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Audit Object Expansion and Theoretical Reconstruction in the Artificial Intelligence Era: From Information Assurance to Intelligent Governance Assurance

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Abstract: Artificial intelligence (AI) is changing both audit practice and the mechanisms that may require assurance. Recent research has developed along two related paths. AI for audit examines the use of AI, large language models, and intelligent agents in audit work. Audit of AI considers the auditability and independent evaluation of AI systems used by organizations. This paper connects these streams with established audit theory and develops Audit Object Expansion Theory. The central argument is that audit objects may expand when AI becomes material to an accountability relationship, its operation is difficult for users to observe, and suitable criteria and evidence make independent examination possible. In AI-enabled organizations, the audit boundary may extend from financial information and traditional controls to three nested objects: data, algorithms, and intelligent decision processes. Auditability determines whether this potential expansion can become actual audit scope. The paper then discusses theoretical reconstruction at three connected levels: audit object, audit process, and assurance objective. The final level extends the discussion from information assurance toward intelligent governance assurance. The basic logic of auditing remains unchanged, but its application changes when intelligent systems become part of the mechanisms that produce accountable outcomes.

Keywords: Artificial intelligence; Audit object; Auditability; Theoretical reconstruction; Intelligent governance assurance

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1.Introduction

Artificial intelligence (AI) is becoming part of ordinary business processes. It is used for prediction, classification, document analysis, risk assessment, and decision support. Generative AI has accelerated this development. In some settings, AI is no longer only an information-processing tool. It participates in the process through which organizational decisions are formed.

This development creates two questions for auditing. The first is how auditors can use AI. Earlier studies focused on automation and machine learning in audit work [1,2]. Recent research has moved towards human-AI collaboration. Gu *et al.* [3] introduced AI co-piloted auditing. Kokina *et al.* [4] provided field evidence on AI adoption in public accounting firms. Xiong *et al.* [5] further developed an AI-agent architecture based on large language models and retrieval-augmented generation. This literature shows that AI for audit is moving from task automation toward deeper participation in audit workflows.

The second question concerns the audited organization. A model may influence a material estimate, fraud response, credit decision, or another important action. The result may be visible, but the process behind it is not always easy to observe. Training data, model design, validation, thresholds, model changes, and human overrides can all affect the outcome. In this case, AI is not simply an audit tool. It becomes part of the mechanism that produces the subject matter or decision being examined.

Recent Audit-of-AI research has begun to address this problem. Li and Goel [6] examine AI auditability and the competencies needed to audit AI systems. Their work covers data, models, processes, and governance. Yet a broader theoretical question remains: under what conditions does organizational reliance on AI justify an expansion of the audit object, and how does such expansion reconstruct the audit process and assurance objective?

This paper addresses the question through Audit Object Expansion Theory. The main argument is that audit objects follow accountability. When AI becomes material to an accountability relationship, makes the production of outcomes less observable, and can be examined through suitable criteria and evidence, the audit boundary may expand. Data, algorithms, and intelligent decision processes can then become nested audit objects.

The theoretical contribution has two steps. First, the paper explains why, where, and under what conditions audit objects expand in the AI era. Second, it shows that this expansion has consequences for audit theory at three levels: the object of auditing, the audit process, and the assurance objective. This provides a theoretical bridge from information assurance to intelligent governance assurance. In practice, the framework can help identify which AI systems deserve audit attention and what type of evidence is needed. It is intended as an accountability- and risk-based structure rather than a technical checklist.

2. Literature review and research gap

The literature on AI and auditing has developed through a clear shift in research focus. Earlier work was mainly concerned with the digitalization of audit evidence. Studies on big data and audit analytics asked whether new technologies could improve evidence collection, analytical procedures, and auditor judgment [7,8]. This stream established the technological foundation for AI-enabled auditing, but technology was still mainly treated as an instrument used by auditors. The audit object itself remained largely unchanged.

The first transition was from audit automation to AI-assisted professional judgment. Issa *et al.* [1] argued that AI could formalize part of audit work and supplement the audit workforce. Kokina and Davenport [2] discussed how automation could change the division of work between auditors and machines. At this stage, research mainly asked whether particular tasks could be automated. Efficiency and task substitution were central concerns.

