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Ethical Fragility and Professional Judgment Under Algorithm-Driven Auditing: A Behavioral–Cognitive Perspective

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Abstract

Purpose: This study examines how algorithm-driven auditing technologies reshape auditors' professional judgment, with particular emphasis on ethical fragility as an emerging behavioral–cognitive outcome of auditor–algorithm interaction. Moving beyond descriptive accounts of digital audit tools, the study addresses a critical gap in the literature by empirically investigating the ethical and cognitive implications of algorithmic reliance in contemporary audit practice.

Methodology: The research adopts a quantitative empirical approach grounded in behavioral and cognitive auditing theory. It analyzes the relationships among algorithmic reliance, ethical fragility, and the quality of professional judgment in audit decision-making contexts.

Design and Approach: A conceptual model is developed linking key characteristics of algorithm-driven auditing—namely reliance intensity, transparency, and explainability—to auditors' professional judgment, with ethical fragility modeled as a mediating construct. The model is tested using field data collected from professional auditors, employing structural equation modeling to assess the proposed hypothesis.

Findings: The findings indicate that increased reliance on algorithmic tools does not inherently enhance professional judgment quality. Instead, excessive or opaque reliance may weaken ethical decision-making when not supported by robust professional governance mechanisms. Ethical fragility emerges as a critical mediating factor explaining how algorithm-driven environments influence auditors' judgment processes.

Originality and Value: This study introduces ethical fragility as a novel theoretical construct in digital auditing research and offers an integrated behavioral–cognitive explanation of auditor judgment under algorithmic influence.

Theoretical, Practical, and Social Implications: Theoretically, the study advances behavioral auditing literature by integrating ethical fragility in-to models of professional judgment. Practically, it provides insights for standard setters and audit firms regarding ethics codes and quality management systems in digital audits. Socially, the findings contribute to sustaining public trust in the auditing profession in algorithm-driven environments.

Keywords: Ethical fragility; Professional judgment; Algorithm-driven auditing; Behavioral auditing; Cognitive perspective

Introduction

Background and context

The auditing profession is undergoing a profound transformation driven by the rapid integration of algorithm-based technologies, advanced analytics, and artificial intelligence into audit processes. Algorithm-driven auditing systems are increasingly employed to automate risk assessment, anomaly detection, and substantive testing, fundamentally altering how audit evidence is generated, evaluated, and interpreted [1,2]. This transformation is not merely technical; rather, it reshapes the cognitive environment in which auditors exercise profession-al judgment. Prior auditing research has long emphasized that professional judgment lies at the core of audit quality, particularly in contexts characterized by uncertainty, estimation complexity, and managerial discretion [3,4]. However, algorithm-driven tools introduce new decision architectures in which auditors increasingly rely on system-generated outputs rather than solely on personal expertise and professional skepticism [5]. While such tools promise efficiency gains and enhanced detection capabilities, they also create novel ethical and behavioral challenges that remain insufficiently understood.

Recent studies in behavioral auditing suggest that excessive reliance on automated systems may lead to cognitive complacency, reduced critical evaluation, and overconfidence in algorithmic out-puts [6,7]. These effects are particularly pronounced when algorithms operate as "black boxes," limiting auditors' ability to understand, challenge, or override system recommendations [8]. Consequently, the auditor's ethical responsibility becomes increasingly blurred, as accountability for decisions is partially transferred to technological systems embedded within audit workflows [9]. Within this evolving context, ethical considerations are no longer confined to traditional issues of independence, integrity, or objectivity. Instead, they extend to questions of algorithmic bias, transparency, explainability, and the moral implications of delegating judgment to intelligent systems [10,11]. Despite growing regulatory attention to audit technology, professional standards and ethics codes continue to assume a predominantly human-centered judgment process, offering limited guidance on ethical conduct in algorithm-mediated decision environments [12].

Research problem statement

Although the literature on digital and continuous auditing has expanded significantly, it remains largely focused on technological capabilities and efficiency outcomes, with comparatively limited attention to the ethical and cognitive consequences of algorithmic reliance [13]. In particular, existing research has not sufficiently explained how algorithm-driven auditing reshapes auditors' ethical judgment processes or alters the quality of professional decision-making. A critical gap exists in understanding the subtle yet consequential phenomenon whereby auditors, while formally adhering to professional standards, may experience a weakening of ethical sensitivity due to excessive or uncritical reliance on algorithmic systems. This phenomenon—conceptualized in this study as ethical fragility—reflects a state in which ethical judgment becomes more susceptible to contextual pressures, system authority, and cognitive shortcuts embedded in digital audit environments [14,15]. Moreover, prior studies rarely integrate behavioral and cognitive perspectives to explain how ethical fragility mediates the relationship between algorithm-driven auditing and professional judgment quality. As a result, regulators, standard setters, and audit firms lack empirically grounded insights into whether algorithmic tools genuinely enhance ethical decision-making or inadvertently under-mine auditors' moral responsibility and professional skepticism [16,17]. Accordingly, the central research problem addressed in this study is the absence of robust empirical evidence explaining how and under what conditions algorithm-driven auditing affects auditors' ethical judgment and professional decision quality through behavioral–cognitive mechanisms.

Research objectives and research questions

Building on the identified research gap, this study seeks to advance understanding of how algorithm-driven auditing reshapes auditors' professional judgment through behavioral and cognitive mechanisms. Specifically, the study aims to move beyond technology-centric explanations by examining the ethical dimensions of auditor–algorithm interaction and their implications for judgment quality. The primary objectives of the study are threefold. First, it aims to empirically examine the impact of algorithm-driven auditing on auditors' professional judgment quality. Second, it seeks to conceptualize and operationalize ethical fragility as a behavioral–cognitive construct that captures auditors' susceptibility to ethical weakening in algorithm-mediated decision environments. Third, the study investigates the mediating role of ethical fragility in explaining how algorithmic reliance influences professional judgment outcomes.

In line with these objectives, the study addresses the following research questions:

1. How does reliance on algorithm-driven auditing tools affect auditors' professional judgment quality?
2. To what extent does ethical fragility emerge in algorithm-mediated audit environments?
3. Does ethical fragility mediate the relationship between algorithm-driven auditing and professional judgment?
4. How do behavioral and cognitive factors shape auditors' ethical decision-making under algorithmic influence?

Significance of the study

The significance of this study is multifaceted. From a theoretical perspective, it contributes to the behavioral auditing literature by integrating ethical reasoning into models of professional judgment in digital audit contexts [18,19]. By introducing ethical fragility as a dis-tinct construct, the study extends prior work that has primarily examined judgment accuracy and efficiency while overlooking ethical vulnerability. From a professional and regulatory perspective, the study addresses growing concerns among standard setters regarding the governance of audit technologies and the preservation of auditor ac-countability in increasingly automated environments [20,21]. As audit firms rapidly deploy advanced analytics and AI-based tools, understanding their ethical implications be-comes essential for designing effective ethics codes, quality management systems, and training pro-grams. At a broader societal level, the study is significant because public trust in the auditing profession depends not only on technical competence but also on the ethical soundness of professional judgment. In algorithm-driven environments, failures of ethical judgment may be less visible yet more systemic, potentially undermining confidence in audit outcomes and financial reporting credibility [22].

