Client Suspicion of AI-Assistance in Tax Professional Communications

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ABSTRACT
Although artificial intelligence (AI) is rapidly changing accounting practice, little is known about how clients perceive professionals' use of AI in client-facing communications. This study addresses that gap by examining whether suspicion of AI-assistance in tax professionals' emails affects client retention. Building on expectancy–disconfirmation theory, we predict that clients who suspect AI involvement will be more likely to seek alternatives and switch preparers, especially if they are more familiar with AI. In a 2×1 online experiment with 145 U.S. taxpayers, participants received either a human-authored or AI-refined email. Results show that while detection of AI cues was imperfect, suspicion of AI-assistance significantly increased switching intentions among AI-familiar clients. Our findings highlight a novel client-side risk of AI adoption in professional services, extending accounting research beyond firm-level outcomes to the client relationship. Importantly, because AI adoption is expanding rapidly and client familiarity with AI continues to rise, the risks we document are likely to become increasingly salient for practice.

Keywords: Tax Professional-Client Communications, Artificial Intelligence, Client Retention, Expectancy-Disconfirmation Theory

JEL Classifications:

Data Availability:

I. INTRODUCTION

AI is transforming professional services, including accounting and tax practice. To date, research has largely focused on the adoption of AI within firms and its influence on outcomes such as audit quality (Fedyk et al. 2022; Commerford, Eilifsen, Hatfield, Holstrom, and Kinserdal 2024; Rahman, Zhu, and Yue 2024), tax compliance (Johnson, Peterson, Sloan, and Valencia 2021; Raddatz, Raddatz, Ogunade, Darsheika, and Williams 2025; Swider 2025), financial reporting (Estep, Griffith, and MacKenzie 2024), and employee effort or creativity (Jia, Luo, Fang, and Liao 2024; Brown, Burke, and Sauciuc 2025). This body of work emphasizes internal processes to the firm, that is, how the application of AI affects internal accounting practices. In contrast, relatively little attention has been paid to the client's perspective of their accountants' utilization of AI.

Existing studies (e.g., O'Reilly 2025; Downen, Kim, and Lee 2024) have primarily examined perceptions of AI in accounting-related processes, but not its role in client-facing tasks such as professional communications with clients. With AI now commonly used to assist with routine tasks such as email drafting and other inter-personal communications (see Jaffe et al. 2024; Microsoft 2024), we investigate how individual tax clients' suspicion that their tax professionals utilized AI to draft email communications shapes their intentions to shop for alternatives and switch preparation services.

Emerging research in computer-mediated and AI-mediated communication (CMC and AIMC, respectively) has begun to evaluate individuals' ability to recognize AI-assisted content. Several studies have shown that individuals are able to identify cues of AI-assistance, albeit with imperfect accuracy (Chein, Martinez, and Barone 2024; Waltzer, Pilegard, and Heyman 2024; Wilson and Rose 2025). Other work has experimentally manipulated an AI disclosure, finding that when authorship is explicitly attributed to AI, recipients tend to evaluate the communication less favorably than that from human authors (Lim and Schmälzle 2024; Fu, Foell, Xu, and Hiniker 2024; Reif, Larrick, and Soll 2025). At the same time, accounting industry evidence suggests that these questions of AI-assistance in communications are no longer merely academic. The AICPA has highlighted AI's role in "email triage" to streamline client communication, while the *State of AI in Accounting Report (2025)* found that 64% of accountants use AI to draft emails and adjust tone (CPA.com 2025). Parallel surveys of knowledge workers indicate that a substantial share are already using generative AI tools, often for tasks such as drafting emails, and that overall interest in adoption remains high (Relyea, Maor, and Durth 2024; Sternfels, and Atsmon 2025). Against this backdrop, it becomes important to examine (1) whether individual clients can accurately recognize AI-assistance in an email from their tax professional and (2) whether such perceptions might prompt individual clients to seek out or switch to another tax preparation service.

We conceptualize suspicion of AI authorship as an expectancy violation. Expectancy–disconfirmation theory (Oliver 1980) holds that satisfaction depends on whether experiences confirm or disconfirm normative expectations. In tax practice, clear and open communication is not only valued but also normatively expected (Bobek, Dalton, Hageman, and Radtke 2019); clients assume that the professional authoring communications is exercising judgment and tailoring advice to their circumstances. We argue that suspicion that a message was machine-assisted disconfirms this expectation, raising concerns that the preparer's expertise and personalized attention have been displaced. This disconfirmation may not directly lead to departure, but it can trigger exploratory behavior such as shopping for alternatives or soliciting second opinions, exposing the relationship to competitive threats (Schiebler, Lee, and Brodbeck 2025).

