The Impact of AI-Generated Audit Evidence on Auditor-Client Negotiations

Nithara Godewatta*
Monash University
Department of Accounting
900 Dandenong Road, Caulfield East, VIC 3145, Melbourne, Australia
nithara.godewattaarachchige1@monash.edu

Soon-Yeow Phang
Monash University
Department of Accounting
900 Dandenong Road, Caulfield East, VIC 3145, Melbourne, Australia
soon-yeow.phang@monash.edu

Ashna Prasad
Monash University
Department of Accounting
29 Ancora Imparo Way, Clayton, VIC 3800, Melbourne, Australia
ashna.prasad@monash.edu

Xinning Xiao
Monash University
Department of Accounting
900 Dandenong Road, Caulfield East, VIC 3145, Melbourne, Australia
xinning.xiao@monash.edu

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*Corresponding author

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Abstract

As artificial intelligence (AI) continues to revolutionize the auditing profession, understanding how client managers perceive and react to AI-generated audit evidence is important for evaluating its influence on auditor-client negotiations. We experimentally investigate whether client managers' reactions to AI-generated audit evidence in negotiation with auditors are contingent upon whether or not their expectations on the proposed audit adjustments have been met. We predict and find that when client managers receive an audit adjustment within their expected range, they will offer greater pre-negotiation concessions for adjustments supported by AI-generated audit evidence (hereon AI-supported audit adjustment) rather than evidence derived by human specialists. Our results indicate that this effect is mediated by positive affect which may originate from a positively valued source. However, in the presence of an expectancy violation, client managers will offer greater pre-negotiation concessions for human-proposed audit adjustments than for AI-supported audit adjustments, an effect driven by the perceived credibility of the source of the audit adjustment. Our findings offer potential practical guidance in navigating AI-generated audit evidence during auditor-client negotiations.

Keywords: AI-generated audit evidence, Expectancy violations, Auditor-client negotiations, Pre-negotiation concessions.

I. INTRODUCTION

Audit firms are strategically investing billions of dollars to harness and embed sophisticated technologies such as Artificial Intelligence (AI hereon)[1] capable of processing large amounts of diverse and unstructured data, within their audit processes (Brownlee 2024; PCAOB 2023; EY Reporting 2018). AI investments enable autonomous systems to perform tasks, solve problems, communicate, interact, and reason at levels comparable to humans (Zúñiga, Goyanes, and Durotoye 2023), having a direct influence on the production of financial statements (Estep, Griffith, and Mackenzie 2023; Kapoor 2020; Kenches, Thomas, and Driskill 2020). Audit Firms are leveraging AI tools to assist auditors in tasks traditionally handled by human experts (KPMG 2017), and to aid auditors in assessing accounting estimates and valuations (AICPA 2020; PCAOB 2020).[2] Auditors are expected to incorporate evidence derived from AI systems into their evaluation of audit adjustments during auditor-client negotiations (Huson, Sierra-Garcia, and Gracia-Benau, 2023; Al-Sayyed, Al-Aroud, and Zayed 2021; Commerford, Dennis, Joe, and Ulla 2021).

Motivated by the increasing use of AI in audit firms and the limited research on its effects, we investigate, experimentally, the effect of the source of the audit evidence on client managers' pre-negotiation positions, and whether such effect is moderated by whether or not the proposed adjustment falls within the client managers' expected range. Pre-negotiation positions refer to a negotiator's initial strategic stance, encompassing their counter offer (proposed initial adjustment), goal (intended outcome), and limit (maximum acceptable concession), which collectively shape their strategy before formal negotiations commence

[1] In this study the term "AI" is used broadly. The term "AI" does not reveal the specific technologies underpinning its operation, as it often encompasses a combination of technologies like natural language processing and machine learning, used collectively by many companies and audit firms (Hood 2021). Using this approach enables the generalizability of the findings beyond any particular technology, focusing instead on the functionality of the AI rather than its operational mechanisms (Estep et al. 2023).

[2] AI tools used by Big 4 firms in tests of transactions and analytics help flag irregularities or exceptions that auditors can then investigate further (KPMG 2017; Deloitte 2017; EY 2018), potentially leading to proposed adjustments (Lombardi, Brown-Liburd and Munoko 2023).

(Dodgson, Agoglia, and Bennett 2023). Pre-negotiation positions are crucial for forecasting the outcomes of negotiations (Van Poucke and Buelens 2002; Kristensen and Gärling 2000). Prior research has largely focused on the use of AI by auditors (Fedyk, Fedyk, Hodson, and Khimich 2023, Lombardi et al. 2023; Samiolo and Spence 2023; Commerford et al. 2021), yet little research attention has been devoted to client managers' reactions to auditors' use of AI (Estep et al. 2023). In this study we examine client managers' pre-negotiation concessions in response to auditors' use of AI-supported audit adjustments.

The financial statement is co-produced by client managers and auditors (Wright and Wright 1997; Antle and Nalebuff 1991; DeAngelo 1981, Knechel, 2021), reflecting the joint effort of both parties (Gibbins, Salterio, and Webb 2001). When auditors propose income-decreasing audit adjustments, managers are incentivized to engage in opportunistic financial reporting (Bamber et al., 2010) and often resist such audit adjustments (Choudhary et al. 2019). Auditors utilize the persuasiveness of audit evidence in overcoming this resistance and increasing managers' acceptance of proposed adjustments (Estep et al. 2023). Prior research indicates that the persuasiveness of information is closely associated with source credibility (Pornpitakpan, 2004). Research across diverse streams of literature suggests that different factors influence individuals' perceptions of the credibility of non-human sources.

When issues arise during an audit engagement, clients and their auditors must interact to resolve their differences (Dodgson et al. 2023; Hatfield, Agoglia, and Sanchez 2008; Gibbins et al. 2001). Throughout these interactions, client managers may formulate expectations regarding the auditor's position, which is driven by the nature and trajectory of these engagements over time (Dodgson et al. 2023). Hence, in instances where the auditor's final position diverges from the client's anticipated expectations, mutual misinterpretation can occur.[3] The resulting breach of the client manager's set expectation is highly likely to induce tension between the involved parties, particularly for the party whose expectations have been violated (Dodgson et al. 2023).

We draw on the Expectancy Violation Theory (EVT hereon) (Burgoon 1993) and predict that client managers' reaction to the source of the audit evidence is moderated by whether the proposed audit adjustment falls within their expected range. Specifically, we posit that when the proposed audit adjustments meet the managers' expectations, client managers are more likely to offer greater pre-negotiation concessions to AI-supported audit adjustments than to human-proposed audit adjustments. We posit that when managers' expectations are met, their attention naturally shifts towards the advantages of the source, rather than its shortcomings (Burgoon et al. 2016). As a result, they are more likely to perceive AI as a more reliable source of judgment, given its ability to process vast datasets with superior efficiency and consistent accuracy than human judgement that is subject to biases (Logg, Minson, and Moore 2019; Davenport and Ronanki 2018).

Contrariwise, an expectancy violation is an undesirable outcome, thus managers will be tempted to challenge the adjustment in question. Managers would become more susceptible to questioning the source of the proposed audit evidence and its credibility (Burgoon 1993, 1978). We posit that when AI systems produce results that violate expectations, the trust in these systems can decrease significantly. Managers might question the reliability of the AI system, considering it flawed or inadequate for handling complex, non-standard situations (Dietvorst, Simmons, and Massey 2015). This results in client managers offering lower pre-

[3] While a client manager's expectations might sometimes be exceeded in a positive way (i.e., if the proposed audit adjustment is smaller than anticipated, leading to a more favourable result that is unlikely to be disputed) our focus is on instances of negative expectancy violations. These occur when the adjustment is larger than expected, potentially leading to significant modifications in the financial statements, and are typically more controversial (Dodgson et al. 2023). Such violations can adversely impact the quality of the audit (Dodgson et al. 2023).

negotiation concessions for AI-proposed adjustments than human-proposed audit adjustments. We predict that client managers may provide greater pre-negotiation concessions for human-proposed adjustments when expectations are violated, as emotionally charged situations often highlight the value of empathy and interpersonal connection that human specialists provide.

