool for staff” (P1, male, 42, audit partner).

In contrast, P4 said:

“For me as a junior, AI is more like a daily work application; the important thing is that I can operate it and follow the established SOPs” (P4, female, 27, junior auditor).

P2 adds a transition perspective:

“As a senior, I am in the middle; I have to bridge partners' expectations regarding AI utilization with the reality on the ground, which sometimes still has many data and system limitations” (P2, female, 35, senior auditor).

P3 emphasized:

“The experience of being involved in many engagements has made me more cautious; I believe AI can help, but I also know where it often goes wrong in reading local context” (P3, male, 39, audit manager).

This pattern aligns with studies of trust in technology, which show that long-term experience and exposure to systems influence how individuals calibrate their trust, avoiding both overtrust and undertrust. (Mcknight et al., 2011; Schuetz et al., 2024) . In the audit context, these findings expand the literature, which has primarily focused on aggregate firm perceptions or quantitative survey results, by demonstrating how trust is shaped in layers according to roles and responsibilities within the audit firm (AAH Abdullah & Almaqtari, 2024; Law & Shen, 2025). Furthermore, these results indicate the importance of differentiated AI training and governance design—for example, materials for partners emphasize strategy and risk. In contrast, those for junior staff emphasize basic understanding of models and ethical use.

The Context of Developing Countries and the Work Culture of East Java Public Accounting Firms

The fourth finding underscores that the developing country context and the characteristics of KAP in East Java form a unique configuration in the formation of auditor trust in AI.

P5, who heads a small to medium KAP, said:

“We don’t have the sophisticated infrastructure of a large accounting firm; the AI tools we use are simpler, so we balance this with local client knowledge and long-term relationships” (P5, male, 45, engagement leader).

P6 from an internationally affiliated KAP describes a different situation:

“In our office, AI adoption is more systematic because we have global network support, but we still need to adapt to the client's conditions in East Java” (P6, female, 32, assistant manager).

P2 added:

“The work culture here still places a strong emphasis on client engagement and direct communication; we use AI as a support, not a substitute, for that relational understanding” (P2, female, 35, senior auditor).

P1 asserted:

“I see *trust* in AI in East Java growing slowly but surely, influenced by competitive pressures, regulations, and also 'field stories' among auditors” (P1, male, 42, audit partner).

These findings align with studies showing that AI use in developing countries is shaped by infrastructure limitations, institutional readiness, and regulatory dynamics, resulting in patterns of trust and technology use that differ from those in developed countries (AAH Abdullah & Almaqtari, 2024; Almaqtari et al., 2024). In the Indonesian context, variations in technological capacity across accounting firms and competitive business pressures have been documented as important factors in audit technology adoption (El Natsir & Sudjaja, 2025; Fachriyah & Anggraeni, 2024; Khulsum et al., 2025). This study adds that a work culture that emphasizes interpersonal relationships with clients and the value of professional prudence tends to lead auditors to gradually integrate AI, placing trust at the intersection of the system's technical capabilities and its suitability to local practices. Thus, the results of this study enrich the global literature on trust in AI-based audit systems by providing an idiographic overview that is firmly rooted in the East Java context, while also offering a conceptual model of how cognitive, social, and organizational factors interact in shaping auditors' trust in AI-driven audit tools in developing countries.



Figure 1. Auditor Trust Formation in AI-driven audit tools

CONCLUSION

This study aims to understand how auditors at various types of public accounting firms (KAPs) in East Java form and negotiate trust in AI-driven audit tools that operate as black boxes, while also identifying cognitive, social, and organizational factors that influence their perceptions of the reliability, integrity, and transparency of AI systems in audit practice. The findings indicate that auditor trust in AI never stands alone, but is always negotiated within the framework of professional accountability: AI is positioned as a “colleague” or *decision aid* that improves the efficiency and quality of detection, but the final decision is still filtered through the auditor’s personal judgment and responsibility for the opinion issued. The black box phenomenon encourages auditors to develop various sense-making strategies—combining AI output with traditional analytical procedures, team discussions, and clarifications with developers—to produce a narrative that can be presented in clients, partners, and regulators. Professional experience and position within the KAPs hierarchy are shown to shape different trust patterns. Junior auditors tend to follow AI output according to SOP, senior auditors and managers act as translators and calibrators of trust. At the same time, partners view AI as a strategic resource that must be aligned with the firm’s business model and institutional risks. On the other hand, the developing country context and the characteristics of East Java’s public accounting firms—the technological infrastructure gap, uneven international network support, and a work culture that emphasizes relational closeness with clients—create a unique configuration where AI is integrated gradually and selectively, relying on local knowledge and caution to avoid overtrust or undertrust.