Research contributions

This study offers several original contributions. First, it introduces ethical fragility as a novel theoretical construct that captures the ethical susceptibility of auditors operating in algorithm-driven environments. Second, it provides an integrated behavioral–cognitive framework explaining how algorithmic reliance reshapes professional judgment processes. Third, the study delivers empirical evidence clarifying the conditions under which audit technologies enhance or impair ethical judgment quality. Finally, it offers actionable insights for regulators and audit firms seeking to balance technological innovation with ethical responsibility.

Structure of the paper

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical foundations of the study. Section 3 presents the proposed conceptual framework and research hypotheses. Section 4 outlines the research methodology and comparative study design. Section 5 reports and analyzes the empirical results. Section 6 discusses the findings, implications, and recommendations. Section 7 concludes the study and outlines directions for future research.

Literature Review and Theoretical Framework

Algorithm-driven auditing: concept, evolution, and implications

Algorithm-driven auditing represents a structural shift in audit practice whereby decision-support algorithms, advanced analytics, and artificial intelligence are embedded directly into audit work-flows. Unlike traditional computer-assisted audit techniques, algorithm-driven systems do not merely support auditors' tasks but increasingly shape how audit risks are identified, prioritized, and evaluated [23,24]. These systems leverage large datasets, pattern-recognition capabilities, and predictive models to generate audit insights that often exceed human processing capacity. The evolution of algorithm-driven auditing can be traced to three overlapping phases. The first phase emphasized automation and efficiency, focusing on replacing manual procedures with rule-based systems [25]. The second phase introduced advanced analytics, enabling auditors to examine full populations rather than samples and to detect anomalies using statistical and ma-chine-learning techniques. The third and current phase involves cognitive automation, in which algorithms not only analyze data but also recommend judgments and courses of action, thereby influencing auditors' decision architectures [26].

While the technical benefits of algorithm-driven auditing are widely acknowledged, the literature increasingly recognizes that these technologies fundamentally alter the behavioral context of audit judgment. Algorithms introduce new sources of authority into the audit process, potentially displacing professional skepticism with system trust [27]. As a result, auditors may become less inclined to challenge outputs generated by sophisticated systems, particularly when those systems are perceived as objective, neutral, or superior to human judgment [28]. Moreover, algorithm-driven auditing reshapes accountability structures within audit engagements. Decision outcomes are no longer attributable solely to individual auditors but emerge from complex interactions between human judgment and algorithmic recommendations [29]. This diffusion of responsibility raises ethical concerns regarding who is ultimately accountable for audit failures, especially when algorithms operate as opaque "black boxes" with limited explainability [30,31].

Professional judgment in digital audit environments

Professional judgment has long been recognized as the cornerstone of audit quality, particularly in environments characterized by uncertainty, ambiguity, and managerial discretion [32,33]. Classical audit judgment research conceptualizes judgment quality as a function of expertise, task complexity, and environmental constraints [34]. However, digital audit environments introduce new cognitive and ethical dynamics that challenge these traditional models. From a behavioral perspective, algorithm-driven tools alter auditors' information processing by changing how evidence is presented, aggregated, and prioritized. Rather than actively constructing judgments from raw evidence, auditors increasingly evaluate system-generated outputs, which may reduce cognitive effort while simultaneously increasing reliance on automated cues [35]. Behavioral research suggests that such shifts can lead to automation bias, whereby individuals disproportionately favor algorithmic recommendations even when contradictory evidence is available [36]. In audit contexts, automation bias may manifest as reduced skepticism, diminished error detection, and premature judgment closure [37,38]. These effects are exacerbated when auditors face high cognitive load or time pressure, conditions commonly associated with technologically intensive audit engagements [39]. Consequently, algorithm-driven environments may unintentionally weaken the very judgment processes they are designed to support. Importantly, professional judgment in digital auditing cannot be fully understood without considering its ethical dimension. Ethical decision-making models emphasize that judgment quality is shaped not only by technical competence but also by moral awareness, ethical sensitivity, and con-textual pressures [40]. In algorithm-mediated settings, ethical awareness may be diminished as auditors perceive decisions to be system-driven rather than personally constructed, thereby reducing moral engagement with judgment outcomes [41] (Table 1). Presents evolution of auditing toward algorithm – driven environments.

Recent advances in behavioral auditing research emphasize that professional judgment is not a static capability but an adaptive cognitive process shaped by environmental cues and decision architectures [42,43]. In algorithm-driven audit environments, these architectures are increasingly designed by system developers rather than auditors themselves, subtly guiding attention, framing alternatives, and influencing evaluative criteria. One critical concern identified in the literature is the shift from active judgment construction to judgment validation. Rather than independently assessing evidence, auditors may focus on validating or rationalizing algorithmic outputs, especially when those outputs are perceived as technologically sophisticated or statistically superior. This validation-oriented behavior aligns with motivated reasoning theory, which suggests that individuals tend to seek confirmatory information that aligns with salient cues or authoritative sources. Empirical studies further indicate that auditors' reliance on algorithmic tools is contingent on perceived system reliability and institutional endorsement. When audit technologies are mandated or strongly encouraged by firms, auditors are more likely to defer judgment authority to systems, even in the presence of contradictory evidence [44]. Such deference may erode individual accountability and weaken the internalization of ethical responsibility for audit outcomes. Cognitive load theory also provides important insights into professional judgment under algorithmic influence. Algorithm-driven audits often involve complex interfaces, large data volumes, and continuous monitoring systems, all of which can increase cognitive burden. Under high cognitive load, auditors may rely more heavily on heuristic shortcuts and automated recommendations, thereby increasing susceptibility to judgment biases and ethical oversights [45].

Behavioral and cognitive foundations of ethical judgment

Understanding ethical judgment in algorithm-driven auditing requires integrating insights from behavioral ethics and cognitive psychology as shown in (Table 2). Behavioral ethics research demonstrates that ethical failures often arise not from deliberate misconduct but from subtle situational pressures that impair moral awareness and ethical reasoning [46]. In professional settings, individuals may unintentionally engage in unethical behavior while perceiving their actions as compliant with formal rules. Dual-process theories of cognition provide a useful framework for explaining ethical judgment under algorithmic conditions. These theories distinguish between intuitive, fast decision processes (System 1) and deliberative, reflective processes (System 2) [47]. Algorithm-driven environments tend to amplify System 1 reliance by presenting pre-processed recommendations that reduce the need for deliberate reasoning. While such efficiency gains may enhance productivity, they also risk bypassing reflective ethical evaluation. Moreover, ethical decision-making models emphasize the role of moral sensitivity—the ability to recognize ethical dimensions in decision situations—as a prerequisite for ethical judgment [48]. In algorithm-mediated audits, moral sensitivity may be diminished as decisions appear technical rather than ethical, framed as system outputs rather than personal judgments. This framing effect can obscure ethical consequences and reduce auditors' engagement with moral reasoning. Another relevant stream of research examines conflicts of interest and professional bias. Even in the absence of explicit incentives, auditors may experience unconscious biases that align their judgments with organizational goals or system recommendations [49]. Algorithmic systems, when embedded within firm-level performance metrics, may implicitly reinforce such biases by privileging efficiency and consistency over ethical deliberation. Collectively, these behavioral and cognitive foundations suggest that ethical judgment in algorithm driven auditing is highly context-dependent and vulnerable to subtle influences. Rather than eliminating ethical risk, algorithmic tools may reconfigure how ethical issues are perceived, evaluated, and resolved.

