

IMPACT OF ARTIFICIAL INTELLIGENCE ON AUDIT QUALITY: PROFESSIONAL JUDGEMENT, RESPONSIBLE AI GOVERNANCE, AND THE INDIAN AUDIT CONTEXT

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Abstract

Artificial intelligence (AI), including machine learning, document intelligence, generative AI and advanced analytics, is reshaping the way audit teams identify risk, analyse transactions and evaluate evidence. Yet greater analytical capacity does not automatically produce higher audit quality. AI outputs may be incomplete, difficult to explain, biased by source data or accepted too readily by time-pressured professionals. This conceptual paper develops a framework for understanding how AI-enabled auditing may influence perceived audit quality in India, with professional judgement positioned as a key conditioning mechanism. Drawing on the Technology–Organisation–Environment perspective, the Technology Acceptance Model, agency theory and research on automation bias, the paper integrates technological capability with governance, competence, scepticism and accountability. It proposes that AI-enabled auditing is more likely to support audit quality when data and models are reliable, use is aligned with audit objectives, and auditors independently evaluate AI-generated outputs. Professional judgement is expected to strengthen the positive association between AI-enabled auditing and audit quality, while automation bias and weak governance may attenuate it. The paper does not report primary-data findings; instead, it offers propositions, a research-ready measurement framework and a rigorous empirical agenda. The Indian context is timely given the Institute of Chartered Accountants of India's AI Innovation Summit in 2026 and the Government of India's risk-aware AI governance direction. The contribution is a practical, testable account of how audit firms can combine AI capability with human responsibility without confusing automation, efficiency and audit quality.

Keywords:

Artificial Intelligence; Audit Quality; Professional Judgement; Automation Bias; AI Governance; India; Audit Analytics; Generative AI

1. Introduction

Auditing is increasingly data-intensive. Digital accounting platforms, enterprise resource planning systems, e-invoicing records, digital payments and cloud-based business applications generate large volumes of information that conventional sampling and manual review cannot always examine efficiently. AI-enabled tools can help auditors classify documents, identify anomalies, compare records, prioritise risks and analyse unstructured evidence. Research on audit-firm AI investment has

associated such investment with improvements in selected audit-quality outcomes, including lower restatement incidence, although that evidence comes from large US firms and should not be assumed to generalise automatically to India (Fedyk et al., 2022).

The central question is therefore not whether AI can process more information, but under what conditions its use improves the quality of audit work. AI can produce false positives, overlook context, reflect poor-quality client data, or provide plausible but unsupported generative outputs. In addition, auditors may defer to automated recommendations,

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especially when systems appear authoritative or workloads are high. Research on automation describes this as a risk of misuse or overreliance, which can weaken monitoring and independent judgement (Parasuraman & Riley, 1997).

The Indian context makes this question particularly important. The Institute of Chartered Accountants of India (ICAI) held its AI Innovation Summit in June 2026, highlighting AI applications across accounting, audit, tax and governance, alongside professional upskilling (ICAI, 2026). India's AI governance guidance also emphasises accountability, understandable systems, fairness, safety and trust (Press Information Bureau, 2026). Internationally, the IAASB's 2026 proposals to revise ISA 330, ISA 500 and ISA 520 reinforce evidence evaluation, risk response and professional scepticism in a technology-evolving environment (IAASB, 2026). These developments increase the need for an audit-specific framework that connects innovation to evidence quality and accountability.

This paper reframes the original proposed survey as a conceptual paper because no primary dataset, completed analysis or empirical findings were supplied. It does not claim to have tested hypotheses. Instead, it synthesises relevant theory and research, defines propositions and specifies a transparent design for future empirical testing.

2. Objectives and Research Questions

The main aim of the study is to develop a theory-informed framework explaining how AI-enabled auditing may affect audit quality in India and how professional judgement conditions that relationship. The objectives of the study are:

1. To synthesise relevant theories and evidence on AI adoption, audit quality and human judgement.
2. To identify the mechanisms through which AI may improve or undermine audit quality.
3. To conceptualise professional judgement as a moderator of the AI-enabled auditing–audit quality relationship.
4. To incorporate governance, AI exposure and organisational context into a future India-focused empirical design.
5. To propose practical safeguards and a testable measurement framework for audit

practitioners and researchers.