Recent studies have moved beyond this view. Gu *et al.* proposed AI co-piloted auditing, while Kokina *et al.* showed that practical adoption is increasing but still faces problems of transparency, reliability, privacy, bias, and overreliance [9]. Torroba *et al.* [10] also identified regulatory and organizational influences. The focus is therefore moving from technology efficiency toward a socio-technical view in which AI capability, human judgment, governance, and professional responsibility interact.

The newest stage concerns generative AI and AI agents. Xiong *et al.* [5] developed an audit-agent architecture combining large language models with retrieval-augmented generation and structured workflows. Such systems can connect several audit tasks, but they also increase the need for evidence verification, review, access control, and documentation.

A second research stream has developed in parallel. It starts not with the auditor's use of AI, but with the AI system as an object of evaluation. Data-governance research shows that quality, access, metadata, and lifecycle decisions require explicit responsibility [11]. Algorithmic-accountability research extends the concern to models and their lifecycle. Raji *et al.*, for example, show how internal algorithmic auditing can be organized across system development and deployment [12]. The focus has shifted from using technology in an audit to governing technology that may itself require assurance.

Recent accounting research makes this shift more explicit. Li and Goel [6] identified auditability requirements for training data, AI models, processes, and governance. They also emphasized multidisciplinary expertise. The importance of this work is not simply that it identifies additional AI risks. It shows that assurance depends on whether an AI system has been designed and governed in a way that allows independent examination. Auditability becomes a precondition for assurance.

The two streams begin from different points. AI for audit asks how AI changes audit work. Audit of AI asks how organizational AI systems can be independently evaluated. The first mainly changes the method of auditing. The second may change the object of auditing. Yet both streams lead back to accountability. When auditors use AI, they remain responsible for the audit conclusion. When management uses AI, management remains responsible for the resulting organizational decisions.

Existing research therefore explains technological change in auditing and increasingly explains the auditability of AI systems. What remains less developed is a theory showing how changes in organizational accountability translate technological change into changes in the boundary of assurance. Identifying AI risk is not enough. Audit scope also depends on materiality, information asymmetry, responsibility, and the possibility of evidence-based evaluation. This gap provides the starting point for Audit Object Expansion Theory.

3. Audit Object Expansion in the AI era

3.1. Theoretical basis of audit-object expansion

Audit Object Expansion Theory starts from the premise that audit objects are not fixed by technology or historical practice. They develop with accountability relationships. An object becomes relevant to assurance when an accountable party is responsible for a claim or decision, users rely on that claim, direct verification is difficult, and an independent evaluator can obtain evidence against suitable criteria. This logic helps explain why auditing historically moved beyond accounting records to internal controls and information systems. These mechanisms entered audit attention because they became important to the reliability of accountable information.

AI can create a similar change. It may sit between management choices and observable outcomes. A user can see the final estimate or decision but may not know which data were used, how the model behaved, or how human reviewers interacted with the output. Information asymmetry then exists not only in reported results but also in the process that generates them. When that process is material, the audit may need to move upstream from the result toward the mechanism.

3.2. Mechanism of audit-object expansion

The expansion can be described as a causal sequence. First, AI becomes embedded in an important organizational activity. Second, part of the analysis or decision process is delegated to an intelligent system. This changes the accountability mechanism. Management remains responsible, but the path between responsibility and the final outcome becomes less visible. Information asymmetry and AI-related risk may therefore increase. These conditions create pressure for the audit boundary to expand.

This sequence provides a stopping rule. Not every AI application needs to be audited. A writing assistant used for routine internal communication may have little relevance to a material accountability claim. A simpler model that automatically determines a material transaction may be much more important. Technical complexity is not the main criterion. Consequence, accountability, and materiality are more important.

Proposition 1 follows: Other things equal, greater reliance on AI in materially consequential organizational activities is associated with a greater pressure for the audit boundary to expand toward AI-related mechanisms.