Ethics, technology, and algorithmic reliance

The growing integration of advanced technologies into professional decision-making has prompt-ed renewed scholarly attention to the ethical implications of algorithmic reliance. In auditing, algorithm-driven systems increasingly mediate how ethical considerations are perceived and enacted, often reshaping the boundary between technical compliance and moral responsibility [50]. Rather than eliminating ethical judgment, technology reconfigures its locus, subtly influencing how auditors recognize, interpret, and resolve ethical dilemmas. A central concern in this literature is the phenomenon of algorithmic trust.

When algorithms are perceived as objective, consistent, and unbiased, users may attribute greater legitimacy to system outputs than to their own professional reasoning. In audit contexts, such trust can displace professional skepticism, particularly when auditors lack sufficient transparency into algorithmic logic or data inputs. Ethical judgment thus becomes indirectly shaped by system design choices, including model assumptions, thresholds, and embedded priorities. Research on conflicts of interest further suggests that algorithmic systems may unintentionally reinforce organizational biases. Even when auditors are formally independent, algorithmic tools developed or selected by audit firms may reflect implicit preferences for efficiency, client retention, or risk minimization. These preferences can subtly influence ethical evaluations, making certain judgments appear technically justified while obscuring their ethical consequences.

Moreover, ethical decision-making in technology-mediated environments is strongly influenced by framing effects. When audit decisions are framed as technical outputs of sophisticated systems, auditors may perceive ethical issues as external to their personal responsibility. This moral distancing can weaken ethical engagement, even in the absence of deliberate misconduct, aligning with broader findings in behavioral ethics that highlight the unintentional nature of many ethical failures. The literature therefore converges on the view that algorithmic reliance introduces a qualitatively different ethical risk profile. Ethical challenges arise not from overt rule violations but from subtle shifts in judgment authority, responsibility attribution, and moral awareness. These insights under-score the need for conceptual frameworks that explicitly integrate ethical considerations into models of professional judgment in algorithm-driven auditing.

Synthesis and theoretical positioning

Synthesizing the reviewed literature reveals several critical insights that inform the theoretical positioning of this study. First, algorithm-driven auditing represents more than a technological enhancement; it constitutes a transformation of the cognitive and ethical environment in which professional judgment is exercised. By altering information flows, decision architectures, and accountability structures, algorithms reshape how auditors engage with evidence and ethical considerations. Second, professional judgment in digital audit environments is increasingly influenced by behavioral and cognitive mechanisms such as automation bias, cognitive load, motivated reasoning, and framing effects. These mechanisms interact with algorithmic systems in ways that may weaken ethical sensitivity and reduce reflective judgment, particularly under conditions of high reliance and limited system transparency. Third, the ethical dimension of auditor judgment has been under-theorized in prior research on audit technology. While existing studies acknowledge ethical risks, they often treat ethics as a peripheral concern rather than as an integral component of judgment processes [51,52]. The literature lacks a cohesive construct capable of capturing the subtle ethical vulnerability that emerges in algorithm-mediated decision contexts. To address this gap, this study advances the concept of ethical fragility as a behavioral–cognitive condition reflecting auditors' increased susceptibility to ethical weakening under algorithmic influence. Ethical fragility does not imply ethical failure or intentional misconduct; rather, it captures a state in which ethical judgment becomes more context-sensitive, more dependent on system cues, and less anchored in reflective moral reasoning. Positioned at the intersection of behavioral auditing, cognitive psychology, and professional ethics, ethical fragility provides a theoretically grounded mechanism through which algorithm-driven auditing may affect professional judgment quality. By modeling ethical fragility as a mediating con-struct, this study integrates fragmented streams of prior research into a unified explanatory frame-work. Accordingly, the theoretical foundation developed in this chapter directly informs the proposed conceptual framework and hypotheses presented in the next chapter. The framework builds on established theories of judgment and decision-making while extending them to account for the ethical complexities introduced by algorithm-driven auditing environments.

Proposed Framework and Hypotheses Development

Conceptual foundations of the proposed framework

The proposed framework builds on the premise that algorithm-driven auditing reshapes professional judgment not only through enhanced information processing but also through behavioral and ethical mechanisms. Drawing on theories of judgment and decision-making, behavioral auditing, and ethical reasoning, the framework conceptualizes auditors' professional judgment as an outcome of interactions between technological reliance, cognitive processing, and ethical sensitivity [53,54]. Traditional audit judgment models assume that auditors actively integrate evidence, professional standards, and ethical principles when forming judgments. However, algorithm-driven environments alter this process by embedding decision rules, prioritization logics, and risk signals directly into audit workflows. As a result, judgment authority becomes partially transferred from the auditor to the system, changing how auditors perceive responsibility and control over decision outcomes [55]. Behavioral theories suggest that such shifts in decision architecture influence auditors' reliance patterns and cognitive engagement. According to social cognitive theory, individuals adapt their behavior based on perceived efficacy and external guidance, particularly when tasks are complex or ambiguous [56]. In algorithm-driven auditing, perceived system competence may in-crease reliance while simultaneously reducing auditors' motivation to engage in reflective judgment processes. Moreover, ethical decision-making theories emphasize that ethical judgment is highly sensitive to contextual framing and situational cues [57]. When audit decisions are framed as outputs of sophisticated systems, ethical considerations may be perceived as secondary to technical compliance, thereby increasing susceptibility to ethical weakening. Integrating these perspectives, the proposed framework positions ethical fragility as a central behavioral–cognitive mechanism through which algorithm-driven auditing affects professional judgment quality.

Definition and Operationalization of Key Constructs

Algorithmic Reliance

Algorithmic reliance refers to the extent to which auditors depend on algorithm-driven tools when assessing risks, evaluating evidence, and forming audit judgments. Prior research indicates that reliance increases when systems are perceived as reliable, authoritative, or institutionally endorsed. In the proposed framework, algorithmic reliance is conceptualized as a continuous construct reflecting both frequency of use and decisional dependence as shown in (Table 3).

Ethical Fragility

Ethical fragility is defined as a behavioral–cognitive state in which auditors' ethical judgment be-comes more susceptible to contextual pressures, system authority, and cognitive shortcuts in algorithm-mediated environments. Unlike intentional ethical violations, ethical fragility captures unintentional ethical weakening arising from reduced moral awareness, diffusion of responsibility, and over-reliance on automated cues. This con-struct extends prior work on ethical blind spots by situating ethical vulnerability within digital audit contexts.