2.1 Research questions

1. Through what mechanisms can AI-enabled auditing support or threaten audit quality?
2. How does professional judgement condition the relationship between AI-enabled auditing and audit quality?
3. Which organisational and engagement-level controls should be considered when evaluating AI-enabled auditing in India?

3. Literature Review and Theoretical Foundations

3.1 AI-enabled auditing: capability rather than outcome

AI-enabled auditing refers here to the use of machine learning, natural language processing, document intelligence, generative AI and advanced analytics to support audit planning, risk assessment, substantive procedures, evidence evaluation and documentation. Rule-based automation and robotic process automation may form part of the digital audit environment, but they should not automatically be labelled AI. The distinction matters because different tools have different failure modes, explainability characteristics and levels of autonomy.

Fedyk et al. (2022) provide empirical evidence that AI investment by large US audit firms is associated with improved selected audit outcomes and lower fees. Their results support the possibility that AI can contribute to quality, but the institutional setting, firm scale and measures used limit direct extrapolation to all Indian audit engagements. More recent field evidence from Kokina et al. (2025), based on interviews with experienced audit professionals, reports widespread use of comparatively mature tools such as document extraction and optical character recognition, while more complex AI and generative applications remain subject to adoption and governance challenges. The same study highlights explainability, bias, privacy, robustness, reliability, overreliance and the need for guidance.

3.2 Defining audit quality

Audit quality should not be reduced to speed, transaction coverage or user satisfaction. It

concerns whether the audit is planned and performed appropriately, whether sufficient appropriate evidence is obtained and evaluated, whether significant risks are addressed, and whether conclusions are supported by the evidence. In a survey-based study, respondents can report perceptions of procedural quality, evidence evaluation and risk coverage; however, these measures are not substitutes for objective engagement outcomes such as restatements, inspection findings or identified deficiencies. The proposed empirical design therefore treats perceived audit quality as a bounded construct and recommends objective or archival indicators where access and ethics permit.

3.3 Professional judgement and professional scepticism

Professional judgement involves applying relevant knowledge, experience, standards and engagement context to make defensible decisions. In AI-assisted work, judgement includes assessing whether a flagged anomaly is material, testing the reliability and relevance of underlying data,

3.5 Theoretical integration

considering contradictory evidence, challenging model limitations and deciding whether further procedures are required. Human review should be substantive rather than ceremonial: a sign-off that merely ratifies an AI recommendation is not meaningful oversight.

3.4 Automation bias and the AI audit-quality paradox

Automation bias occurs when people give automated outputs undue weight or fail to seek disconfirming evidence. Parasuraman and Riley (1997) distinguish appropriate use from misuse, disuse and abuse of automation. In auditing, misuse can arise when auditors accept a model-generated risk score without considering the population, data lineage, false-negative risk or relevant qualitative evidence. The term “AI Audit Quality Paradox” is used in this paper as a descriptive label coined for the framework, not as the title of an independently verified source paper: AI may widen analytical coverage while simultaneously creating new risks to judgement, evidence evaluation and accountability.

Table No 1: Theoretical Perspectives Informing the Framework

Theory	Relevance to this paper	Expected insight
Technology–Organisation–Environment (TOE)	Explains adoption in relation to technological, organisational and environmental conditions (Tornatzky & Fleischer, 1990).	AI capability alone is insufficient; data quality, skills, governance and professional/regulatory context matter.
Technology Acceptance Model (TAM)	Perceived usefulness and ease of use shape acceptance (Davis, 1989).	Adoption may be more likely when auditors see practical value, but acceptance does not establish quality.
Agency theory	Auditing helps reduce information asymmetry and supports accountability (Jensen & Meckling, 1976).	AI may improve monitoring but can also obscure responsibility if decisions are delegated to systems.
Automation-bias research	Explains overreliance and failures to monitor automated advice (Parasuraman & Riley, 1997).	Independent challenge and verification are mechanisms that may preserve audit quality.

Source: Author's conceptual development.

Together, these perspectives separate three questions that are often conflated: whether an organisation adopts AI, whether auditors use it appropriately, and whether its use contributes to high-quality audit work.