We develop a moderated mediation model to explain how an AI-drafted email from a tax professional shapes tax clients' opinion shopping and preparation service switching behaviors (Kaszak, Iyer, and Reckers 2024). Drawing on evidence that individuals can detect stylistic and linguistic cues of AI-generated content (e.g., Waltzer et al., 2024; Chein et al., 2025), we theorize that clients will be more likely to detect AI involvement when an email is refined by a generative AI platform (ChatGPT-4) than solely drafted by a human practitioner. Building on CMC and AIMC findings that recipients tend to evaluate AI-generated or refined communications less favorably than human-authored ones (Arriaga et al., 2020), we anticipate that clients who perceive their practitioner's email as AI-assisted will be more inclined to engage in opinion shopping and, ultimately, to switch tax preparers. Finally, we expect this mediated relationship to be conditioned by clients' personal familiarity with AI. Consistent with expectancy–disconfirmation theory (Oliver 1980, 2010; Schiebler et al. 2025), we hold that clients who are more familiar with AI are also more aware of its shortcomings, making them more likely to evaluate a practitioner unfavorably when they perceive AI-assistance in professional communication (Lankton and Wilson 2007).

To test our hypotheses, we conducted a 2×1 online experiment with 145 Prolific participants who had significant taxpaying experience. Participants reviewed a scenario adapted from Kaszak et al. (2024) involving a sole proprietor confronted with an expense reclassification decision. They were randomly assigned to receive one of two email messages from a tax professional, ultimately disallowing the reclassification: one written solely by a human with no AI-assistance or one written by a human with AI-assistance. To create the AI-assisted email condition, we entered the solely-human authored email into ChatGPT-4 with the prompt: 'Can you clean this email up for me?' We selected this prompt because it reflects a realistic way professionals might use AI tools in practice, not to generate entirely new content, but to refine an existing message. This approach ensured the two conditions were comparable in substance while differing only in whether the final message had been refined by AI. After reviewing the scenario and email, participants reported their perceptions of the AI-likeness of the email received from the hypothetical tax professional, their intentions to shop for alternatives and switch preparers, as well as other process measures and demographic information.

Our results support our theoretical model. Participants in the AI-assisted condition rated the email, on average, about 10 points higher (out of 100 points) on "AI-likeness" than those in the human condition, suggesting that clients could detect cues of AI-assistance in their communication with their tax professional. This suspicion of AI-assistance, in turn, predicted clients' willingness to shop for alternatives and switch preparation services, but only among individuals with greater familiarity with AI. In other words, suspicion of AI-assistance alone was not enough to drive switching; it was the combination of perceiving AI use and being AI-familiar that produced stronger intentions to opinion shop and switch their preparer.

Our study makes several contributions to both the literature and professional practice. Accounting research thus far has examined AI's wide-ranging effects on professional accountants' (Fedyk et al. 2022; Commerford et al. 2024) (and other users of accounting information [Downen, et al. 2024; O'Reilly 2025]) judgment and decision-making. More closely related to our study, Raddatz et al. (2024) and Swider (2025) examine taxpayer preference for AI-generated tax advice as compared to human (CPA)-prepared tax advice, revealing that taxpayers tend to hold higher confidence in advice provided by human experts (Dietvorst, Simmons and Massey 2015). We contribute to this burgeoning conversation in the literature by considering taxpayer perception of AI-generated communications; that is, the method in which the tax professional transmits advice to the taxpayer, not the method in which the advice itself is generated. We show that clients' perceptions of AI-assisted communications in professional interactions can undermine retention, offering a cautionary message for practitioners considering how to incorporate AI into their client-facing work. Furthermore, our finding that AI familiarity amplifies this effect suggests that the challenge will only intensify as the general population becomes more experienced with AI.

Our research also contributes to the conversation within the AIMC literature examining individual perceptions of AI-authored messages and information. As noted by Sundar and Lee (2022):

> Artificial intelligence (AI) technology has profoundly affected virtually all areas of our lives over the past decade. Communication is no exception. Communication is so sacredly and fundamentally human that a machine performing this function raises a number of questions of urgent importance to our discipline. How well can AI replace a human in

> serving as a communicator? How can AI mediate the relationship between two individuals or a group, in personal and organizational settings? How does the entry of AI alter basic mechanisms such as persuasion, and influence applied domains? (p. 379).