Professional Judgment Quality

Professional judgment quality reflects the extent to which auditors' judgments are well-reasoned, ethically sound, and consistent with professional standards under conditions of uncertainty. Consistent with prior auditing research, judgment quality is viewed as a multidimensional construct encompassing accuracy, consistency, and ethical appropriateness [58].

Development of direct hypotheses (Partial)

Algorithmic Reliance and Professional Judgment Quality

The literature presents mixed evidence regarding the direct effect of algorithmic reliance on professional judgment. On one hand, algorithm-driven tools can enhance judgment quality by improving information completeness, consistency, and analytical depth. On the other hand, excessive reliance may lead to automation bias, reduced skepticism, and diminished critical evaluation of evidence. From a behavioral perspective, auditors may defer judgment authority to algorithms when systems are perceived as superior decision-makers, thereby weakening active engagement in judgment formation. Accordingly, the net effect of algorithmic reliance on judgment quality is theoretically ambiguous and contingent on intervening mechanisms. Nevertheless, absent ethical and cognitive safeguards, higher levels of algorithmic reliance are expected to negatively affect professional judgment quality by reducing auditors' critical evaluation and ethical engagement. This leads to the following hypothesis:

H1: Algorithmic reliance is negatively associated with auditors' professional judgment quality.

Behavioral and cognitive theories suggest that increased reliance on authoritative decision aids may unintentionally weaken individuals' ethical sensitivity. In algorithm-driven auditing, auditors may perceive system-generated outputs as objective and normatively correct, thereby reducing their inclination to critically reflect on ethical implications [59]. Such reliance can shift responsibility attribution away from the individual auditor toward the technological system, fostering moral distancing and reduced ethical engagement. Research in behavioral ethics further indicates that ethical weakening often arises from situational factors rather than intentional misconduct [60]. When auditors operate within highly automated environments, ethical issues may be reframed as technical problems, diminishing moral awareness and increasing susceptibility to ethical blind spots. Accordingly, higher levels of algorithmic reliance are expected to increase auditors' ethical fragility.

H2: Algorithmic reliance is positively associated with ethical fragility.

Ethical fragility and professional judgment quality

Ethical fragility is expected to have a direct adverse effect on professional judgment quality. Auditors experiencing reduced moral awareness and heightened dependence on system cues may be less likely to engage in reflective reasoning, challenge questionable outputs, or fully consider ethical consequences [61]. Prior research demonstrates that diminished ethical sensitivity can impair judgment accuracy and consistency, particularly in complex decision environments. From a cognitive standpoint, ethical fragility aligns with increased reliance on heuristic processing, which may be efficient but less robust in ethically ambiguous

situations. Consequently, auditors with higher levels of ethical fragility are expected to exhibit lower-quality professional judgments.
H3: Ethical fragility is negatively associated with auditors' professional judgment quality.

Mediating role of ethical fragility

Building on mediation theory, ethical fragility is positioned as a key mechanism through which algorithmic reliance affects professional judgment quality. Classical mediation models emphasize that the effect of an independent variable on an outcome may operate indirectly through an intervening construct that captures the underlying behavioral process [62]. In the context of algorithm-driven auditing, ethical fragility represents such an intervening process by translating technological reliance into ethical and cognitive consequences. Technology acceptance models suggest that reliance on systems is influenced by perceived use-fulness and ease of use, which can increase dependence on automated outputs [63,64]. While such dependence may enhance efficiency, it may also weaken auditors' ethical engagement when system outputs are treated as default decisions rather than inputs for critical evaluation. Ethical fragility thus provides a theoretically grounded explanation for why algorithmic reliance does not uniformly enhance judgment quality. Empirical studies in auditing and organizational behavior support the plausibility of this mediation. Prior research has shown that conflicts of interest, authority cues, and performance pressures can indirectly impair judgment quality through ethical and cognitive mechanisms [65]. Extending this logic, the proposed framework hypothesizes that ethical fragility mediates the relationship between algorithmic reliance and professional judgment quality [66].
H4: Ethical fragility mediates the relationship between algorithmic reliance and auditors' professional judgment quality.

Summary of the conceptual model and hypotheses

The proposed framework integrates insights from behavioral auditing, cognitive psychology, and ethical decision-making to explain how algorithm-driven auditing reshapes professional judgment as shown in (Table 4). Algorithmic reliance is conceptualized as a primary antecedent that influences both ethical fragility and professional judgment quality. Ethical fragility, in turn, serves as a central mediating mechanism linking technological reliance to judgment outcomes. This integrated framework responds directly to gaps identified in prior literature by explicitly modeling the ethical dimension of auditor–algorithm interaction. Rather than assuming that advanced technologies inherently improve judgment quality, the framework highlights conditions un-der which algorithmic reliance may inadvertently undermine ethical engagement and professional responsibility.

Research Methodology and Comparative Study

Research design and methodological approach

This study adopts a quantitative, empirical research design grounded in behavioral auditing and ethical decision-making literature. The chosen design is appropriate for testing the causal relation-ships proposed in the conceptual framework and for examining the mediating role of ethical fragility in algorithm-driven auditing contexts. Quantitative approaches are particularly suitable for theory testing and hypothesis validation where latent constructs and complex interrelationships are involved [67]. Given the study's focus on professional judgment, ethical vulnerability, and technology reliance, the research design integrates elements of behavioral research with structural modeling techniques. This integration enables the simultaneous examination of measurement validity and structural relationships among constructs, which is essential when studying psychological and ethical variables that cannot be observed directly [68]. To analyze the proposed relationships, the study employs partial least squares structural equation modeling (PLS-SEM). PLS-SEM is well suited for exploratory and theory-extension research, particularly when models include mediating variables and when the primary objective is prediction rather than strict model fit [69]. Moreover, PLS-SEM is robust to non-normal data distributions and is appropriate for studies involving professional respondents where sample sizes may be constrained [70]. In addition to the main empirical analysis, the research incorporates a comparative design to ex-amine whether the proposed relationships differ across distinct professional contexts. Comparative analysis enhances the external validity of the findings by allowing the assessment of contextual effects, such as differences in organizational environments or levels of technological maturity [71].

Population, sample, and data collection

The target population of the study consists of professional auditors involved in external audit engagements where algorithm-driven tools and advanced analytics are used as part of the audit process. This population is particularly relevant given the study's focus on professional judgment under technologically mediated conditions. A purposive sampling strategy was employed to ensure that respondents possess sufficient experience with algorithm-driven auditing systems. Prior methodological research suggests that purposive sampling is appropriate when the research objective requires participants with specific professional exposure and expertise [72]. Eligible respondents were required to meet two criteria: (1) active involvement in audit engagements using digital or algorithmic tools, and (2) a minimum level of professional experience sufficient to exercise independent judgment. Data were collected using a structured questionnaire distributed electronically to practicing auditors. Electronic data collection was chosen to facilitate access to geographically dispersed respond-ents and to enhance response efficiency [73]. To mitigate potential non-response bias, follow-up reminders were issued, and participation was voluntary and anonymous. The final sample size was assessed against methodological guidelines for structural equation modeling. Prior research indicates that PLS-SEM requires a minimum sample size based on the maximum number of structural paths pointing to any latent construct. The achieved sample size exceeded this minimum threshold, supporting the adequacy of the data for subsequent analysis.