To test our predictions, we conduct a 2 × 2 between-participants experiment with financial executives. We manipulate the presence or absence of AI in the auditor's valuation procedures to mirror the varying utilization of AI by auditors in real-world scenarios. As both managers and auditors rely on specialists when dealing with complex estimates in practice, we include human valuation specialists in the experimental conditions in which AI is absent, consistent with Estep et al. (2023) and Commerford et al. (2021). We manipulate the expectancy violation condition (i.e. the audit partner proposes an audit adjustment that falls within or surpasses the range that the client manager initially expects) following Dodgson et al. (2023). Following a review of background details concerning the company and the ongoing audit engagement, participants were presented with an audit-related concern pertaining to patent valuation, along with the proposed adjustment to the financial statements put forth by the audit partner. Our study looks into the pre-negotiation stances of client managers, including their planned counteroffers, limits, and goals as they prepare for forthcoming discussions with the audit partner aimed at resolving the issue

Consistent with our predictions, we find that when no expectancy violation occurs, client managers offer greater pre-negotiation concessions for AI-supported audit adjustments than for human proposed audit adjustments. This effect is driven by positive affect.[4] Specifically, we find that client managers express greater positive affect towards AI-supported audit adjustments, resulting in greater pre-negotiation concessions for adjustments proposed

[4] Positive affect refers to the experience of pleasurable emotions such as joy, enthusiasm, and satisfaction, which influence an individual's perceptions, behaviors, and decision-making processes (Watson et al., 1988).

by AI systems than those by human specialists. When expectations are violated, client managers respond more negatively to AI-supported adjustments. That is, client managers offer lower pre-negotiation concessions when AI-generated audit evidence violates their expectations than when human proposed evidence violates their expectations. In such cases we find that when expectations are violated, the perceived credibility of AI-generated audit evidence decreases significantly, resulting in lower pre-negotiation concessions for AI-supported adjustments than those for human proposed audit adjustments.

Our study makes several contributions. First, our study contributes to auditor-client negotiation literature. Our findings complement the growing literature on the impact of AI on auditor and manager judgment and decision-making (e.g. Estep et al. 2023; Commerford et al. 2021; Dodgson et al. 2023). Estep et al. (2023) investigate how familiarity with AI influences client managers' preferences for AI-supported adjustments. Commerford et al. (2021) examine how algorithm aversion affects auditors and their reliance on AI-generated evidence, and how this aversion impacts their proposed adjustments to management's estimates. Dodgson et al. (2023) explores how relational familiarity and expectancy violations affect client managers pre-negotiation positions with human auditors. Our research extends this body of literature by exploring how AI-supported audit adjustments are perceived and acted upon by client managers in the negotiation setting, specifically when their expectations are either met or violated. Our study not only addresses the understudied area of AI's impact on pre-negotiation concessions but also provide insights into the conditions under which AI recommendations are accepted or resisted by client managers.

Second, our study offers practical implications for the implementation of AI systems in auditing, underscoring the importance of managing and aligning expectations for successful integration. Negotiation literature suggests that both parties develop cognitive representations of how their counterpart is likely to behave during the negotiation process (Brown-Liburd et al., 2008) thereby enabling negotiators to adjust their strategies in accordance with anticipated behaviors (Schei and Rognes, 2003). As such, our findings offer auditors valuable insights into client managers' reactions to AI-supported audit adjustments. When expectations are not met, auditors can rebuild trust by providing additional evidence, engaging in transparent discussions about the AI's decision-making process, and addressing client concerns or misconceptions. These findings should be of interest to auditors who seek to better understand and implement negotiation tactics to mitigate negative client reactions to their proposed adjustments. Furthermore, our study demonstrates that the source of a proposed audit adjustment can influence client manager's judgement and subsequent negotiation behavior. Our findings may help educate client managers about their susceptibility to source-driven bias, encouraging more objective engagement with AI-supported audit evidence. This, in turn may encourage client managers to focus on the substantive content of the audit evidence, allowing them to formulate more informed and objective pre-negotiation positions.

Last, our study provides valuable insights for standard setters as they seek to refine guidelines for the effective integration of AI systems into auditing practices (PCAOB 2024). While the adoption of AI systems offers significant potential to improve financial decision reporting, these benefits will only materialize if company management regards AI as a reliable source of information and integrates AI-generated outputs into their decision-making processes (Stöckle 2023; Commerford et al. 2021; EY Reporting 2018) in a negotiating setting. To this end, our study informs standard setters about the extent to which AI systems are accepted by client managers, enabling the development of best practices that promote transparency in auditors' use of AI, while clearly communicating its capabilities, limitations, and appropriate applications within the auditing process.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Background on the Use of AI in Auditing

AI refers to the use of computational technologies to accomplish tasks that typically require human-like intelligence (Deloitte 2017). This includes employing various AI technologies such as natural language processing, both supervised and unsupervised machine learning (including deep learning and neural networks), cognitive analytics and robotics (Deloitte 2017). Audit firms are increasingly leveraging these AI technologies to process and analyze data volumes that exceed human capabilities (AICPA 2020).

AI's impact on evidence gathering and transaction testing has been revolutionary. Traditionally, auditors relied on sampling techniques, testing only a portion of transactions, which left room for errors or missed discrepancies. AI now enables whole population testing, analyzing entire datasets rather than samples, allowing for more thorough and accurate transaction testing. Auditors use machine learning tools to analyze diverse datasets, such as third-party product reviews, to assess the alignment of customer feedback with underlying assumptions for warranty reserves (Hood 2021). EY uses AI-powered tools like "Document Intelligence for Transactions" and "Smart Sampling" to automate the extraction and verification of financial data. These tools apply machine learning to analyze documents, vouch data back to original sources and determine statistically valid sample sizes (E.Y, n.d) Traditionally, auditors identified potential risks by manually reviewing financial statements, board minutes and contracts, a process that is both time-consuming and prone to mistakes. With advancements in AI, these tasks have become more efficient and accurate (Seethamraju and Hecimovic 2023). AI-powered systems can now analyze documents at scale, detecting patterns, anomalies, and high-risk areas with greater precision. For example, AI tools can sift through board minutes to flag potential risks and recommend targeted sampling strategies. By automating these processes, AI not only reduces manual effort but also enables auditors to allocate resources more strategically, prioritizing areas of greatest concern and enhancing the overall quality of risk assessments (Seethamraju and Hecimovic 2023).

Furthermore, the application of AI can assist auditors in analyzing information that may not be present in a company's existing estimation model, potentially enhancing both business operations and auditing processes (Estep et al. 2023). "The superior accuracy of algorithmic judgment relative to human judgment (Dawes, Faust, and Meehl 1989) has led organizations to invest in the power of algorithms" (Logg et al. 2019). Audit firms are investing billions of dollars to incorporate such technologies into audit practices (PCAOB 2023; PCAOB 2020; EY Reporting 2018).

Motivated by the growing use of AI, researchers have begun to evaluate how AI systems affect auditor judgement and objectivity. Commerford et al. (2021) contribute to this line of literature by examining how algorithm aversion affects auditor judgments. They find that auditors propose smaller adjustments to management's complex estimates when receiving contradictory evidence from an AI system rather than a human specialist, particularly when estimates are based on objective inputs. Prior studies have looked at the impact of AI through a lens of algorithm aversion (Commerford et al. 2021; Dietvorst et al. 2015; Eastwood, Snook, and Luther 2012). This perspective seems odd given the widespread adoption of algorithms in decision-making processes. Thus, recent literature reassessed the concept of human distrust of algorithm output. For instance, Logg et al. (2019) found that individuals tend to place greater trust in equivalent advice when it is labelled as coming from an algorithmic source versus a human source. Furthermore, Libby and Witz (2024) finds that AI significantly reduces the negative effects of perceived independence conflicts on jurors' assessments by enhancing auditor objectivity and fostering trust. These findings underscore the significant role of AI in addressing independence concerns.

The growing use of AI prompts the need of understanding the implications of auditor's use of AI on client managers. Prior qualitative studies investigating the perception of managers on auditors' use of AI have yielded mixed results (Estep et al. 2023). Thus, prompting the development of experimental research focused on the nuanced responses of managers to AI under various conditions (Estep et al. 2023). Prior studies explore factors such as the environmental context, task-specific conditions, and personal attributes influencing individuals' attitudes toward AI (Logg et al., 2019; Dietvorst et al. 2015). For instance, Estep et al. (2023) examined the impact of managers familiarity with AI technology. Our research builds on this foundation but takes a distinct direction by examining whether managers have an inherent preference for AI-generated audit evidence and by examining the potential shifts in their attitudes after an expectancy violation.

Auditor-Client Negotiation and Expectancy Violations Theory

According to PCAOB (2010), auditors must obtain sufficient and appropriate audit evidence to support their conclusions, a process that involves continuous review, assessment, and extensive communication with clients over days, weeks, or even months to refine their testing and judgments (Gibbins et al. 2001). This frequent communication during the audit process establishes an environment where expectations can be formed and then disrupted, with both auditors and clients experiencing such unexpected outcomes during negotiations (Gibbins et al. 2001). To that end, we use EVT, a communication theory, to understand how managers react to unforeseen violations of their expectations (Burgoon 1993). In the context of our study, we aim to understand the impact of an AI-proposed audit adjustment on client managers' pre-negotiation concessions based on the premise of EVT.

EVT serves as a framework for understanding expectancy confirmations and focuses on three primary aspects: expectedness, valence, and importance (Bevan, Ang, and Fearns 2014). The theory first assesses how expected a violation or confirmation might be by comparing the actual outcomes with potentially unexpected outcomes. EVT then explores how valence could affect the manner in which the violator and the violator's communication are perceived by the victim. Lastly, EVT delves into the potential effects of these violations on the relationship between the violator and the victim, providing a comprehensive view of interpersonal interactions following expectancy deviations.