4. Indian Context and Developments in 2026

India's audit environment includes large international networks, domestic firms of different sizes,

listed and unlisted companies, public-sector entities and internal-audit functions. Their access to technology, data infrastructure, specialist staff and formal AI governance may differ substantially. A model developed for a large firm with centralised technology support may not perform similarly in a smaller practice or on a client whose records are fragmented.

Three developments provide immediate context. First, ICAI's AI Innovation Summit 2026 signalled active professional attention to AI skills and

applications in accounting, audit, tax and governance (ICAI, 2026). Second, the Government of India's AI governance guidance foregrounds trust, accountability, fairness, transparency and safety, all of which can be translated into audit-tool governance requirements (Press Information Bureau, 2026). Third, the IAASB's 2026 proposed revisions to ISA 330, ISA 500 and ISA 520 place renewed emphasis on the relevance and reliability of audit evidence, risk responses and professional scepticism as technology evolves (IAASB, 2026). These proposals were under consultation in 2026 and should be described as proposed revisions, not as already effective requirements.

For Indian audit practice, the implication is practical: firms need documented approval of tools, safeguards for client confidentiality, controls over data access and retention, testing of outputs,

escalation of anomalous results, and training that combines AI literacy with audit methodology. Use of generative AI should also include checks against fabricated citations, unsupported summaries and disclosure of confidential client information.

5. Conceptual Framework and Propositions

The proposed framework treats AI-enabled auditing as the focal explanatory construct, perceived audit quality as the outcome, and professional judgement as a moderator. Firm type, years of relevant experience, role, industry exposure and level of AI use are proposed as control variables. AI governance and data quality are contextual conditions that may shape whether AI capability translates into reliable audit work.

Table No 2: Key Constructs, Definitions and Suggested Indicators

Construct	Conceptual definition	Suggested indicators
AI-enabled auditing (AIA)	Extent to which AI and advanced analytics are used in relevant audit tasks.	Transaction-population analysis; anomaly identification; risk assessment support; document analysis; timeliness; traceability of outputs.
Professional judgement (PJ)	Independent evaluation of AI outputs using standards, evidence and engagement context.	Verification of source data; evaluation of contradictory evidence; challenge of model recommendations; decisions on additional procedures.
Perceived audit quality (PAQ)	Perceived quality of audit procedures and evidence-based conclusions.	Risk coverage; evidence relevance/reliability; appropriate followup; documentation quality; defensible conclusions.
AI governance (AIG)	Controls governing approved use, validation, access, monitoring and accountability.	Tool approval; access control; output validation; incident escalation; audit trail; human review.
Controls	Respondent and engagement characteristics that may affect relationships.	Firm type/size; role; years of experience; industry; AI exposure; audit type; training.

Source: Author's conceptual development.

Conceptual relationship: AI-enabled auditing → perceived audit quality. Professional judgement is expected to strengthen this relationship. AI governance and data quality are important contextual conditions; they should be measured separately rather than folded into the audit-quality outcome.

5.1 Propositions

P1: Greater appropriate use of AI-enabled auditing is positively associated with perceived audit quality, particularly where AI improves risk coverage and evidence analysis.

P2: Stronger professional judgement is positively associated with perceived audit quality because auditors independently evaluate evidence and determine appropriate responses.

P3: Professional judgement positively moderates the relationship between AI-enabled auditing and perceived audit quality; the association is expected to be stronger when professional judgement is high.

P4: Stronger AI governance and reliable input data are expected to support the conversion of AI capability into audit-quality benefits.

P5: Automation bias is expected to weaken the benefits of AI-enabled auditing when auditors accept outputs without independent verification.

These are theoretical propositions, not findings from the present paper. Their direction and magnitude require empirical testing.

6. Proposed Empirical Research Agenda

A future study can test the propositions through a cross-sectional survey of audit and assurance professionals in India, ideally supplemented by interviews or archival indicators. This section is a proposed protocol; data collection, pilot testing, ethics approval and statistical analysis have not been represented as completed.