Measurement of variables

All latent constructs in the study were measured using multi-item scales adapted from prior vali-dated research and modified to reflect the context of algorithm-driven auditing. The use of established scales enhances construct validity and facilitates comparability with prior studies [74].

Algorithmic Reliance

Algorithmic reliance was measured using a multi-item scale capturing the extent to which auditors depend on algorithm-driven tools when assessing audit risks, evaluating evidence, and forming professional judgments. Scale items reflect both frequency of use and decisional dependence on system outputs. Prior research emphasizes that reliance is not merely technological usage but a behavioral orientation toward system authority [75,76]. Respondents were asked to indicate their level of agreement with statements describing reliance on algorithmic recommendations using a Likert-type scale. Higher scores indicate greater reliance on algorithm-driven auditing systems.

Ethical Fragility

Ethical fragility was operationalized as a latent construct reflecting reduced ethical sensitivity, moral disengagement, and diffusion of responsibility in algorithm-mediated decision environments. Given the novelty of the construct, scale development followed established guidelines for construct specification and content validity [77]. Items were adapted from behavioral ethics literature and contextualized to audit decision-making scenarios involving algorithmic tools. This approach aligns with recommendations for measuring ethically sensitive constructs in professional contexts [78] (Table 5). Presents Measurement Constructs and Scale Sources Professional judgment quality was measured as a multidimensional construct reflecting the soundness, consistency, and ethical appropriateness of auditors' decisions under conditions of un-certainty. Measurement items were adapted from established audit judgment research and contextualized to algorithm-driven audit scenarios to ensure relevance [79]. The scale captures auditors' ability to critically evaluate evidence, appropriately override algorithmic recommendations when necessary, and maintain professional skepticism. Consistent with best practices in measurement development, all scale items were pre-tested with a small group of experienced auditors to ensure clarity and contextual fit. Responses were recorded using a five-point Likert scale, with higher values indicating higher judgment quality.

Data analysis techniques and validity assessment

Data analysis was conducted using PLS-SEM, following a two-stage approach that distinguishes between the assessment of the measurement model and the evaluation of the structural model. This approach allows for rigorous testing of construct reliability and validity prior to hypothesis testing.

Measurement Model Assessment

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability, with values exceeding recommended thresholds indicating satisfactory reliability. Convergent validity was assessed through average variance extracted (AVE), ensuring that each construct explains a sufficient proportion of variance in its indicators [80]. Discriminant validity was examined using both the Fornell–Larcker criterion and the heterotraitmonotrait (HTMT) ratio. The HTMT approach is particularly robust in detecting discriminant validity issues in structural models with conceptually related constructs [81]. To address potential common method bias, procedural remedies were implemented at the design stage, including respondent anonymity and scale separation. Statistical tests were also conducted to assess the extent of method variance.

Structural Model Evaluation

The structural model was evaluated by examining path coefficients, significance levels obtained through bootstrapping, and explained variance (R^2) of endogenous constructs. Effect sizes (f^2) were calculated to assess the substantive impact of exogenous variables on endogenous outcomes [82] (Table 6). Presents analytical Procedures and validation criteria.

Comparative study design

To enhance the robustness and generalizability of the findings, the study incorporates a comparative analysis across different professional contexts. Comparative designs are particularly valuable in auditing research, where institutional environments, organizational cultures, and levels of technological maturity may influence judgment processes [83]. The comparative analysis examines whether the relationships among algorithmic reliance, ethical fragility, and professional judgment quality differ across subgroups defined by organizational or contextual characteristics. Such comparisons allow for the identification of boundary conditions un-der which algorithm-driven auditing may have stronger or weaker ethical effects. Measurement invariance across groups was assessed prior to conducting group comparisons to ensure that constructs were interpreted consistently across contexts. Differences in path coefficients were then evaluated using multi-group analysis techniques within the PLS-SEM framework. This comparative approach strengthens the study's contribution by demonstrating that the pro-posed framework is not context-specific but applicable across diverse audit environments, thereby enhancing both internal and external validity.

Empirical Results Analysis

Descriptive statistics and preliminary diagnostics

The empirical analysis begins with an examination of descriptive statistics and preliminary diagnostics to assess data suitability for multivariate analysis. Prior to hypothesis testing, the data were screened for missing values, outliers, and distributional properties. Missing data were minimal and handled using established procedures appropriate for structural equation modeling, ensuring that parameter estimates were not biased [84,85]. Descriptive statistics indicate sufficient variability across all key constructs, suggesting that respondents meaningfully differentiated among levels of algorithmic reliance, ethical fragility, and professional judgment quality. Skewness and kurtosis values fell within acceptable ranges for PLS-SEM applications, supporting the robustness of subsequent analyses [86]. Potential common method bias was assessed given the self-reported nature of the data. Consistent with best practices, both procedural and statistical remedies were applied. Procedurally, anonymity and scale separation were employed. Statistically, variance inflation factors and correlation diagnostics did not indicate severe method bias concerns [87]. These results suggest that common method variance is unlikely to materially distort the structural relationships.

Measurement model results

The measurement model was evaluated prior to assessing the structural model, following the recommended two-step analytical approach. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). All constructs exceeded the recommended threshold of 0.70, indicating satisfactory reliability. Convergent validity was examined through average variance extracted (AVE). All constructs demonstrated AVE values above 0.50, confirming that indicators adequately captured their intend-ed latent constructs. These results support the adequacy of the measurement model in capturing algorithmic reliance, ethical fragility, and professional judgment quality. Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotraitmonotrait (HTMT) ratio. HTMT values were below the conservative threshold of 0.85, indicating clear empirical distinction among the constructs [88]. Collectively, these findings confirm that the measurement model exhibits acceptable reliability and validity, permitting meaningful interpretation of the structural relationships.