EVT has been applied in various accounting and auditing research contexts. For instance, studies have investigated how investors respond to changes in financial disclosures (Dong, Liu, and Wong-On-Wing 2017), client managers' reaction to violations by audit partners (Dodgson et al. 2023), and the connections between CSR practices, irresponsible actions, and corporate reputation (Lin-Hi and Blumberg 2016). We add to this line of literature by examining how the violation of a client manager's expectation could be influenced by the source of the proposed audit adjustment.

We extend the growing body of literature on AI adoption and acceptance by drawing on EVT to understand how individuals react to deviations from expected outcomes in the context of AI. Building upon prior research, we explore how individuals interpret and react to deviations in AI-supported outcomes. Specifically, we investigate the effects of AI within the specific context of conflict management during auditor-client negotiations, which will be theorized in the next section.

The Joint Effect of Expectancy Violation and Source of the Proposed Audit-Adjustment

EVT (Burgoon 1993) guides our theoretical predictions concerning the relationship between the source of the proposed audit adjustment and manager's pre-negotiation concessions. EVT emphasizes the crucial role of valence, a psychological term that denotes the inherent attractiveness (positive valence) or aversiveness (negative valence) of an entity, event, or situation (Frijda 1986). Within EVT, the concept of valence is linked to both the violator and the violator's communication. As such EVT literature discusses the importance of considering how the source of the information (i.e., violator) affect the individuals' (i.e., target) judgement (Burgoon et al. 2016).

In general, when events unfold as expected, EVT states that there is a tendency for the target to express a positive valence. This positive valence originates from a positively valued source, have positive interpretations associated with them or have positive valence within a community (Burgoon 1978). In simpler terms, this suggests that when an expectation is met, the target is likely to focus more on the benefits of the source, assessing the degree of positive valence attributed to it. As a result, the target tends to offer greater concessions to sources perceived to have higher positive valence (Burgoon et al. 2016). This behavioral pattern indicates that when expectations are met, the target will respond to the proposed judgment by evaluating the benefits of the source and offering greater concessions to the source they believe to be more credible.

Prior literature suggests that client managers generally hold a positive outlook on AI-generated information (Estep et al. 2023).[5] Estep et al. (2023) reveals that client managers believe that audits will become more efficient and effective with auditors' use of AI. Given this perspective, when audit adjustments fall within client managers' expected range, they may perceive this as an indication of AI's efficiency and accuracy. Meeting expectations reinforces trust in AI's ability to process vast amounts of data without bias, aligning with the widely held belief that non-human sources can outperform human specialists in various domains (Christ, Emett, Summers, and Wood 2021; Ding, Lev, Sun, and Vasarhelyi et al 2020; Yeomans, Shah, Mullainathan, and Kleinberg 2019). Additionally, prior research demonstrates that individuals tend to rely more on AI-generated information when they have not yet encountered errors from AI systems (Logg et al. 2019; Dietvorst et al. 2015). This suggests that, as long as AI-generated

[5] In interviews conducted by Estep et al. (2023) one client manager stated, "I would feel more confident that fewer things are missed if AI was involved. There's so much open to human error" (Estep et al. 2023).

audit evidence aligns with their expectations, client managers may see AI as a more reliable tool that enhances the audit process.

These findings collectively suggest a growing trend in managerial behavior where AI is perceived as not only more reliable but also more capable than humans in certain decision-making contexts. According to EVT, when an expectation is met, the client manager (i.e., target) mentally attributes a certain level of positive valence to the source of the audit adjustment (i.e., violator). In the context of AI-generated audit evidence, we posit that when an adjustment aligns with client managers' expectations, they are more likely to view AI as a reliable and efficient tool, reinforcing trust in its outputs. Thus, we predict that managers will offer greater pre-negotiation concessions for AI-supported audit adjustments compared to those proposed by humans.

H1a: In the absence of an expectancy violation, client managers will offer greater pre-negotiation concessions for AI-supported audit adjustments than for human-proposed audit adjustments.

On the other hand, when expectations are not met, naive conjectures may lead one to predict that client managers maybe more inclined to offer greater pre-negotiation concessions to AI-supported audit adjustments. One may expect client managers to perceive the inherent benefits of AI and thus, accept the proposed audit adjustment with the perception that it is accurate. However, EVT suggests that a negative expectancy violation can cause client managers to evaluate the credibility and legitimacy of the source to determine their response (Dodgson et al. 2023; Burgoon et al. 2016).

When a violation occurs, EVT posits a dual-appraisal process involving interpretations and evaluations of the communication act itself. Violations increase attention by making the violation more salient (Burgoon 1978) and prompting more detailed observations of the violator (Newtson 1973). This shift in focus from the initial activity to the violation heightens awareness of the violator's reward valence, which refers to the degree to which the target of the violation perceives the violator positively or negatively (Burgoon et al. 2016). This in turn triggers the dual process of interpreting and evaluating the violation, both of which can be influenced by the source of the violation.

When an audit adjustment leads to an expectancy violation, client managers are likely to challenge the proposed adjustment. This often activates a typical behavioral pattern in which clients believe they possess a strategic advantage and may seek to exploit ambiguities in order to pressure auditors into accepting more aggressive financial reporting alternatives (Brown-Liburd and Wright 2008). EVT literature further suggests that negative violations lead to heightened negative affect and more unfavorable evaluations of the source of the information and that the severity of these affective reactions depends on the perceived credibility of the source (Dodgson et al. 2023; Burgoon et al. 2016). Despite advancements in AI technology, prior studies have documented various concerns humans have about the bias and error in AI algorithm systems (Castelo and Lehmann 2019; Dietvorst et al. 2015). The "black box" nature of AI significantly affects an individuals' perceived credibility of AI systems (Estep et al. 2023). The lack of transparency regarding the underlying rationale or considerations driving the proposed changes can lead to increased resistance and diminished trust in certain situations (Estep et al. 2023). Research by Dietvorst et al. (2015) further reveals that participants tend to be more forgiving of errors made by humans than those made by algorithms, often penalizing the algorithm estimate more severely after witnessing an incorrect estimate.[6]

While AI systems offer efficiency and consistency, they may lack the perceived accountability, transparency, and interpretability associated with human specialists (Castelo and Lehmann 2019). In the context of an expectancy violation, where precision and accuracy

[6] Furthermore, Human specialists are often perceived as possessing extensive domain knowledge, experience, and expertise in auditing, which can enhance their credibility and trustworthiness in the eyes of managers (Choudhary, Merkley, and Schipper 2021; Nelson, Elliott, and Tarpley 2002; Braun 2001).

are crucial for resolving discrepancies, managers may perceive AI-generated adjustments as "black box" decisions due to the lack of transparency regarding the underlying rationale or considerations driving the proposed changes (Estep et al. 2023). As a result, managers may attribute a greater negative valence towards audit adjustments generated by AI systems than human systems based on their perceived credibility of the source.

Thus, we predict that a negative expectancy violation will lead client managers to attribute a greater negative valence towards AI systems compared to human specialists based on their perceived credibility of the source. As a result, client managers will offer greater pre-negotiation concessions when audit adjustments are proposed by human specialists than when they are supported by audit evidence generated from AI systems.

> **H1b:** In the presence of an expectancy violation, client managers will offer greater pre-negotiation concessions for human-proposed audit adjustments than for AI-supported audit adjustments.

These hypotheses are not without tension. When expectations are met, the source of the audit adjustment might carry less significance in shaping client managers' decisions, as the absence of the violation reduces the need for deeper scrutiny or skepticism about the evidence provided. In such scenarios, client managers are likely to attribute the outcome to the routine functioning of the audit process rather than to the unique qualities of the source itself (Dodgson et al., 2023). As a result, the source (i.e. human specialist or AI system) may not significantly influence pre-negotiation concessions when their expectations are met.

Furthermore, when expectations are violated, there is a tendency for client managers to offer greater concessions for AI-proposed audit evidence due to automation bias. As defined by the IESBA Code (2022), automation bias reflects a predisposition to favor outputs generated by automated systems, even when contradictory information or human reasoning raises doubts about their reliability. Client managers' inherently positive perceptions of AI technologies

(Logg et al. 2019) may lead them to trust AI-generated evidence, regardless of whether their expectations are violated. This bias could result in client managers offering greater pre-negotiation concessions even under expectancy violation conditions, creating a tension with the theoretical prediction that unmet expectations diminish trust and reduce concessions.

III. MAIN EXPERIMENT

Participants

We recruit 100 financial executive participants with the assistance of Dynata, a third-party data collection service.[7] Dynata identifies and invites participants who meet the pre-screening criteria to take part in the experiment.[8] For this study, the target participants are financial executives from publicly listed companies in the US.[9] Of the 100 participants majority are upper-level management (29 percent CFOs, 15 percent CEOs, 31 percent managers, and 16 percent Controllers); 67 percent of the participants are men; 61 percent of the participants are below 50 years of age; 75 percent hold a degree in accounting or finance; 49 percent are CPAs; 64 percent have experience working with Big4 auditors; participants have been in their current position for 10.44 years on average and hold 11.92 years of experience with the annual audit process on average; participants further rate their experience working through issues with auditors as a 7.57 on a scale from 0 (Not at all experienced) to 10 (Very experienced).