3.3. Three nested AI audit objects

The first expanded object is data. In traditional auditing, data are often treated as evidence. In an AI system, data also shape model behavior. Training and operational data can therefore become part of the subject matter. Relevant issues include provenance, completeness, representativeness, authorization, transformation, and changes in the data population. Poor data can produce unreliable decisions even when the algorithm performs as designed.

The second object is the algorithmic system. Machine-learning models depend on training choices, features, parameters, thresholds, validation, deployment settings, and later changes. The audit focus should depend on the use of the system. Reliability, robustness, traceability, explainability, or fairness may be relevant, but they should not be treated as a universal checklist. The criterion must follow from the risk and assurance objective.

The third object is the intelligent decision process. A model produces an output, but the organization decides how that output is used. A prediction may support a manager or automatically trigger an action. Human review may be substantive or only formal. Thresholds, overrides, escalation, and exception handling therefore become relevant when they affect a material decision.

These are not three independent objects. They form a nested AI-enabled accountability system. Data affect the model; the model produces an output; the output enters a human or automated decision process. Weakness at an earlier layer can pass into later layers, while controls at a later layer may reduce its effect. The audit object therefore moves closer to the full mechanism through which accountable outcomes are produced.

3.4. Auditability as the boundary condition

Accountability determines whether assurance is needed, but auditability determines whether that need can be converted into an auditable engagement. A governance problem may be important and still be difficult to audit. An AI-related mechanism becomes more auditable when the subject matter can be identified, criteria are sufficiently clear, reliable evidence can be obtained, important tests can be repeated, and responsibility can be traced. Li and Goel [6] supported this view by showing that auditability extends across data, models, processes, and governance.

Auditability has technical and institutional elements. Technical auditability includes logs, data lineage, model versions, validation results, and monitoring records. Institutional auditability includes clear ownership, approved criteria, access rights, and responsibility for changes and decisions. Either side can fail. Strong documentation without suitable criteria does not create meaningful assurance. Clear policies without reliable records do not provide sufficient evidence.

Auditability is therefore a boundary condition rather than a simple next stage in a linear model. Material AI use can create a potential expansion of the audit object, but only sufficiently auditable elements can enter actual audit scope. This condition prevents the theory from turning every AI governance concern into an audit requirement.

4. Theoretical reconstruction of auditing in the AI era

4.1. Reconstruction of the audit object

Audit-object expansion has a broader theoretical implication. The object of auditing moves upstream from reported outcomes toward the mechanisms that generate accountable outcomes. Traditional financial auditing remains centered on financial representations, but auditors already consider controls and information systems when they are important to those representations. AI extends the same logic. When data, algorithms, and intelligent decisions materially shape an accountable outcome, the mechanisms themselves may require independent examination.

The important change is that AI can participate not only in processing information but also in producing organizational decisions. A conventional information system mainly records or processes transactions according to predefined rules. An AI system may classify, predict, recommend, or initiate an action. The boundary between information processing and decision-making therefore becomes less clear. When such decisions are material, examining only the final output may provide an incomplete basis for assurance.

This is more than an increase in the number of audit objects. The unit of analysis changes. The relevant subject matter may become a nested accountability system in which technical and organizational elements jointly produce an outcome. Data affect model behavior; models generate outputs; and organizational controls determine how these outputs enter decisions. A technically reliable model may still lead to poor outcomes if it is used for an inappropriate purpose or without effective human review.

The theoretical reconstruction therefore lies in treating the production mechanism, rather than only its final representation, as a possible object of assurance. Traditional audit objects are not replaced. Instead, the audit boundary moves upstream when accountability requires examination of the mechanisms behind an outcome. In this sense, audit objects can be understood as a function of accountability rather than as a fixed category of information or systems.

4.2. Reconstruction of the audit process

A change in the audit object changes the evidence architecture of auditing. Traditional procedures remain necessary, but new objects require additional evidence. Data assurance may involve lineage, access, quality, and distribution testing. Algorithm assurance may use validation records, independent performance tests, version control, and monitoring evidence. Decision assurance may use walkthroughs, approvals, override records, and reconstruction of important decisions.