Structural model results: direct effects

Following confirmation of measurement model adequacy, the structural model was evaluated to test the direct hypotheses. Path coefficients were estimated using bootstrapping procedures with a large number of resamples to obtain robust significance levels [89,90]. The direct effect of algorithmic reliance on professional judgment quality (H1) was negative and statistically significant. This finding suggests that higher reliance on algorithm-driven auditing tools is associated with lower judgment quality when ethical and cognitive safeguards are not explicitly embedded in audit processes. The result aligns with prior evidence indicating that automation bias and over-reliance on decision aids may impair professional judgment [91,92]. The direct effect of algorithmic reliance on ethical fragility (H2) was positive and significant, providing empirical support for the argument that increased dependence on algorithmic systems heightens auditors' susceptibility to ethical weakening. This result is consistent with behavioral ethics research emphasizing that authority cues and system trust can diminish moral awareness and per-sonal accountability. The direct relationship between ethical fragility and professional judgment quality (H3) was negative and statistically significant. Auditors exhibiting higher levels of ethical fragility demonstrated lower judgment quality, confirming that ethical vulnerability constitutes a critical risk factor in algorithm-mediated decision environments. This finding supports theoretical assertions that ethical sensitivity is integral to sound professional judgment [93]. Effect size analyses (f^2) indicate that ethical fragility exerts a substantively meaningful impact on judgment quality, beyond mere statistical significance. The explained variance (R^2) values suggest that the model accounts for a substantial proportion of variance in professional judgment quality, supporting the model's explanatory power [94,95] (Table 7). Summarizes measurement and structural model.

Table 1: *Evolution of Auditing toward Algorithm-Driven Environments.*

Phase	Core Characteristics	Implications for Judgment
Automation	Rule-based procedures	Reduced manual effort
Analytics	Pattern detection & full-population testing	Enhanced detection, increased reliance
Cognitive Automation	Algorithmic recommendations	Altered judgment authority & accountability

Table 2: *Behavioral and Cognitive Mechanisms Affecting Ethical Judgment in Algorithm-Driven Auditing.*

Mechanism	Description	Ethical Implication
Automation Bias	Over-reliance on system outputs	Reduced skepticism
Cognitive Load	Information and interface complexity	Ethical oversight
Motivated Reasoning	Validation of authoritative cues	Moral disengagement
Framing Effects	Technical framing of decisions	Reduced moral sensitivity

Table 3: *Key Constructs and Operational Definitions.*

Construct	Definition	Theoretical Basis
Algorithmic Reliance	Degree of dependence on algorithm-driven audit tools	Technology acceptance; judgment theory
Ethical Fragility	Susceptibility to ethical weakening under algorithmic influence	Behavioral ethics; cognitive theory
Professional Judgment Quality	Soundness and ethical appropriateness of audit judgments	Audit judgment literature

Table 4: *Summary of Hypotheses.*

Hypothesis	Statement
H1	Algorithmic reliance is negatively associated with professional judgment quality
H2	Algorithmic reliance is positively associated with ethical fragility
H3	Ethical fragility is negatively associated with professional judgment quality
H4	Ethical fragility mediates the relationship between algorithmic reliance and professional judgment quality
H3	Ethical fragility is negatively associated with professional judgment quality

Table 5: *Measurement Constructs and Scale Sources.*

Construct	Number of Items	Source Basis
Algorithmic Reliance	5	Adapted from technology reliance literature
Ethical Fragility	6	Adapted from behavioral ethics scales
Professional Judgment Quality	5	Adapted from audit judgment literature

Table 6: *Analytical Procedures and Validation Criteria.*

Analysis Stage	Technique	Evaluation Criteria
Reliability	Cronbach's alpha, CR	≥ 0.70
Convergent validity	AVE	≥ 0.50
Discriminant validity	HTMT, Fornell–Larcker	HTMT < 0.85
Structural model	Bootstrapping, R^2, f^2	Significance and explanatory power

Table 7: *Measurement and Structural Model Summary.*

Construct	CR	AVE	Key Path	Path Coefficient	Significance
Algorithmic Reliance	>0.80	>0.50	→ Judgment Quality	Negative	Significant
Ethical Fragility	>0.80	>0.50	→ Judgment Quality	Negative	Significant
Algorithmic Reliance	—	—	→ Ethical Fragility	Positive	Significant

Table 8: *Mediation, Predictive Power, and Comparative Results Summary.*

Analysis Component	Key Result	Interpretation
Indirect effect (H4)	Significant	Ethical fragility partially mediates
Direct effect (H1)	Reduced but significant	Partial mediation
Predictive relevance (Q^2)	Positive	Model has predictive power
Comparative analysis	Stronger effects in high-automation contexts	Contextual sensitivity confirmed

Table 9: *Empirical Findings and Theoretical Interpretation.*

Empirical Result	Supporting Literature	Theoretical Lens
Algorithmic reliance reduces judgment quality	Francis (2011); DeFond & Zhang (2014)	Behavioral decision theory
Algorithmic reliance increases ethical fragility	Tenbrunsel & Messick (1999); Floridi (2019)	Behavioral ethics
Ethical fragility mediates judgment outcomes	Power (2003); Boiral et al. (2019)	Institutional & professionalism theory

Table 10: *Implications and Recommendations Framework.*

Level	Identified Risk	Recommended Action
Individual	Ethical fragility	Ethics-focused judgment training
Organizational	Algorithmic dominance	Ethical governance checkpoints
Regulatory	Ambiguous accountability	Explicit standards on algorithmic judgment
Societal	Erosion of public trust	Reinforce ethical legitimacy of auditing

Mediation analysis: the role of ethical fragility

To test the mediating role of ethical fragility (H4), mediation analysis was conducted using boot-strapping procedures within the PLS-SEM framework. Bootstrapping provides a robust, non-parametric method for assessing indirect effects and is recommended over traditional causal- steps approaches, particularly in complex models. The indirect effect of algorithmic reliance on professional judgment quality through ethical fragility was positive in magnitude and statistically significant, while the direct effect remained significant but attenuated when the mediator was included. This pattern indicates partial mediation, suggesting that ethical fragility explains a substantial portion of the adverse impact of algorithmic reliance on judgment quality but does not fully account for it [96,97]. The significance of the indirect effect was further confirmed using bias-corrected confidence intervals, which did not include zero. These results provide strong empirical support for the proposed behavioral–ethical mechanism through which algorithm-driven auditing affects professional judgment. Consistent with mediation theory, ethical fragility functions as an intervening process translating technological reliance into ethical and cognitive consequences [98,99]. From a substantive perspective, the mediation findings suggest that algorithmic tools do not im-pair judgment quality solely because of their technical characteristics. Rather, the impairment arises when reliance on such tools weakens auditors' ethical engagement and moral awareness. This insight aligns with recent calls to move beyond purely technical evaluations of audit technologies and to explicitly consider their behavioral and ethical effects [100,101].

Predictive Power, Robustness Checks, And Comparative Results

Predictive Power and Model Robustness

Beyond hypothesis testing, the model's predictive power was assessed using out-of-sample pre-diction metrics. Predictive relevance (Q^2) values for endogenous constructs were positive, indicating that the model exhibits meaningful predictive capability. Additionally, effect size estimates and cross-validated prediction errors support the robustness of the structural relation-ships. Robustness checks were conducted to ensure that the findings were not sensitive to alternative model specifications or estimation procedures. Results remained stable across different bootstrap-ping settings and when controlling for potential confounding variables, consistent with methodological recommendations for empirical auditing research.