At this point, overarching conclusions from this research about AI-mediated communication are somewhat mixed. For instance, individuals find AI-authored communication more professional and effective (Coman and Cardon 2024), precise and expressive (Fu et al. 2024). Hohenstein et al. (2023) documents another positive outgrowth of AI-assisted messaging: quicker communication speed (Hohenstein et al. 2023). On the other hand, research has also shown that individuals view messages labeled as AI-generated as less credible and intelligent (Henestrosa & Kimmerle 2024) as well as less trustworthy (Jakesch, French, Ma, Hancock, and Naaman 2019). Our study adds to this stream of literature by considering how AIMC influences an economically-relevant decision (tax professionals' client retention) in a setting where a tax professional is attempting to persuade a client to not claim an overly-aggressive deduction. Moreover, we add additional context to this literature by documenting that a certain type of individual, those with greater AI familiarity, are more likely to respond negatively to a professional who they perceive utilizes AI in their communications. By doing so, we extend the findings of Kaszak et al. (2024) by introducing a novel and practically relevant contextual factor (AI authorship) as an influence on taxpayer opinion shopping and switching intentions. Our study also complements Rosenthal, Brown, Higgs and Rupert (2023), who examine taxpayer motivations for choosing between software and professional preparers, by showing how suspicions of AI use within professional communications may further shift client preferences.

II. HYPOTHESIS DEVELOPMENT

To develop our hypotheses, we build on prior research in computer-mediated and AI-mediated communication (CMC; AIMC), which demonstrates that individuals are sensitive to cues of AI-assistance or AI-generation in communications and often evaluate such content less favorably. Extending this literature to the tax professional–client context, we argue that clients' suspicion of AI-assistance in professional communications will shape their behavioral intentions toward their preparer. Consistent with expectancy–disconfirmation theory (Oliver 1980), we contend that such suspicions can violate clients' normative expectations that professional communications should reflect personalized service from their preparer, thereby fostering dissatisfaction and increasing the likelihood of switching. Such suspicions may not directly cause clients to depart but can trigger exploratory behaviors such as shopping for alternatives or soliciting second opinions, exposing the relationship to competitive threats. Specifically, we expect that clients' suspicion of AI-assistance mediates the relationship between AI involvement and client switching intentions, and that this process is conditioned by clients' familiarity with AI. Accordingly, we present a moderated mediation model that captures how AI-assistance influences perceptions and, in turn, client retention. We develop hypotheses for each stage of this process. See Figure 1.

Email Communication to Perceptions of AI Authorship

Research in computer-mediated and AI-mediated communication demonstrates that individuals are often attentive to cues that suggest machine authorship. Although detection accuracy is imperfect, participants consistently rate AI-refined content as more "AI-like" than comparable human-authored content (Waltzer et al. 2024; Chein et al., 2025; Wilson & Rose 2025). Studies show that individuals frequently rely on stylistic and linguistic heuristics, such as repetitiveness, overly polished phrasing, or reduced anthropomorphic quality, when forming judgments of authorship (Henestrosa et al. 2023; Gallegos et al. 2025; Kirk and Givi 2025). These heuristics do not guarantee correct classification, yet they do produce systematic differences in perceptions across AI- versus human-generated texts.

Extending this literature to the tax domain, we argue that clients will similarly be sensitive to cues of AI utilization when evaluating professional communications. Even without explicit disclosure, we expect that emails refined by a generative AI tool (e.g., ChatGPT) will be suspected as more AI-authored than substantively identical emails written solely by a human preparer.

> *HYPOTHESIS 1:* Tax clients will suspect greater AI-assistance in emails refined by AI than in substantively identical emails written solely by a human tax professional.