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[7] Dynata operates differently from other online labour markets such as M-Turk, where a large number of users independently browse and select tasks that they find appealing. Rather Dynata, identifies and cater to our request of a specific participant group. Upon request Dynata will reach out to members in their database and invite participants with the pre-set requirements to participate in our study.

[8] This project was approved by the authors' institutional review board. Our use of Dynata's services to recruit participants s consistent with other studies (Dodgson et al. 2023; Estep et al. 2023; Pyzoha 2015; Kang 2019). Leiby et al. (2021) further states that Dynata is a productive platform for behavioral research, particularly when targeting participants who are challenging to reach.

[9] In order to make certain that participants possess the required experience and knowledge with the financial reporting process and addressing auditor discrepancies we followed the pre-screening process outlined by Estep et al. (2023). First, Dynata targeted individuals from its pre-screened pool who hold financial executive positions at US listed companies. Secondly, we asked participants two screening questions. The first question screens for appropriate experience working with external auditors (Dodgson et al. 2023) and the second question screens for appropriate accounting knowledge (Estep et al. 2023). Following the experiment, additional questions were asked to validate the participants' professional experience, demographic alignment with the target group, and their exposure to external auditors. Lastly, participant effort was assessed through a self-reported effort scale and time spent completing the study. Additionally, we implemented an extra measure by ensuring that all participants provided context-specific answers to open-ended questions, further validating their suitability for our study.

Engagement with the experiment is reasonably high, with participants reporting an average effort level of 6.76 out of 10. Furthermore, we also review the time spent by participants in completing the experiment. On average participants had spent approximately 25.69 minutes in completing the experiment.

Task and Procedure

We adapt the background and financial information from the studies of Estep et al. (2023) and Dodgson et al. (2023). Participants are asked to assume the role of a CFO of a fictional company named "TechWave". The case involves a hypothetical energy company that specializes in alternative energy sources such as solar and wind and its products are sold throughout the US (extracted from Estep et al. 2023). Participants receive the background information of the company, financial information of the company, brief information about the firm's external auditors and the status of the current year audit thus far.

After reviewing the background information, participants are informed about a single significant audit discrepancy concerning patent valuation that needs resolution with the auditors. At this stage, the auditors are still in the process of collecting the necessary evidence before reaching a conclusion regarding the patents. However, based on their latest discussion with the auditors, participants form an expectation of what they expected the audit partners' final stance on the patent would be (refer to the expectancy condition manipulation in Appendix 1). Participants then read an email from the audit partner, which states that after completing their audit testing, the auditors have developed their own independent estimate and are proposing an $8,000,000 adjustment to the fictional company's initial estimate (Dodgson et al. 2023). Participants further reads information about the auditor's assumptions and method (i.e., AI or human specialist) used to arrive at the proposed audit adjustment (refer to the source manipulation in Appendix 1).

Next, the participants state their pre-negotiation positions, including their planned counteroffer, goal, and limit (the dependent variables), in preparation for the meeting. After reporting these pre-negotiation positions, participants then answer the post-experimental questions, which include the manipulation check questions and demographic information.

Manipulation of the Source

We manipulate the source of the audit adjustments at two levels (i.e., AI system vs human valuation specialist) following Estep et al. (2023) and Commerford et al. (2021). As detailed out in Appendix 1, participants read that the auditors use the "propriety AI system" in the audit firm to evaluate the fair value of the patents in the AI system condition. By contrast, in the human valuation specialist condition, the participants read that the auditors use the "valuation specialist department" in the audit firm to evaluate the fair value of the patent (Estep et al. 2023; Commerford et al. 2021).

Manipulation of the Expectancy Condition

Following Dodgson et al. (2023) we hold auditor's actual proposed adjustment of $8,000,000 constant to ensure the materiality of the adjustment does not vary across the two conditions. Instead, we manipulate the client expectation so that the auditor's proposed adjustment will either be above (indicating an expectancy violation) or within (indicating no expectancy violation) the range anticipated by the client manager based on interactions during audit fieldwork. As detailed out in Appendix 1, in the expectancy violation condition, the audit partner's $8,000,000 adjustment exceeds the expected range of $3,000,000 to $5,000,000. In the no expectancy violation condition, the partner's $8,000,000 adjustment fall within the expected range of $7,000,000 to $9,000,000 (Dodgson et al. 2023).

Dependent Variables

A pre-negotiation position refers to the initial stance or strategy that a participant plan to take before entering negotiations. To understand participants strategies for the upcoming meeting with the audit partner, we request them to report their pre-negotiation positions. Prior studies such as Dodgson et al. (2023) capture pre-negotiation concessions using managers' counteroffer, goal, and limit. These pre-negotiation positions are expressed as adjustments to the company's original unaudited patent balance, resulting in a range of responses from \$0 (no adjustment) to \$8,000,000 (accepting the full amount of the proposed adjustment) (Dodgson et al. 2023). Specifically, the "goal" will represent the patent adjustment participants aim to achieve, the "limit" will indicate the maximum adjustment they would accept, and the "counteroffer" will be the adjustment they initially propose to the audit partner at the beginning of discussions. This approach ensures a clear understanding of participants' strategies and expectations for the negotiation process.

IV. MAIN RESULTS

Manipulation Checks

To check the effective manipulation of the expectancy condition, we follow Dodgson et al. (2023) and Clor-Proell (2009). We ask participants to rate their surprise at the magnitude of the audit partner's proposed adjustment on a 11-point Likert scale, with 0 being "Not at all surprised" to 10 being "Very surprised". Participants in the expectancy violation condition are significantly more surprised by the auditor's adjustments than participants whose expectations are not violated (6.86 vs 5.80, $t_{98} = 2.17$, $p = 0.03$, untabulated).[10] Furthermore, participants are asked to rate how the auditor's proposed adjustment compared to their expectations. Participants whose expectations are violated rate the adjustment significantly higher relative to their expectations than participants whose expectations were not violated (7.27 vs 5.39, $t_{98} = 3.83$, $p < 0.01$, untabulated).

To check our manipulation of the source of the audit adjustment we follow Commerford et al. (2021) and Estep et al. (2023) in asking participants whether they received the proposed

[10] Unless otherwise noted, all reported p-values are two-tailed.

audit adjustment from the audit firm's "AI system" or "Valuation specialist department". A total of 73 (73 percent) participants answered this question correctly. We receive similar results by excluding the participants that failed the manipulation check, as such we have included all participants in our analysis.

Hypotheses Testing

Descriptive statistics for all participants' pre-negotiation positions (i.e., counteroffer, goal and limit) are reported in Panel A of Table 1 (graphically presented in Figure 1, Figure 2 and Figure 3). We conduct three separate 2 x 2 ANOVAs with the source of audit adjustment and expectancy condition as the independent variables and counteroffer, goal and limit as the dependent variables in each analysis respectively (See Table 1 Panel B). We detect a significant interaction between the source of audit adjudgment and expectancy condition across all three pre-negotiation positions, counteroffer ($F_{1,96} = 8.44$, $p = 0.005$, two-tailed), goal ($F_{1,96} = 13.46$, $p < 0.01$, two-tailed) and limit ($F_{1,96} = 9.94$, $p < 0.01$, two-tailed).

H1a states that in the absence of an expectancy violation (i.e., when events unfold as expected), client managers will offer greater pre-negotiation concessions for AI-supported audit adjustments than for human-proposed audit adjustments. Table 1, Panel C presents the simple effects analysis. The results indicate that when client managers' expectations are met, counteroffer (4,949,230.77 vs. 3,304,347.83, $t_{47} = 3.03$, $p < 0.01$, one-tailed), goal (6,055,769.23 vs. 4,504,347.83, $t_{47} = 3.57$, $p < 0.01$, one-tailed) and limit (6,713,461.54 vs. 5,847,826.09, $t_{47} = 2.44$, $p = 0.01$, one-tailed) are all significantly higher for AI-supported audit adjustments than for human-proposed audit adjustments. These results suggest that client managers are more generous (i.e., offer greater pre-negotiation concessions) when the proposed audit adjustments align with their expected range, and when the auditor uses AI to support the proposed adjustment compared to when it is solely supported by human specialists. Thus, H1a is supported.