6.1 Population and sampling

Target population: professionals currently working in statutory audit, internal audit, assurance, risk advisory, forensic accounting, technology risk or audit analytics in India, with sufficient exposure to audit work to answer the instrument. The sampling frame should be defined before recruitment, using professional networks, firms and relevant professional bodies where permission is granted. Purposive recruitment can ensure role relevance, but convenience and network-based sampling should be acknowledged as limits to representativeness.

Recommended target: approximately 300 usable responses, subject to an a priori power analysis using the smallest interaction effect considered practically meaningful, the number of predictors, desired power (at least .80, preferably .90) and alpha of .05. A sample-size number should not be described as statistically powered until the assumptions and calculation are documented. Recruitment should aim for variation across Big Four and non-Big Four firms, internal audit, firm size, experience levels and AI-exposure levels.

6.2 Pilot, instrument development and validity

Develop the questionnaire from established constructs and audit standards rather than treating the current draft items as a validated scale. Conduct expert review with audit-methodology and research-method specialists, followed by cognitive interviews and a pilot of approximately 20–30 eligible respondents. Refine ambiguous, double-barrelled or leading items before the main survey. Where possible, adapt published validated measures with permission and document each source and adaptation. Do not claim a scale is validated solely because it has high internal consistency.

For measurement quality, report item distributions, missingness and floor/ceiling effects; Cronbach's alpha and preferably McDonald's

omega for internal consistency; confirmatory factor analysis (CFA) for factor structure; and convergent and discriminant validity (for example, composite reliability and average variance extracted where appropriate). If the sample supports it, compare measurement properties across major respondent groups. Predefine rules for item removal rather than deleting items only to improve fit.

6.3 Analysis plan

1. Screen for duplicate submissions, eligibility, missing data, straight-lining and implausibly rapid completion; document exclusions transparently.
2. Report respondent characteristics and descriptive statistics before hypothesis testing.
3. Evaluate the measurement model before interpreting structural relationships.
4. Estimate the main effects of AI-enabled auditing and professional judgement, controlling for firm type/size, role, experience, audit type, industry and AI exposure.
5. Test moderation with a mean-centred AI-enabled auditing $\times$ professional judgement interaction term, report confidence intervals and effect sizes, and probe significant interactions using simple slopes or Johnson–Neyman analysis. PROCESS Model 1 may be used where appropriate; the model and software version should be reported.
6. Assess common-method risk through procedural remedies (anonymity, neutral wording, separating predictor and outcome sections where feasible) and statistical diagnostics. A single-factor test alone is not sufficient proof that common-method bias is absent.
7. Use robust standard errors and sensitivity analyses where assumptions are violated; distinguish statistical significance from practical significance.

6.4 Ethics and data protection

Obtain approval from the relevant institutional ethics committee before recruitment where required. Participation must be voluntary, based on informed consent, and withdrawable without penalty. Collect only necessary demographic and professional data; avoid identifiable client or engagement information. Store data securely, restrict

access, define retention and deletion periods, and disclose how data will be used. Do not upload confidential audit evidence or personally identifiable information into public generative-AI systems. Any institutional or organisational permissions should be obtained before contacting employees or using firm channels.

7. Proposed Questionnaire Items

Use a five-point response scale (1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree), with a “Not applicable / insufficient exposure” option where necessary. These are draft items for expert review and pilot testing, not a validated instrument.

A. AI-enabled auditing

- In my audit work, AI-enabled tools help analyse large populations of relevant transactions or records.
- AI-enabled tools help identify unusual patterns that warrant further audit attention.
- AI-enabled tools support risk assessment and prioritisation of audit procedures.
- AI-generated outputs are traceable to the underlying data and procedures used.
- AI-enabled tools improve the timeliness of relevant audit analysis.

B. Professional judgement

- I independently assess whether AI-generated findings are relevant to the audit objective.
- I evaluate the reliability and completeness of the data underlying AI outputs.
- I seek and evaluate contradictory evidence even when it conflicts with an AI-generated recommendation. ☐ I consider engagement-specific circumstances before acting on an AI-generated finding.
- I determine whether additional procedures are required rather than relying solely on an AI recommendation.

C. Perceived audit quality

- Audit procedures in my work address the significant risks relevant to the engagement.
- Audit conclusions are supported by relevant and reliable evidence.