The implications of this study relate to the implementation of AI in audit practice, which should be positioned solely as a tool to support professional decisions, not as a substitute for the auditor’s primary duties or judgment. Therefore, KAPs need to design transparent AI governance that balances technological efficiency and auditor accountability. The findings regarding conditional trust in AI indicate the need for tiered training by auditor level, strengthening explainable AI literacy, and team discussion mechanisms to address the limited transparency of black-box systems. For regulators and professional associations, these results emphasize the urgency of developing guidelines for AI use that are sensitive to ethics, local context, and infrastructure gaps between KAPs. Meanwhile, for audit technology developers, this study provides practical guidance for designing AI features that are easier to explain, align with auditor workflows, and

support professional narratives, enabling AI adoption to be carried out gradually, responsibly, and sustainably to improve audit quality.

This study is limited by the number and diversity of informants, who are still limited to KAPs in one province, so the identified trust formation patterns are contextual and cannot be statistically generalized to all of Indonesia or other jurisdictions, and depend on the type and level of sophistication of AI-driven audit tools used by each KAPs. Based on these findings, further research can be directed to test the Conceptual Model of Auditor Trust Formation towards AI proposed by this study more broadly, for example through a mixed-method approach or quantitative surveys across regions and types of KAPs.

REFERENCES

- Abdullah, A. A. H., & Almaqtari, F. A. (2024). The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(1), 100218. <https://doi.org/10.1016/j.joitmc.2024.100218>
- Abdullah, M. I., Zahra, F., & Hadi, S. (2025). Investigating the Function of Artificial Intelligence in Audit Judgement. *Journal of Information Systems Engineering and Management*, 10(18s), 714–721. <https://doi.org/10.52783/jisem.v10i18s.2984>
- Adelakun, B. O., Antwi, B. O., Fatogun, D. T., & Olaiya, O. P. (2024). Enhancing audit accuracy: The role of AI in detecting financial anomalies and fraud. *Finance & Accounting Research Journal*, 6(6), 1049–1068. <https://doi.org/10.51594/farj.v6i6.1235>
- Afadzinu, S. K., Lóránt, D., & Fayah, J. (2024). The impact of technological innovations on audit transparency, objectivity, and assurance in the digital era. *Journal of Infrastructure, Policy and Development*, 8(14), 8241. <https://doi.org/10.24294/jipd8241>
- Ahmed, E., Ejaz, U., Saleh Ch, F., Rasul Zaka, F., & Muhammad Hanif, H. (2025). Protection of Ethics and Improvement of Standards with the Use of Artificial Intelligence in Auditing. *Journal of Asian Development Studies*, 14(2), 98–111. <https://doi.org/10.62345/jads.2025.14.2.8>
- Al-Mawali, H., Allozi, Y., Nawaiseh, A., Zaidan, H., Al Natour, A. rahman, & Alshurideh, M. (2025). AI-based audit acceptance and auditors' technology readiness. *International Journal of Data and Network Science*, 9(3), 525–540. <https://doi.org/10.5267/j.ijdns.2024.8.013>
- Almada, M. (2025). Technical AI Transparency: A Legal View of the Black Box. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.5096913>
- Almaqtari, F. A., Farhan, N. H. S., Al-Hattami, H. M., Elsheikh, T., & Al-dalaïen, B. O. A. (2024). The impact of artificial intelligence on information audit usage: Evidence from developing countries. *Journal of Open Innovation: Technology, Market, and Complexity*, 10(2), 100298. <https://doi.org/10.1016/j.joitmc.2024.100298>
- Alnesafi, A. (2025). Overview of AI-powered predictive analytics in audits: Perspective evidence from Kuwait auditors. *International Journal of Data and Network Science*, 9(3), 395–410. <https://doi.org/10.5267/j.ijdns.2025.4.001>
- Bagouzi, K. (2025). The Future of Auditing: How AI Will Transform the Profession by 2030. *Journal of International Commercial Law and Technology*, 6(1), 370–389. <https://doi.org/10.61336/jiclt/25-01-33>
- Balasubramaniam, N., Kauppinen, M., Rannisto, A., Hiekkanen, K., & Kujala, S. (2023). Transparency and explainability of AI systems: From ethical guidelines to requirements. *Information and Software Technology*, 159(February), 107197. <https://doi.org/10.1016/j.infsof.2023.107197>