H1b states in the presence of an expectancy violation, client managers will offer greater pre-negotiation concessions for human-proposed audit adjustments than for AI-supported audit adjustments. As presented in Table 1, the results indicate that when client managers' expectations are violated, goal (5,193,333.33 vs. 4,533,333.33, $t_{49} = 1.58$, $p = 0.06$, one-tailed) and limit (6,023,333.33 vs. 5,202,380.95, $t_{49} = 2.06$, $p = 0.02$, one-tailed) are both significantly higher for human-proposed audit adjustments than for AI-supported audit adjustments. However, counteroffers for human-proposed audit adjustments are not significantly higher than that for AI-supported audit adjustments (4,336,666.67 vs. 3,676,190.48, $t_{49} = 1.14$, $p = 0.13$, one-tailed). One plausible reason for this marginal difference could be that the goal and limit set by client managers may vary significantly across the two conditions. However, even if their goal is set at $5 million for human-proposed adjustments or $3 million for AI-supported adjustments, managers might still initiate negotiations with a lowball counteroffer as a strategic starting point. Overall, the results support H1b, demonstrating that when client managers' expectations are violated, they react more negatively (i.e., offering lower pre-negotiation concessions) to audit adjustments supported by AI-generated audit evidence compared to those proposed by human specialists.

Additional Analyses

Positive Affect influence on client managers

H1a suggests that when events unfold as expected, client managers will express a positive valence to the source of the information. This positive valence originates from a positively valued source, have positive interpretations associated with them or have positive valence within a community (Burgoon 1978). We posit that when expectations are met, client managers will express a greater positive affect towards AI-generated audit evidence compared to human proposed audit evidence. To test this, we examine whether positive affect explains the interaction effect of the source of the audit adjustment and expectancy condition on client managers' pre-negotiation concessions (i.e., counteroffer, goal, limit).

The participants are required to answer two questions relating to how positive they feel. They rated the extent to which they feel happy or appreciated on a 11-point scale from 0 (Not at all) to 10 (Very much). We use factor analysis with a principal axis factoring extraction method to create a composite measure of the positive affect scale items.[11] The untabulated simple effects results indicate that, when client managers' expectations are met, client managers' positive affect reactions are significantly higher when the audit adjustment is supported by AI-generated audit evidence than when it is supported by human proposed audit evidence (0.10 vs. -0.34, $t_{47} = 1.75$, p = 0.04, one-tailed).

We ran the three separate moderated mediation models (Hayes Process Model 8, number of bootstraps = 10,000, 90% confidence interval, see panel B of Table 3), using the source of audit adjustment as the independent variable, expectancy condition as the moderator, positive affect as the mediator and counteroffer, goal and limit as the dependent variables in each analysis respectively. We find significant moderated mediation effect for counteroffer (index = 1134896.05, SE = 462107.32, 90% CI = [460443.50, 1966105.73]), goal (index = 719194.82, SE = 276338.73, 90% CI = [304802.68, 1211185.32]) and limit (index = 571573.46, SE = 265395.33, 90% CI = [203952.02, 1061930.91]). When expectancy conditions are not violated, the indirect effect of positive affect on counter offer (effect = -437468.74, 90% CI [-964082.06, -12606.91]), goal (effect = -277228.25, 90% CI [-578464.92, -5802.66]) and limit (effect = -220324.60, 90% CI [-479169.80, -9189.73]) are significant. These findings are consistent with our predictions that, when expectations are met client managers' express a greater positive affect towards AI systems than human sources and thus

[11] As expected, these two measures of positive affect load onto a single underlying factor (coefficients are unstandardized), which explains 69.45 percent of the total variance. The affect items making up this factor are taken from an abbreviated version of the PANAS scale validated by Watson et al. (1988) and used in Dodgson et al. (2023).

offer greater pre-negotiation concessions for audit adjustments supported by AI generated audit-evidence than those supported by human specialists.

Source credibility influences on client managers

H1b suggests that when expectations are violated, managers will become more susceptible to questioning the source of the proposed audit evidence and its credibility. We posit that when AI systems produce results that violate expectations, the trust in these systems can decrease significantly compared to human sources. To test this, we examine whether the perceived credibility of the source explain the interaction effect of the source of the audit adjustment and expectancy condition on client managers' pre-negotiation concessions (i.e., counteroffer, goal, limit).

The participants are required to answer three questions relating to the credibility of the source. They rated the extent to which they agree that the audit adjustment is trustworthy, objective and accurate on a 11-point scale from 0 (Not at all [trustworthy/ objective/ accurate]) to 10 (Very [trustworthy/ objective/ accurate]). The average of these three responses is our measure for the perceived credibility of the source. The untabulated simple effects results indicate that, when client managers' expectations are violated, client managers' perception of the credibility of the source is significantly lower when the audit adjustment is supported by AI-generated audit evidence than when it is supported by human proposed audit evidence (6.02 vs. 7.82, $t_{49} = 3.52$, $p < 0.01$, two-tailed). However, when the proposed audit adjustment falls within client managers' expected range, participants are not significantly affected by the credibility of the source (6.96 vs. 6.78, $t_{47} = 0.35$, $p = 0.73$, two-tailed, untabulated). A potential reason for client managers being indifferent to the source when expectations are met might lie in EVT. EVT suggests that when expectations are met individuals are less likely to critically evaluate the source of the information, as the alignment with expectations reinforces a sense of normalcy and reduces cognitive dissonance (Dodgson et al., 2023). In such cases, the focus shifts away from scrutinizing the source and toward the content of the adjustment itself, as the outcome is perceived as routine and expected.

We ran the three separate moderated mediation models (Hayes Process Model 8, number of bootstraps = 10,000, 95% confidence interval, see panel B of Table 3), using the source of audit adjustment as the independent variable, expectancy condition as the moderator, source credibility as the mediator and counteroffer, goal and limit as the dependent variables in each analysis respectively. We find significant moderated mediation effect for counteroffer (index = 783229.13, SE = 419271.82, 95% CI = [37082.16, 1695669.97]), goal (index = 631702.60, SE = 330772.75, 95% CI = [39014.20, 1355465.87]) and limit (index = 522081.61, SE = 283736.00, 95% CI = [27296.29, 1142044.57]). In the expectancy violated condition, the indirect effect of source credibility on counter offer (effect = 873832.23, 95% CI [310519.94, 1591992.53]), goal (effect = 704777.30, 95% CI [264216.05, 1267945.55]) and limit (effect = 582475.46, 95% CI [179529.08, 1084093.48]) are significant. In the absence of an expectancy violation, the indirect effect of source credibility on counter offer (effect = 90603.13, 95% CI [-436120.97, 602111.79]), goal (effect = 73074.70, 95% CI [-339947.09, 497055.81]) and limit (effect = 60393.86, 95% CI [-279714.14, 411996.43]) are insignificant. Overall, this is consistent with our prediction that, an expectancy violation results in a greater depletion of credibility for AI-generated audit evidence compared to human-supported evidence and thus, client managers offer greater pre-negotiation concessions for audit adjustments proposed by human specialists than those supported by AI generated audit-evidence.

Analysis of Decision-Making Rationales

To better understand client managers' negotiation behavior, we collected qualitative responses by asking participants to state what guide their decision-making in the experimental task. When expectations were violated, client managers exhibit skepticism toward AI-generated audit evidence, often questioning its reliability and credibility. For example, one manager stated that

"AI valuation is not a proven method," while another cautioned that "the AI model should not be weighted so much." This distrust extended to concerns about AI's "black box" nature as highlighted by a participant who noted, "We do not know that data; the fact that it is associated with AI does not impress us." These comments reflect a reduced willingness to concede to AI-supported adjustments under expectancy violated conditions.

In contrast, client managers demonstrate greater openness and a cooperative tone towards audit adjustments that violate their expected range but are supported by human specialist. As evidenced by statements such as "trying to negotiate in good faith" and "acknowledging the recommended amount but meeting a more modest adjustment so we can have a better P&L for investors." This suggests that violations are perceived as less severe when dealing with human supported evidence, fostering more constructive negotiation behavior. Overall, the qualitative data align with the study's quantitative results (H1b), reinforcing that expectancy violations diminish trust and concession toward AI supported audit adjustments than that for human-supported audit evidence.

V. CONCLUSION

Our study examines the impact of the source of the audit evidence on client managers' pre-negotiation positions. Drawing on EVT, we predict an find that client managers' reaction to the source of audit adjustment is contingent on whether their expectations are met. Client managers offer greater pre-negotiation concessions to AI-supported audit adjustments than human-proposed audit adjustments when their expectations are met. Specifically, when expectations are met, client managers attribute greater positive affect to AI-generated audit evidence than to human-proposed audit evidence, enhancing their willingness to make concessions for AI-supported audit adjustments. Whereas, when their expectations are not met, they are more generous (i.e., offer greater pre-negotiation concessions) towards human-proposed adjustments over AI-supported audit adjustments. We further find that when expectations are violated, the perceived credibility of AI-generated audit evidence decreases significantly. As a result, client managers offer greater pre-negotiation concessions for audit adjustments proposed by human specialists than those supported by AI generated audit-evidence.