- Identified anomalies receive appropriate investigation and follow-up.
- Audit documentation provides a clear basis for significant judgements and conclusions.
- AI-assisted work, when appropriately reviewed, supports rather than substitutes for evidence-based conclusions.

D. AI governance and automation-bias checks

- My organisation has clear rules about which AI tools may be used for audit work.
- AI-generated outputs are subject to documented validation or review appropriate to their risk.
- Responsibility for decisions based on AI outputs remains clearly assigned to a qualified professional.
- I sometimes feel pressure to accept an AI recommendation without sufficient time to verify it. (reverse/risk indicator)
- Staff receive training on AI limitations, confidentiality, bias and verification.

Avoid embedding the expected result inside the audit-quality measure. In particular, statements such as “Appropriate use of AI strengthens audit quality” are leading because they ask respondents to endorse the hypothesis rather than report an observable aspect of audit quality. Human oversight belongs primarily in the professional-judgement or governance construct, not as a duplicate audit-quality item.

8. Discussion and Implications

The framework advances a conditional rather than technologically deterministic view of audit innovation. AI can extend the scale and speed of analysis, but quality depends on the reliability of the data, suitability of the tool for the audit objective, auditor competence, evidence evaluation and accountability. This view is consistent with research documenting both the potential quality benefits of AI investment and persistent implementation challenges (Fedyk et al., 2022; Kokina et al., 2025).

8.1 Implications for audit firms

- Adopt a risk-based AI inventory that records tool purpose, model/vendor, data inputs, limitations, approved uses and responsible

owners.

- Require documented human review for material or high-risk AI-generated findings, with escalation paths for anomalies and contradictory evidence.
- Validate data lineage, completeness, access permissions and model outputs; periodically test false positives and false negatives.
- Train auditors in AI literacy, professional scepticism, prompt and output verification, confidentiality, and the limits of generative systems.
- Track quality indicators such as review-note themes, unresolved anomalies, inspection findings and rework, rather than measuring success only through time saved.

8.2 Implications for professional bodies and educators

Professional education should connect AI skills to audit standards and case-based judgement, not treat tool familiarity as a proxy for competence. Indian professional bodies and universities can develop practical exercises in which trainees verify model outputs, investigate false positives, identify unsupported generative summaries and document why they accepted or rejected an AI recommendation.

8.3 Implications for regulators and standard setters

Guidance should remain technology-aware without assuming that a particular tool guarantees quality. It should clarify expectations for evidence reliability, documentation, responsibility, confidentiality and professional scepticism when AI contributes to audit procedures. The IAASB's 2026 proposed revisions to ISA 330, ISA 500 and ISA 520 are relevant to this debate, but their status as proposals must be preserved until finalised.

9. Limitations and Future Research

As a conceptual paper, this study does not provide original survey evidence and cannot establish whether the propositions hold in Indian audit practice. The framework relies on literature and policy materials that may not fully represent differences across sectors, firm sizes and engagement types.

Future research should test the propositions using a pre-registered survey, interviews and, where feasible, objective engagement-level quality indicators. Longitudinal or experimental designs could better examine causality and auditor responses to AI recommendations. Studies should distinguish conventional analytics, machine learning and generative AI because they differ in explainability, autonomy and failure modes. Further work should also examine whether AI capability and governance are distributed unevenly between large and smaller practices.

10. Conclusion

AI is changing the audit process, but audit quality remains an evidence-based professional outcome rather than a technological feature. The conceptual framework developed here proposes that AI-enabled auditing can support perceived audit quality when its outputs are relevant, reliable, traceable and critically evaluated. Professional judgement is expected to strengthen this relationship by preserving independent challenge, contextual interpretation and responsibility. Conversely, automation bias, weak governance and unreliable input data may erode the benefits of increased analytical capacity.

For India in 2026, professional upskilling, national AI-governance discussions and international attention to audit evidence make this a timely research agenda. The paper's contribution is a transparent, testable framework and a proposed empirical protocol, not a claim of completed findings. The practical objective is not to choose between people and machines, but to use AI to broaden analytical reach while keeping audit decisions accountable to professional standards and human judgement.

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