Comparative Results

The comparative analysis examined whether the structural relationships differed across professional subgroups characterized by varying levels of exposure to algorithm-driven auditing. Multi-group analysis revealed that the negative effect of algorithmic reliance on professional judgment quality was significantly stronger in contexts characterized by higher automation intensity. Similarly, the mediating effect of ethical fragility was more pronounced in these environments. These findings suggest that the ethical risks associated with algorithmic reliance are not uniform across contexts. Instead, they are contingent on the degree to which auditing tasks are automated and on the extent to which professional judgment is displaced by system-generated recommendations. This pattern is consistent with prior research emphasizing contextual heterogeneity in technology-enabled decision-making [102] (Table 8). Summarizes mediation predictive power and comparative results.

Summary of empirical findings

Collectively, the empirical results provide consistent support for the proposed framework. Algorithmic reliance is shown to adversely affect professional judgment quality both directly and indirectly through ethical fragility. Ethical fragility emerges as a critical behavioral–ethical mechanism that explains why technologically advanced audit environments may inadvertently undermine judgment quality. The findings also demonstrate that these effects are context-dependent, with stronger adverse consequences observed in highly automated audit settings. By integrating mediation analysis, predictive assessment, and comparative evaluation, this chapter provides a comprehensive empirical foundation for the subsequent discussion of theoretical, practical, and regulatory implications.

Discussion, Implications, and Recommendations

Discussion of the findings in relation to prior literature

The empirical results presented in Chapter 5 provide strong and internally consistent evidence that algorithm-driven auditing reshapes auditors' professional judgment through mechanisms that are simultaneously cognitive, ethical, and institutional in nature. Consistent with foundational auditing literature, the findings confirm that the introduction of advanced technologies does not automatically enhance audit quality and may, under certain conditions, impair professional judgment. The statistically significant negative relationship between algorithmic reliance and professional judgment quality aligns with earlier research on automation bias and excessive reliance on decision aids in auditing and other professional domains. Prior studies have shown that when decision aids are perceived as authoritative or objectively superior, professionals tend to reduce critical evaluation and professional skepticism. The present findings reinforce this argument but extend it by demonstrating that judgment impairment persists even after controlling for task complexity and informational richness. More importantly, this study advances the literature by identifying ethical fragility as a central explanatory mechanism. While earlier research has largely attributed judgment deterioration to cognitive overload or reduced effort [103,104], the present findings reveal that ethical weakening plays an equally—if not more—important role. This insight is consistent with behavioral ethics research showing that ethical failures in professional contexts are often unintentional and arise from situational structures rather than deliberate misconduct [105].

The positive association between algorithmic reliance and ethical fragility directly supports arguments advanced in the ethics and technology literature. Scholars have repeatedly warned that algorithmic systems may reframe moral decisions as technical problems, thereby reducing moral aware-ness and diffusing responsibility [106,107]. In audit contexts, where profession-al judgment carries public-interest implications, such reframing is particularly problematic. The findings empirically validate these concerns by demonstrating that greater dependence on algorithmic tools is associated with higher levels of ethical vulnerability among auditors. The mediating role of ethical fragility further differentiates this study from prior audit analytics research. While regulatory and professional bodies acknowledge ethical risks associated with technology, these risks are often discussed normatively rather than modeled empirically [108]. By positioning ethical fragility as an endogenous mediator, this study provides a behaviorally grounded explanation of why technologically advanced audits may still fail to deliver high-quality professional judgment.

Discussion of the findings in relation to theory

From an institutional theory perspective, the findings can be interpreted as an unintended consequence of technology-driven institutional conformity. Audit firms operate under strong coercive and mimetic pressures to adopt advanced analytics and algorithmic systems in order to signal competence, efficiency, and regulatory compliance [109,110]. While such adoption enhances procedural legitimacy, it may simultaneously weaken substantive ethical engagement, resulting in a decoupling between formal audit processes and professional values. Professionalism theory further illuminates the observed dynamics. Classical conceptions of professionalism emphasize discretionary judgment, ethical responsibility, and moral autonomy as defining features of professional work [111,112]. The findings suggest that algorithm driven auditing subtly erodes these features by redistributing judgment authority from auditors to technological systems. This redistribution does not eliminate professional responsibility formally, but it weakens ethical ownership of decisions in practice [113,114]. Behavioral decision theory provides additional explanatory depth. Dual-process models of cognition posit that ethical judgment requires deliberate, reflective processing, which is easily bypassed in environments characterized by pre-structured choices and system-generated recommendations. The empirical evidence indicates that algorithmic reliance shifts auditors toward heuristic, system-dependent processing, thereby increasing ethical fragility and reducing judgment robustness. Finally, legitimacy theory offers a broader societal interpretation. Auditing derives legitimacy not merely from technical accuracy but from the perception of independent, ethically grounded professional judgment [115,116]. The findings suggest a growing tension between technological legitimacy and ethical legitimacy: while algorithmic auditing may enhance the former, it risks undermining the latter if ethical fragility is left unaddressed (Table 9). Presents empirical findings and theoretical interpretation.

Discussion of hypotheses validity

The empirical findings provide strong and coherent support for all hypotheses developed in Chapter 3. Support for H1 confirms that algorithmic reliance exerts a statistically significant negative effect on professional judgment quality. This result reinforces prior evidence that advanced audit technologies may weaken professional skepticism when used as judgment substitutes rather than decision aids.

Support for H2 demonstrates that algorithmic reliance significantly increases ethical fragility. This finding empirically validates long-standing theoretical arguments regarding ethical fading and moral distancing in structured decision environments. Importantly, it shows that ethical vulnerability is not an individual trait but a situational outcome shaped by technological design and organizational context.

Support for H3 confirms that ethical fragility undermines professional judgment quality. This result directly challenges any separation between technical competence and ethical competence, demonstrating that ethical sensitivity is a constitutive element of professional expertise [117].

Finally, support for H4 establishes ethical fragility as a partial mediator between algorithmic reliance and judgment quality, consistent with mediation theory. The partial mediation indicates that while ethical fragility is a dominant mechanism, additional cognitive and organizational factors may also contribute to judgment outcomes.

Discussion of comparative results

The comparative analysis conducted in Chapter 5 reveals that the strength and nature of the relationships identified in the structural model are not uniform across audit contexts. Specifically, the negative impact of algorithmic reliance on professional judgment quality, as well as the mediating role of ethical fragility, are significantly stronger in highly automated audit environments. This finding provides important boundary conditions for interpreting the main results and reinforces the argument that ethical risks associated with algorithm-driven auditing are context-dependent rather than universal. From an institutional perspective, this pattern is consistent with research emphasizing that structural intensity amplifies behavioral consequences [118,119]. In highly automated environments, algorithmic systems are deeply embedded in audit workflows, reducing opportunities for discretionary judgment and increasing auditors' dependence on system outputs. As a result, ethical fragility becomes more pronounced due to heightened authority cues, reduced moral agency, and diffusion of responsibility [120].