Our study makes several important contributions to practice and academic literature. For example, prior research has focused on client manager's reactions to AI supported audit evidence via a lens of client familiarity with AI, we extend the literature by examining how affective reactions caused by expectancy violations affect client manager's reaction to AI generated audit evidence. Additionally, by showing that violations caused by AI systems and human specialist do not create the same consequences, our findings provide valuable insights to auditors, regulators and practitioners about the implications that the source of the audit evidence can have on the resolution of audit issues during auditor-client negotiations. In practice, auditors can utilize our research to understand and implement negotiation tactics to mitigate negative reactions. When expectations are violated, auditors can rebuild trust by providing additional evidence, engaging in transparent discussions about the AI system's decision-making process, and addressing any client concerns or misconceptions. Practitioners may further test and develop interventions to improve the acceptance and effectiveness of AI tools in auditing, ultimately enhancing the overall audit process. Additionally, our study offers valuable insights for standard setters by highlighting client managers trust levels and acceptance of AI technologies in the industry. Understanding these perspectives can help identify and address specific concerns such as accuracy, transparency, and bias, leading to improved standards for AI in auditing..

Our study has limitations that open up interesting avenues for future research. Specifically, to maintain experimental control, both the human specialist and the AI system conditions used identical information and provided the same audit evidence, which aligns with firms' current development of "narrow" AI systems to replicate human judgments. However, our findings may not apply to more advanced AI systems with greater autonomy and adaptability that firms might adopt in the future (Commerford et al., 2021). Furthermore, given that managers are skeptic about the "black box" nature of AI, the amount of information provided to them during the experiment is crucial to the evaluation of such systems, hence, the results are highly contingent on the information available to managers. It would be beneficial for future studies to explore the communication of the application of AI and negotiation tactics surrounding the implications of AI to provide a more nuanced understanding of the impact of AI on auditor client negotiations.

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T A B L E 1

Client Managers' Pre-Negotiation Concessions in a 2X2 Design

Panel A: Descriptive Statistics: mean (standard deviations) [sample size]

Condition	Counter offer	Goal	Limit
AI and expectancy violation	3,676,190.48 (2,033,938.24) [21]	4,533,333.33 (1,295,505.05) [21]	5,202,380.95 (1,141,980.32) [21]
Human and expectancy violation	4,336,666.67 (2,030,369.99) [30]	5,193,333.33 (1,574,348.98) [30]	6,023,333.33 (1,555,343.03) [30]
AI and no expectancy violation	4,949,230.77 (2,043,559.49) [26]	6,055,769.23 (1,391,713.11) [26]	6,713,461.54 (1,135,038.12) [26]
Human and no expectancy violation	3,304,347.83 (1,710,523.12) [23]	4,504,347.83 (1,654,327.18) [23]	5,847,826.09 (1,352,058.89) [23]

Panel B: ANOVA Results

		Counteroffer		Goal		Limit	
Variable	**df**	**F-test**	**p-value**	**F-test**	**p-value**	**F-test**	**p-value**
Source	1	1.54	0.22	2.19	0.14	0.01	0.93
Expectancy Condition	1	0.09	0.76	1.91	0.17	6.23	0.01
Source X Expectancy Condition	1	8.44	0.01	13.46	<0.01	9.94	<0.01
Error	96						

Panel C: Simple effect comparisons

		Counteroffer		Goal		Limit	
Source of Variation	**df**	**t-statistic**	**p-value**	**t-statistic**	**p-value**	**t-statistic**	**p-value**
Effect of Source at Violated Expectancy	49	1.14	0.13*	1.58	0.06*	2.06	0.02*
Effect of Source at No Violated Expectancy	47	3.03	<0.01*	3.57	<0.01*	2.44	0.01*
Effect of Expectancy Condition at AI Source	45	2.13	0.04	3.84	<0.01	4.53	<0.01
Effect of Expectancy Condition at Human	51	1.96	0.06	1.56	0.13	0.43	0.67

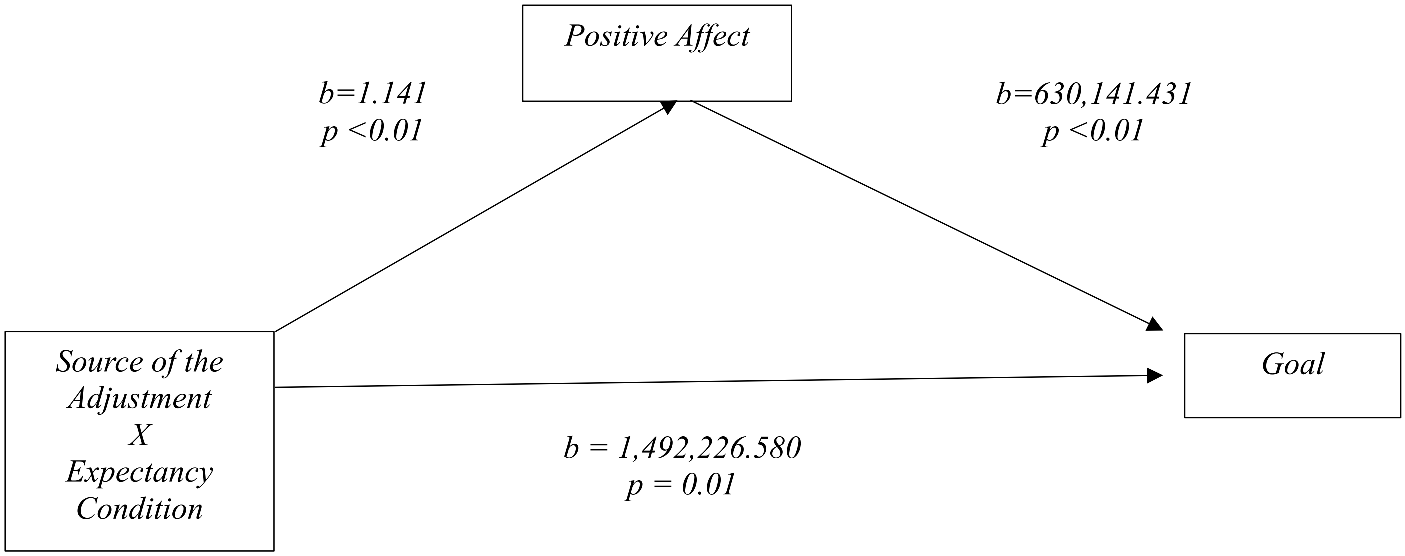
The *"counter offer"* represents the adjustment that the client would counter-propose to the audit partner as discussions first begin. The *"goal"* represents the adjustment that they are hoping to achieve. The *"limit"* represents the maximum adjustment that they would accept. The *source* of the audit adjustment is either AI (audit evidence generated by audit firms' AI system) or human (audit evidence proposed by the valuation specialist). The *expectancy condition* is either violated (the proposed audit adjustment surpasses the expected range) or not violated (the proposed audit adjustment falls within the expected range).
* *p*-values are one-tailed

TABLE 2
Client Managers' Positive Affect

Panel A: Descriptive statistics: mean (standard deviation) [sample size]

	Source								
Expectancy Condition	AI			Human			Overall		
Expectancy Violated	-0.31	(0.86)	[21]	0.39	(0.99)	[30]	0.11	(0.99)	[51]
Expectancy Not Violated	0.10	(0.79)	[26]	-0.34	(0.97)	[23]	-0.11	(0.90)	[49]
Overall	-0.08	(0.84)	[47]	0.07	(1.04)	[53]	0.00	(0.95)	[100]

Panel B: Mediation Analysis



Note: Panel B depicts the results of mediation analysis using the SPSS PROCESS macro (Model 8) which is described by Hayes (2013). Positive affect is measured by asking participants to indicate how happy or appreciated they feel using an 11-point scale, ranging from 0 (Not at all) to 10 (Very much). Source of the audit evidence is manipulated on two-levels: Human specialist or AI system. Expectancy condition is manipulated on two-levels: Expectancy violated, or Expectancy not violated. The "counteroffer" represents the adjustment that the client would counter-propose to the audit partner as discussions first begin. The "goal" represents the adjustment that they are hoping to achieve. The "limit" represents the maximum adjustment that they would accept. The significance of the indirect effects is assessed using 90 percent confidence intervals gained through bootstrapping approaches (10,000). Only the results for "goal" are graphically represented above, the results for "counteroffer" and "limit" are presented in the table below due to manuscript length constraints.