The main theoretical change is therefore not the simple addition of technical procedures. It is a change in the relationship between the audit object and audit evidence. When the object becomes a nested system, evidence from one layer may not be sufficient. Reliable data do not necessarily imply a reliable model, and reliable model performance does not necessarily imply an accountable organizational decision. Evidence must therefore be evaluated across the relationships among data, algorithms, controls, and human judgment.

This produces a mixed evidence architecture. Traditional transaction and control evidence remains relevant, but it may need to be combined with technical and governance evidence. The auditor's role is not to replace professional judgment with technical testing. Rather, technical evidence must be interpreted through established concepts such as materiality, risk, relevance, and sufficiency.

The process may also become more dynamic. AI models can change through retraining, new data, parameter adjustment, or external system updates. Evidence obtained at one point may therefore lose relevance more quickly than in a relatively stable information system. The timing of audit procedures should consequently reflect both the materiality of the system and the rate at which it changes.

Audit-object expansion therefore reconstructs the audit process through a mixed and more dynamic evidence model. The change is not a rejection of traditional procedures. It extends evidence from transactions and controls toward the technical and governance mechanisms behind AI-enabled outcomes.

Proposition 2: When material AI-related objects enter audit scope, audit work is likely to combine traditional procedures with data-governance evaluation, model-related testing, and decision-accountability tracing. The extent of this reconstruction increases as AI becomes more material to the production of accountable outcomes.

4.3. Reconstruction of the assurance objective

The final reconstruction concerns the objective of assurance. Traditional auditing is strongly associated with increasing the credibility of reported information. AI-enabled organizations create situations in which users may also need confidence in the governance arrangements that produce consequential decisions. This suggests a movement from information assurance toward intelligent governance assurance.

Intelligent governance assurance is defined here as independent assurance, based on suitable criteria and sufficient appropriate evidence, over whether a consequential AI-enabled organizational system operates with an acceptable level of reliability, transparency, accountability, and controllability for a defined purpose. Reliability concerns fitness for use. Transparency concerns the traceability needed for accountability. Accountability requires identifiable responsibility. Controllability concerns the ability to monitor, constrain, override, and correct system behavior.

The concept is broader than assurance over the technical properties of a single AI model. Its object is the organizational arrangement through which data, algorithms, and human decision-makers jointly produce accountable outcomes. For this reason, intelligent governance assurance is not equivalent to a general claim that an AI system is trustworthy, fair, or error-free. The conclusion must remain bounded by the subject matter, criteria, period, evidence, and system version.

Proposition 3 follows: when sufficient appropriate evidence can be obtained over material data, algorithmic, and intelligent-decision objects, the assurance objective may extend from the credibility of reported information toward intelligent governance assurance. Theoretical reconstruction in the AI era therefore occurs at three connected levels: the audit object moves toward the mechanisms that generate accountable outcomes; the audit process incorporates new forms of technical and governance evidence; and the assurance objective extends beyond information credibility toward the governance of intelligent systems.

5. Conclusion

The proposed theory creates several directions for empirical research. Proposition 1 can be tested by examining whether material reliance on AI predicts broader audit attention, specialist involvement, or separate AI-governance assurance. Measures of AI use should capture decision importance and autonomy rather than simply count applications. Proposition 3 requires evidence from users of assurance. Investors, boards, regulators, and other users may respond differently to AI-related assurance. The relevant outcome should be calibrated trust. Useful assurance should help users distinguish stronger governance from weaker governance rather than simply increase confidence in all AI systems.

In conclusion, recent AI-auditing research is developing in two directions. AI for audit studies how AI changes audit work. Audit of AI studies how AI systems themselves can be evaluated. Audit Object Expansion Theory connects the second direction with established assurance logic and clarifies its relationship with the first. AI does not reconstruct auditing simply because it introduces new technology. Reconstruction occurs when intelligent systems alter the mechanisms of organizational accountability. The audit object then moves toward the mechanisms that generate accountable outcomes; the audit process incorporates new technical and governance evidence; and the assurance objective may extend from information credibility to intelligent governance assurance. The basic logic of auditing remains intact. Its application changes as organizations increasingly rely on data, algorithms, and intelligent decision processes.

Disclosure statement

The author declares no conflict of interest.

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