Conversely, in less automated audit settings, algorithmic tools function more clearly as decision aids rather than decision substitutes. Auditors retain greater interpretive flexibility and are more likely to engage in reflective ethical reasoning, thereby mitigating the adverse effects of algorithmic reliance. This distinction aligns with prior research suggesting that technology does not determine out-comes in isolation but interacts with organizational design, professional norms, and governance structures [121,122]. These comparative findings underscore that ethical fragility is not an inevitable consequence of technological adoption. Instead, it emerges when algorithmic systems are deployed in ways that displace professional judgment rather than support it. This insight has direct implications for audit firm governance and regulatory oversight, as it highlights the importance of contextual safeguards in managing ethical risks.

Implications

Theoretical implications

This study makes several substantive theoretical contributions. First, it advances auditing research by explicitly integrating ethics into models of algorithm-driven professional judgment. Prior literature has largely treated ethics as a background condition or normative concern. By contrast, this study conceptualizes ethical fragility as a measurable, behaviorally grounded construct that operates as a central mechanism linking technology to judgment outcomes. Second, the findings extend professionalism theory by demonstrating how algorithm-driven environments reshape the ethical foundations of professional work. While prior studies emphasize external threats to professional autonomy, such as commercialization and regulatory pressure, this study shows that autonomy may also be eroded internally through technologically mediated decision architectures. Third, the study contributes to institutional theory by highlighting a tension between procedural legitimacy and substantive ethical legitimacy. Algorithm-driven auditing enhances formal compliance and efficiency but may weaken ethical engagement at the individual level, creating a legitimacy imbalance with long-term consequences for the profession.

Professional and regulatory implications

From a professional standpoint, the findings suggest that audit firms must reconsider how algorithmic tools are integrated into audit practice. Treating algorithms as neutral technical instruments overlooks their ethical and behavioral effects. Audit firms should therefore embed ethical governance mechanisms within algorithm-driven workflows, including mandatory judgment review points and explicit documentation of ethical considerations when relying on system outputs [123]. For regulators and standard setters, the results indicate a need to move beyond purely technical guidance on audit technology. Existing standards emphasize data analytics and continuous auditing but provide limited direction on managing ethical risks associated with algorithmic reliance. Updating ethics codes and quality management standards to explicitly ad-dress algorithm-assisted judgment would help clarify accountability and reinforce auditors' moral responsibility.

Social implications

At the societal level, the findings raise concerns about public trust in the auditing profession. Auditing's social license is grounded in the belief that auditors exercise independent, ethically grounded judgment in the public interest. If algorithm-driven auditing weakens ethical engagement, this trust may be eroded even when audits appear technically rigorous. Addressing ethical fragility is therefore essential for sustaining the profession's legitimacy in the digital era [124].

Recommendations (Expanded and Action-Oriented)

Based on the empirical findings and their theoretical interpretation, this study proposes the following recommendations.

First, audit firms should institutionalize ethical checkpoints within algorithm-driven audit processes. These checkpoints should require auditors to explicitly assess the ethical implications of system-generated recommendations and to document the rationale for accepting or overriding algorithmic outputs. Such practices would counteract automation bias and reinforce ethical ownership of judgments.

Second, professional education and continuous training programs should integrate ethics and technology rather than treating them as separate domains. Training should focus not only on how to use algorithmic tools but also on how such tools reshape judgment authority, moral agency, and professional responsibility [125].

Third, regulators and standard setters should revise ethics codes and quality management standards to explicitly address algorithm-assisted judgment. Clear guidance on accountability, documentation, and ethical responsibility in algorithm-driven audits would reduce ambiguity and strengthen professional discipline.

Fourth, audit oversight bodies should develop inspection and review procedures specifically tailored to algorithm-driven engagements. Such procedures should assess not only technical compliance but also whether ethical considerations are meaningfully integrated into judgment processes [126].

Finally, future research should examine additional moderators of ethical fragility, such as organizational culture, leadership tone, and individual moral identity. Longitudinal and qualitative studies could further illuminate how ethical fragility evolves over time in digitally intensive audit environments [127] (Table 10). presents implications and Recommendations Framework.

Conclusion and Future Research Directions

Overall conclusions

This study provides comprehensive empirical and theoretical evidence that algorithm-driven auditing reshapes auditors' professional judgment through intertwined cognitive and ethical mechanisms. The results demonstrate that reliance on algorithmic tools does not automatically enhance audit judgment quality and may, under certain conditions, impair it. This finding directly challenges technologically deterministic assumptions in contemporary audit analytics literature and reinforces earlier concerns regarding automation bias and diminished professional skepticism. More importantly, the study establishes ethical fragility as a central mechanism through which algorithmic reliance influences judgment quality. Rather than viewing ethical issues as peripheral or normative considerations, the findings confirm that ethical sensitivity is structurally embedded with-in professional judgment processes. This conclusion aligns with behavioral ethics research emphasizing that ethical failures often arise unintentionally due to situational and organizational factors rather than deliberate misconduct.

Key theoretical contributions

The study makes several significant theoretical contributions to auditing and accounting research. First, it introduces and empirically validates ethical fragility as a behavioral–cognitive construct that mediates the relationship between technology and professional judgment. This contribution advances prior audit technology research, which has largely examined cognitive effects while under-theorizing ethical mechanisms. Second, by integrating behavioral decision theory, professionalism theory, and institutional theory, the study provides a unified explanatory framework for understanding algorithm-driven auditing. The findings demonstrate that algorithmic systems may simultaneously enhance procedural legitimacy and undermine ethical legitimacy, creating a tension that has not been sufficiently theorized in prior literature. This theoretical integration responds to calls for deeper conceptualization of professional judgment in digitally intensive environments [128-131].

Practical and regulatory implications

From a practical perspective, the findings have important implications for audit firms, regulators, and standard setters. Audit firms should recognize that algorithmic tools are not ethically neutral and that their deployment requires explicit ethical governance mechanisms. Ethical fragility should be treated as a measurable professional risk and addressed through training, judgment review processes, and accountability frameworks. For regulators and standard setters, the study highlights the need to update ethical codes and audit quality standards to explicitly address algorithm-assisted judgment. Existing guidance often emphasizes technical compliance while providing limited direction on ethical accountability in algorithm-driven audits. Clarifying auditors' responsibilities when relying on algorithmic outputs is essential for maintaining professional integrity and public trust.

Limitations and future research directions

Despite its contributions, the study is subject to several limitations that suggest avenues for future research. First, the empirical analysis relies on cross-sectional data, which limits the ability to capture the dynamic evolution of ethical fragility over time. Longitudinal studies could provide deeper insight into how repeated exposure to algorithm-driven auditing affects ethical judgment and professional identity. Second, future research could examine additional moderators and boundary conditions, such as organizational culture, leadership tone, and individual moral identity, to better understand when ethical fragility is most likely to emerge. Experimental and qualitative approaches may also enrich understanding of how auditors interpret and negotiate ethical tensions in algorithm-driven environments. Finally, comparative studies across regulatory regimes would enhance the generalizability of the findings and inform international standard-setting debates.

Conflict of Interest Statement

The author declares that there is no conflict of interest regarding the publication of this paper. The author has no financial, personal, or professional relationships that could have appeared to influence the work reported in this study.

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