Test of Indirect Effects	**Counteroffer**		**Goal**		**Limit**		
Source → Positive Affect → DV (i.e., Counteroffer, goal or limit)	***Effects***	***Confidence Interval***	***Effects***	***Confidence Interval***	***Effects***	***Confidence Interval***	***Sig.***
Index of moderated mediation	1,134,896.05	[460,443.50, 1,966,105.73]	719194.82	[304,802.68, 1,211,185.32]	571,573.46	[203,952.02, 1,061,930.91]	Significant
No expectancy violated	-437,468.74	[-964,082.06, -12,606.91]	-277228.25	[-578,464.92, -5,802.66]	-220,324.60	[-479,169.80, -9189.73]	Significant
Expectancy violated	697,427.31	[255,560.49, 1,204,595.85]	441966.57	[155,251.02, 772,301.65]	351,248.86	[101,620.26, 690,550.92]	Significant

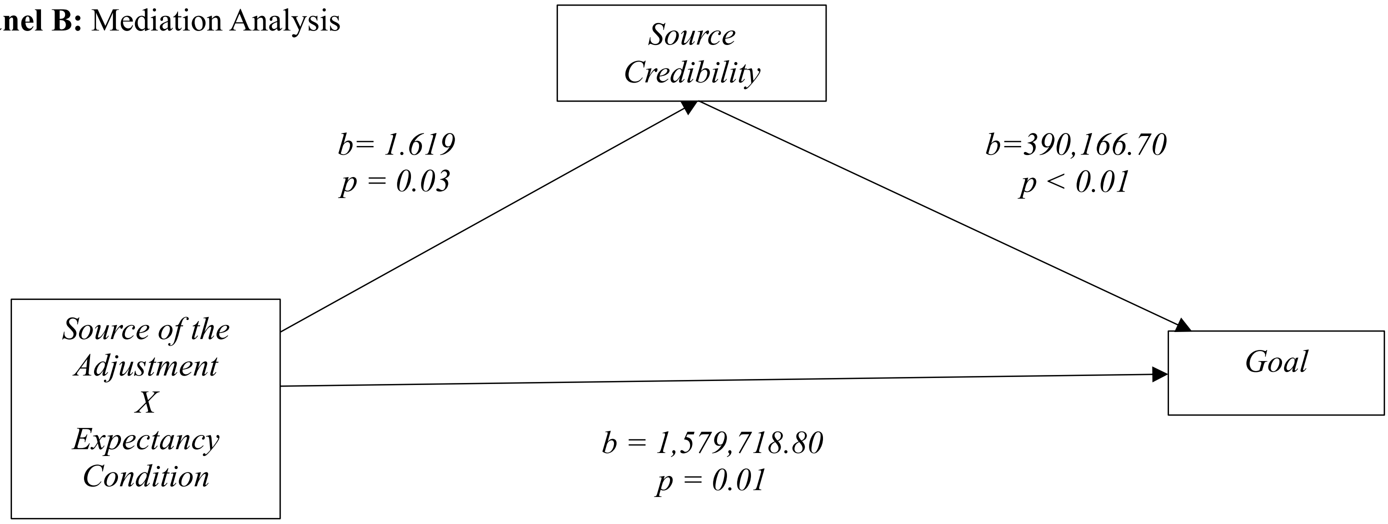
TABLE 3

Client Managers' Perceived Level of Source Credibility

Panel A: Descriptive statistics: mean (standard deviation) [sample size]

	Source								
Expectancy Condition	AI			Human			Overall		
Expectancy Violated	6.02	(2.22)	[21]	7.82	(1.45)	[30]	7.08	(2.00)	[51]
Expectancy Not Violated	6.77	(1.97)	[26]	6.96	(1.78)	[23]	6.86	(1.87)	[49]
Overall	6.43	(2.10)	[47]	7.45	(1.64)	[53]	6.97	(1.93)	[100]

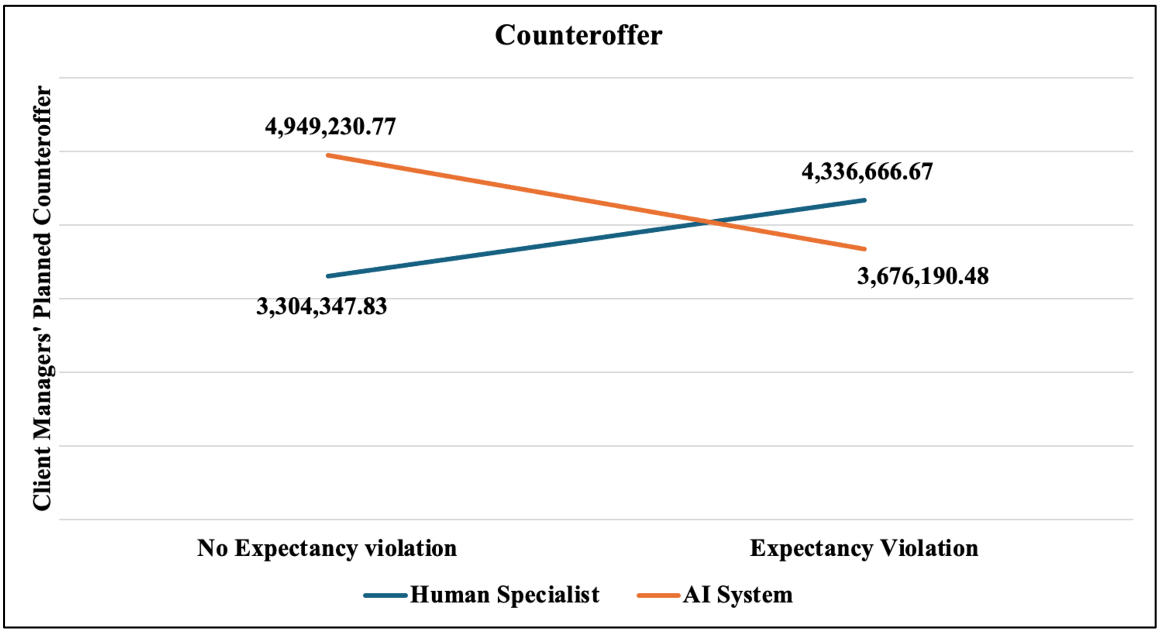
Panel B: Mediation Analysis



Note: Panel B depicts the results of mediation analysis using the SPSS PROCESS macro (Model 8). Source credibility is measured by asking participants to indicate how trustworthy, objective and accurate the audit adjustment is using a 11-point scale, ranging from 0 (Not at all) to 10 (Very much). Source of the audit evidence is manipulated on two-levels: Human specialist or AI system. Expectancy condition is manipulated on two-levels: Expectancy violated, or Expectancy not violated. The "counteroffer" represents the adjustment that the client would counter-propose to the audit partner as discussions first begin. The "goal" represents the adjustment that they are hoping to achieve. The "limit" represents the maximum adjustment that they would accept. The significance of the indirect effects is assessed using 90 percent confidence intervals gained through bootstrapping approaches (10,000). Only the results for "goal" are graphically represented above, the results for "counteroffer" and "limit" are presented in the table below due to manuscript length constraints.

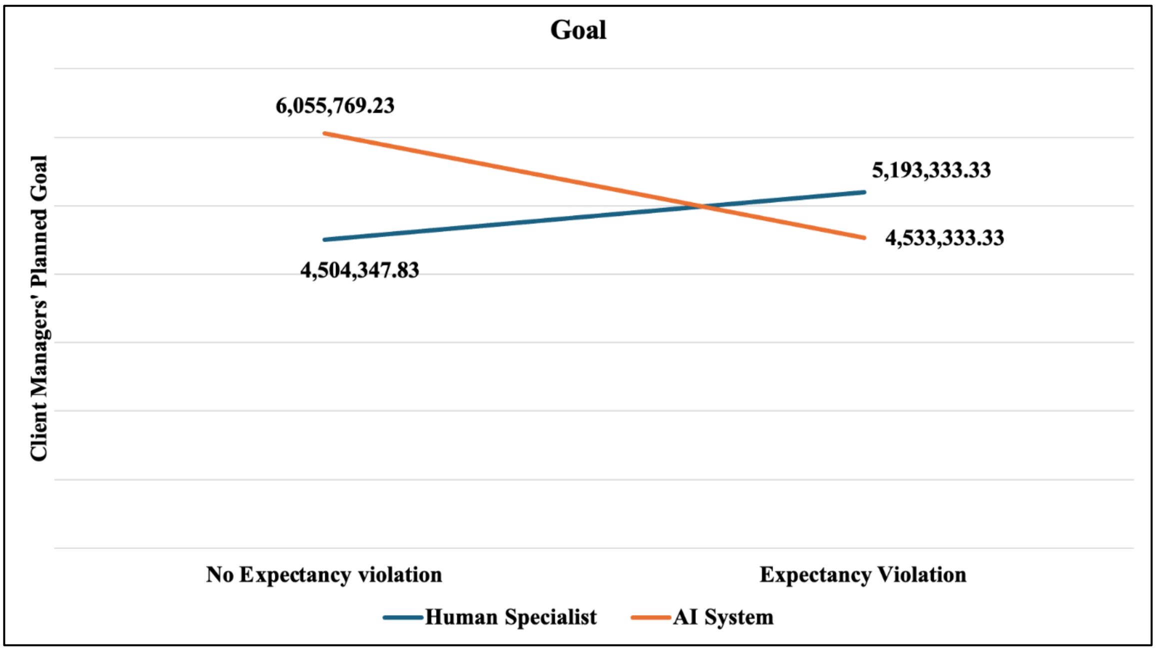
Test of Indirect Effects	**Counteroffer**		**Goal**		**Limit**		
Source → Source Credibility → DV (i.e., Counteroffer, goal or limit)	***Effects***	***Confidence Interval***	***Effects***	***Confidence Interval***	***Effects***	***Confidence Interval***	***Sig.***
Index of moderated mediation	783,229.13	[37,082.16, 1,695,669.97]	631,702.60	[39,014.20, 1,355,465.87]	522,081.61	[27,296.29, 1,142,044.57]	Significant
Expectancy violated	873,832.23	[310,519.94, 1591,992.53]	704,777.30	[264,216.05, 1,267,945.55]	582,475.46	[179,529.08, 1,084,093.48]	Significant
No expectancy violated	90,603.13	[-436,120.97, 602,111.79]	73,074.70	[-339,947.09, 497,055.81]	60,393.86	[-279,714.14, 411,996.43]	Insignificant