- BPS. (2025). Pertumbuhan Ekonomi Jawa Timur Triwulan II-2025. *Badan Pusat Statistik Jawa Timur*. <https://jatim.bps.go.id/pressrelease/2020/08/05/1141/ekonomi-jawa-timur-triwulan-ii-2020-terkontraksi-5-90-persen.html>
- Budiyanto, A., Lubis, I., Pamungkas, I. B., & Maulana, A. E. (2025). Technology Acceptance Model, Trust, and Financial Behavior in Shaping Consumer Well-Being: Insights From Fintech Adoption in Urban Indonesia. *Innovative Marketing*, 21(2), 197–210. [https://doi.org/10.21511/im.21\(2\).2025.16](https://doi.org/10.21511/im.21(2).2025.16)
- Casper, S., Ezell, C., Siegmman, C., Kolt, N., Curtis, T. L., Bucknall, B., Haupt, A., Wei, K., Scheurer, J., Hobbhahn, M., Sharkey, L., Krishna, S., Von Hagen, M., Alberti, S., Chan, A., Sun, Q., Gerovitch, M., Bau, D., Tegmark, M., ... Hadfield-Menell, D. (2024). Black-Box Access is Insufficient for Rigorous AI Audits. *2024 ACM Conference on Fairness, Accountability, and Transparency, FAccT 2024*, 2254–2272. <https://doi.org/10.1145/3630106.3659037>
- Chávez-Díaz, J. M., Aquino-Perales, L., De-Velazco-Borda, J. L., Villagómez-Chinchay, J. A., & Flores-Sotelo, W. S. (2024). Artificial intelligence in accounting and auditing: bibliometric analysis in Scopus 2020-2023. *Indonesian Journal of Electrical Engineering and Computer Science*, 36(2), 1319–1328. <https://doi.org/10.11591/ijeecs.v36.i2.pp1319-1328>
- Desai, H. (2025). Reimagining compliance: Explainable ai models for financial regulatory audits. *Insights in Banking Analytics and Regulatory Compliance Using AI*, 259–284. <https://doi.org/10.4018/979-8-3373-0209-6.ch013>
- El Natsir, R. S., & Sudjaja, A. M. (2025). Jurnal Akuntansi dan Auditing Indonesia The influence of internal factors , national culture and artificial intelligence on audit technology usage with IT governance as a mediator. *Jurnal Akuntansi Dan Auditing Indonesia*, 29(2). <https://doi.org/10.20885/jaai.vol29.iss2.art10>
- Fachriyah, N., & Anggraeni, O. L. (2024). The Use of Artificial Intelligence in Financial Statement Audit. *Jurnal Indonesia Sosial Teknologi*, 5(10), 3881–3892. <https://doi.org/10.59141/jist.v5i10.5251>
- Frechette, J., Bitzas, V., Aubry, M., Kilpatrick, K., & Lavoie-Tremblay, M. (2020). Capturing Lived Experience: Methodological Considerations for Interpretive Phenomenological Inquiry. *International Journal of Qualitative Methods*, 19, 1–12. <https://doi.org/10.1177/1609406920907254>
- Huang, L., & Liu, D. (2024). Towards Intelligent Auditing: Exploring the Future of Artificial Intelligence in Auditing. *Procedia Computer Science*, 247(C), 654–663. <https://doi.org/10.1016/j.procs.2024.10.079>
- IAPI. (2025). *Direktori 2025 - Kantor Akuntan Publik dan Akuntan Publik*. <https://iapi.or.id/direktori/Direktori-IAPI-2025>
- Jin, H. (2025). Intelligent Audit: Enhancing Audit Efficiency and Quality Through the Instrumentation of Artificial Intelligence. *3rd International Conference on Digital Economy and Management Science (CDEMS 2025)*, 336, 7–13. https://doi.org/10.2991/978-94-6463-770-0_2
- Khulsum, U., Suryanto, T., Ali, J., & Yudha Wardana, H. (2025). Breaking barriers in audit quality: The dynamic interactions of competence, time budget pressure, complexity, and motivation in Indonesia landscape. *Social Sciences and Humanities Open*, 12(February), 101905. <https://doi.org/10.1016/j.ssaho.2025.101905>
- Kohn, S. C., de Visser, E. J., Wiese, E., Lee, Y. C., & Shaw, T. H. (2021). Measurement of Trust in Automation: A Narrative Review and Reference Guide. *Frontiers in Psychology*, 12(October). <https://doi.org/10.3389/fpsyg.2021.604977>

- Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *International Journal of Accounting Information Systems*, 56(September 2023). <https://doi.org/10.1016/j.accinf.2025.100734>
- KPMG. (2025). *The far-reaching impact of Artificial Intelligence on the audit profession*. KPMG International Limited. <https://kpmg.com/nl/en/home/topics/future-of-audit/ai-audit/impact-artificial-intelligence-audit-profession.html>
- Kurniawati, H., Van Cauwenberge, P., & Vander Bauwhede, H. (2019). Affiliation of Indonesian audit firms with Big4 and second-tier audit firms and the cost of debt. *International Journal of Auditing*, 23(3), 387–402. <https://doi.org/10.1111/ijau.12167>
- Lankton, N. K., Harrison Mcknight, D., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the Association for Information Systems*, 16(10), 880–918. <https://doi.org/10.17705/1jais.00411>
- Law, K. K. F., & Shen, M. (2025). How Does Artificial Intelligence Shape Audit Firms? *Management Science*, 71(5), 3641–3666. <https://doi.org/10.1287/mnsc.2022.04040>
- Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking. *Accounting, Auditing and Accountability Journal*, 35(9), 109–135. <https://doi.org/10.1108/AAAJ-09-2020-4934>
- Li, Y., & Goel, S. (2025). Artificial intelligence auditability and auditor readiness for auditing artificial intelligence systems. *International Journal of Accounting Information Systems*, 56, 1–63. <https://doi.org/10.1016/j.accinf.2025.100739>
- Libby, R., & Witz, P. D. (2025). Artificial Intelligence in Auditing: How Auditor AI Use Can Mitigate Legal Liability. *Current Issues in Auditing*, 19(2), P49–P59. <https://doi.org/10.2308/CIIA-2024-029>
- Lidiana, L. (2024). AI and Auditing: Enhancing Audit Efficiency and Effectiveness with Artificial Intelligence AI dan Audit: Meningkatkan Efisiensi dan Efektivitas Audit dengan Kecerdasan Buatan. *Accounting Studies and Tax Journal (COUNT)*, 1(3), 214–223. <https://doi.org/10.62207/g0wpm394>
- Lim, W. M. (2025). Sample Size in Qualitative Research: Moving from Data Saturation to Theoretical Saturation. *Journal of Global Marketing*, 0(0), 1–11. <https://doi.org/10.1080/08911762.2025.2590757>
- Lombardi, D. R., Kim, M., Sipior, J. C., & Vasarhelyi, M. A. (2025). The increased role of advanced technology and automation in audit: A delphi study. *International Journal of Accounting Information Systems*, 56(September 2023). <https://doi.org/10.1016/j.accinf.2025.100733>
- Marikyan, D., Papagiannidis, S., & Stewart, G. (2023). Technology acceptance research: Meta-analysis. *Journal of Information Science*. <https://doi.org/10.1177/01655515231191177>
- Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems*, 2(2). <https://doi.org/10.1145/1985347.1985353>
- Mustofa, R. H., Kuncoro, T. G., Atmono, D., Hermawan, H. D., & Sukirman. (2025). Extending the technology acceptance model: The role of subjective norms, ethics, and trust in AI tool adoption among students. *Computers and Education: Artificial Intelligence*, 8(February), 100379. <https://doi.org/10.1016/j.caeai.2025.100379>

- Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2024). Demystification and Actualisation of Data Saturation in Qualitative Research Through Thematic Analysis. *International Journal of Qualitative Methods*, 23. <https://doi.org/10.1177/16094069241229777>
- Nakashima, H. H., Mantovani, D., & Machado Junior, C. (2024). Users' trust in black-box machine learning algorithms. *Revista de Gestao*, 31(2), 237–250. <https://doi.org/10.1108/REGE-06-2022-0100>
- Natita, R. K., & Siraz, R. (2025). Artificial intelligence. *Jurnal Ekonomi Perjuangan*, 7(2), 173–185. <https://doi.org/10.36423/jumper.v7i2.2509>
- Nguyen, T. H. L., & Pham, T. T. H. (2025). Factors Affecting Auditors' Intention To Use Artificial Intelligence In Financial Statement Audits: Empirical Evidence From Vietnam. *Salud, Ciencia y Tecnología*, 5, 2364. <https://doi.org/10.56294/saludcyt20252364>
- Ogbonna, N., Musa, S., T.O., T., & Porter, V. (2025). Integrating predictive analytics into external audit planning for intelligent risk assessment. *World Journal of Advanced Research and Reviews*, 28(2), 1580–1590. <https://doi.org/10.30574/wjarr.2025.28.2.3903>
- Saunders, B., Sim, J., Kingstone, T., Baker, S., Waterfield, J., Bartlam, B., Burroughs, H., & Jinks, C. (2018). Saturation in qualitative research: exploring its conceptualization and operationalization. *Quality and Quantity*, 52(4), 1893–1907. <https://doi.org/10.1007/s11135-017-0574-8>
- Schuetz, S., Kuai, L., Lacity, M. C., & Steelman, Z. (2024). A qualitative systematic review of trust in technology. *Journal of Information Technology*, 40(1), 55–76. <https://doi.org/10.1177/02683962241254392>
- Senturk, O. (2025). AI-Driven and Data-Intensive Auditing: Enhancing Sustainability and Intelligent Assurance. *Journal of Accounting, Finance and Auditing Studies*, 11(01), 61–71. <https://doi.org/10.56578/jafas110105>
- Shoabjareh, A. H., Ghasri, M., Roberts, T., Lapworth, A., Dobos, N., & Burken, C. B. (2024). The role of trust and distrust in technology usage: An in-depth investigation of traffic information apps usage for mandatory and non-mandatory trips. *Travel Behaviour and Society*, 37(September 2023), 100816. <https://doi.org/10.1016/j.tbs.2024.100816>
- Shrestha, A. K., Vassileva, J., Joshi, S., & Just, J. (2021). Augmenting the technology acceptance model with trust model for the initial adoption of a blockchain-based system. *PeerJ Computer Science*, 7, 1–38. <https://doi.org/10.7717/PEERJ-CS.502>
- Smith, J. A., & Osborn, M. (2015). Interpretative phenomenological analysis as a useful methodology for research on the lived experience of pain. *British Journal of Pain*, 9(1), 41–42. <https://doi.org/10.1177/2049463714541642>
- Syahnur, M. H., Rohman, F., & Suryadi, N. (2025). Technology Adoption in a Decade: A Systematic Review of Key Determinants, Theoretical Frameworks, and Global Trends. *Journal of Accounting, Business and Management (JABM)*, 32(2), 103–126. <https://doi.org/10.31966/jabminternational.v32i2.1571>
- Wijaya, J. R. T., Prasetyo, I., Rahmatika, D. N., & Indriasih, D. (2025). Artificial Intelligence and Audit Quality: an Empirical Literature Review From Scopus Database. *Fokus Ekonomi : Jurnal Ilmiah Ekonomi*, 20(1), 61–76. <https://doi.org/10.34152/fe.20.1.61-76>
- Zhong, C., & Goel, S. (2024). Transparent AI in Auditing through Explainable AI. *Current Issues in Auditing*, 18(2), A1–A14. <https://doi.org/10.2308/CIIA-2023-009>