FIGURE 1: The diagrammatical representation of client managers' planned counteroffer



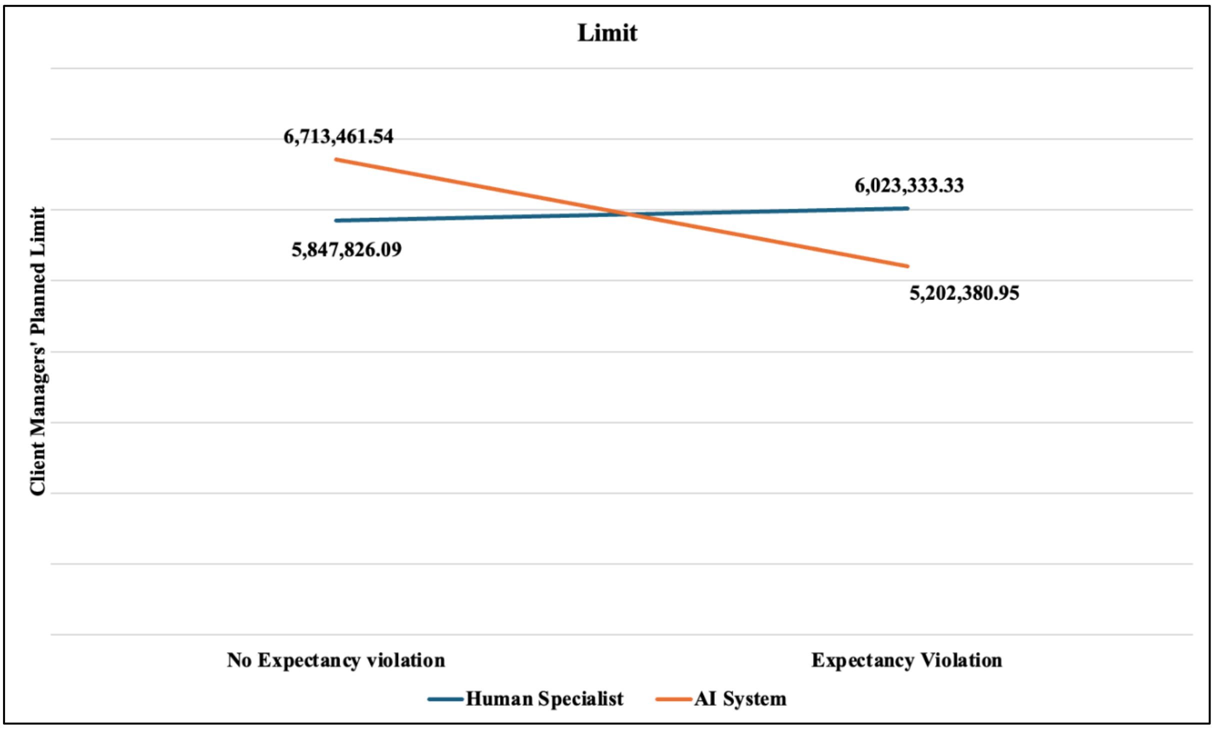
Note: The *"counter offer"* represents the adjustment that the client would counter-propose to the audit partner as discussions first begin. The *source* of the audit adjustment is either AI (audit evidence generated by audit firms' AI system) or human (audit evidence proposed by the valuation specialist). The *expectancy condition* is either violated (the proposed audit adjustment surpasses the expected range) or not violated (the proposed audit adjustment falls within the expected range).

FIGURE 2: The diagrammatical representation of client managers' planned goal



Note: The *"goal"* represents the adjustment that they are hoping to achieve. The *source* of the audit adjustment is either AI (audit evidence generated by audit firms' AI system) or human (audit evidence proposed by the valuation specialist). The *expectancy condition* is either violated (the proposed audit adjustment surpasses the expected range) or not violated (the proposed audit adjustment falls within the expected range).

FIGURE 3: The diagrammatical representation of client managers' planned limit



Note: The *"limit"* represents the maximum adjustment that they would accept. The *source* of the audit adjustment is either AI (audit evidence generated by audit firms' AI system) or human (audit evidence proposed by the valuation specialist). The *expectancy condition* is either violated (the proposed audit adjustment surpasses the expected range) or not violated (the proposed audit adjustment falls within the expected range).

APPENDIX 1
EXPERIMENT 1 INSTRUMENT EXTRACT

Manipulation of the Expectancy Condition

[Expectancy Violated Condition]

Audit Test Work Continued

At this point, you and the audit team have spoken on several occasions to aid in their understanding of the facts surrounding a potential patent valuation issue. These discussions have led you to expect that the auditors will formally propose a patent decreasing adjustment between $3,000,000 and $5,000,000 of the patent balance.

You are now waiting for the auditors to contact you with a final number once all documentation provided is taken into consideration. Overall, the net impact of this patent write-down would result in an equivalent decrease in the company's reported income, due to the increase in impairment loss. A quick calculation of the impact on net income and earnings per share (EPS) is as follows:

	Range
Anticipated Adjustment	$3,000,000 - $5,000,000
% Reduction in Net Income After Adjustment	5.34% - 8.90%

[No Expectancy Violated Condition]

Audit Test Work Continued

At this point, you and the audit team have spoken on several occasions to aid in their understanding of the facts surrounding a potential patent validation issue. These discussions have led you to expect that the auditors will formally propose a patent decreasing adjustment between $7,000,000 and $9,000,000 of the patent balance.

You are now waiting for the auditors to contact you with a final number once all documentation provided is taken into consideration. Overall, the net impact of this patent write-down would result in an equivalent decrease in the company's reported income, due to the increase in impairment loss. A quick calculation of the impact on net income and earnings per share (EPS) is as follows:

	Range
Anticipated Adjustment	$7,000,000 - $9,000,000
% Reduction in Net Income After Adjustment	12.45% - 16.01%

Manipulation of the Source of the Audit Adjustment

Note: Please note that the words in bold represent the source manipulation. The words within the brackets are used in the AI source condition manipulation, the words in italics in bold represent the human proposed condition manipulation.

Finalization of Audit Test Work

The auditors have finalized their test work surrounding the patent valuation issue. Julia sent you the following e-mail to describe the team's final position in more detail. A meeting has been scheduled to discuss the issue tomorrow.

From: Julia Johnson, Audit Partner at Harris & Clark (HC), LLP

We have audited the significant estimates included in the 2023 financial statements. During our testing, we found one discrepancy between our estimates and TechWave's. This discrepancy involves the estimate for a patent.

Based on our understanding of the relevant information and our review of the work prepared by TechWave, it is our opinion that the assumption of 10% annual growth in sales of solar panels over the next five years is not adequately supported by the available evidence.

In order to evaluate the fair value of the patent, we utilized our HC **valuation specialist department (*proprietary artificial intelligence (Al) system*).** Our HC **valuation specialists (*Al system*)** apply firm-approved methodologies to evaluate information from a variety of sources as well as information obtained from TechWave. Harris & Clark considers conclusions reached by our HC **valuation specialists (*Al system*)** to be reliable, objective audit evidence.

The audit evidence provided by our HC **valuation specialists (*Al system*)** suggests an annual growth rate of 7% is more reasonable, based on a weighted average of forecasts, adjusted for the 2026 expiration of a popular solar tax credit in California. Additionally, the audit evidence from our HC **valuation specialists (*Al system*)** suggests that market saturation in the southwest U.S. is likely to occur in the next 3-5 years, and as such greater weight should be placed on national forecasts in anticipation of TechWave shifting its focus from the regional to the national solar panel market as regional saturation occurs.

Based on this information obtained from our HC **valuation specialists (*Al system*),** we believe that the impairment loss for patent should be <u>increased by $8,000,000</u> to $28,000,000. Therefore, our audit team proposes the following adjusting entry as a decrease to reported income and patent:

Dr. Patent Impairment Loss	$8,000,000	
Cr. Patent		$8,000,000

I would like to meet tomorrow to discuss this proposed adjustment.

Julia Johnson
Audit Partner