Perceptions of AI Authorship to Client Opinion Shopping and Switching

Beyond whether clients can detect cues of AI authorship, an important question is how such perceptions influence their willingness to remain with or switch to a new preparation service. The literature on AI-mediated communication suggests that suspicion of AI involvement can meaningfully alter how recipients respond to the communicator. Sundar and Lee (2022) argue that communication is considered a deeply human activity, such that AI's presence as a communicator disrupts expectations. Guzman and Lewis (2020) similarly contend that when audiences suspect machine authorship, they evaluate the communicator differently than when authorship is clearly human. Empirical research across diverse domains supports this idea. For example, Jakesch et al. (2019) document a "Replicant Effect," whereby Airbnb hosts' advertisements suspected of AI-assistance were evaluated less favorably. Reis, Reis and Kunde (2025) find that patients described as seeing physicians who use AI reported reduced willingness to book an appointment. In workplace settings, Coman and Cardon (2024) show that AI-generated writing, while often judged as polished and professional, was nonetheless evaluated less positively in interpersonal terms.

Although these studies examine different contexts, together they illustrate a consistent pattern: when individuals suspect AI involvement, they often respond less favorably to the source.

Expectancy–disconfirmation theory (EDT) (Oliver 1980; 2010) provides a theoretical lens for this dynamic. EDT posits that satisfaction with a product or service depends on whether the experience confirms or disconfirms prior expectations. Schiebler et al. (2025) conduct a comprehensive meta-analysis and show that *disconfirmation* (i.e., the gap between initial client expectations and ultimate perceived performance) is a powerful predictor of satisfaction, with particularly strong effects in service contexts where relational and delivery quality expectations are salient (Santos and Boote 2006). The literature further distinguishes between predictive expectations (what will happen) and normative expectations (what should happen), with normative expectations being more strongly tied to evaluations (Spreng, MacKenzie, and Olshavsky 1996; Schiebler et al. 2025).

Applied to tax practice, we argue that clients hold the normative expectation that their preparer will personally compose communications. This expectation is rooted in the nature of the service: clients pay professional fees not only for technical accuracy but also for personalized guidance, reassurance, and the sense that their preparer's expertise is directly applied to their case. When clients suspect that a message is authored by AI, this expectation is disconfirmed. Such disconfirmation can undermine satisfaction with the preparer and prompt clients to consider alternatives (Homburg, Koschate and Hoyer 2006). Put differently, suspicion of AI-assisted communications may trigger doubts about whether the preparer is delivering the full value of a professional service, thereby increasing intentions to shop for alternatives and switch preparation services.

> *HYPOTHESIS 2:* Tax clients who suspect greater AI-assistance in their preparer's communications will report higher intentions to shop for alternatives and switch tax professionals.

The Moderating Role of AI Familiarity

Although we expect suspicion of AI-assistance to increase clients' likelihood of shopping for alternatives and switching (H2), these effects are not likely to be uniform across individuals. Prior research indicates that individuals more familiar with technology and AI hold sharper expectations about both its capabilities and its shortcomings, making them more critical of its use in human services (Benbasat and Wang 2005; Gursoy, Chi, Lu, and Nunkoo 2019). This aligns with broader work in human–AI interaction showing that users with more knowledge of AI are less forgiving of its limitations. For example, Jakesch et al. (2019) find that awareness of algorithmic involvement reduces trust and credibility in communication contexts, while Langer, König, and Fitili (2018) report that individuals familiar with algorithmic decision-making perceive AI-driven recruitment practices as less fair.

Applied to tax practice, these findings suggest that once AI-assistance is suspected in an email from their tax professional, AI-familiar clients are especially likely to view such reliance as a violation of normative expectations about professional communication. In turn, they may interpret this AI-assistance as evidence that the preparer is not fully delivering on the value of personalized expertise, particularly as similar AI-enabled functionality is becoming increasingly available in lower-cost tax software. Thus, the relationship between suspicion of AI authorship and switching intentions should be amplified among clients with greater AI familiarity.

> *HYPOTHESIS 3:* The positive relationship between suspicion of AI-assistance in professional communications and clients' intentions to shop for alternatives and switch tax professionals will be stronger among clients with greater familiarity with AI.

Conditional Indirect Effect

Taken together, our arguments suggest that the influence of their tax professionals' email drafting method (AI-assisted or no AI-assistance) on client switching intentions operates indirectly through clients' suspicion of such assistance, and that this indirect effect is conditional on clients' familiarity with AI. Specifically, whether an email was refined with AI effects the degree to which clients suspect AI involvement (H1), these suspicions increase switching intentions (H2), and this latter relationship is amplified among clients more familiar with AI (H3). Accordingly, the full process we theorize is one of moderated mediation: the indirect effect of tax professional's email drafting method on switching intentions, via suspicion of AI involvement, should become stronger as clients' familiarity with AI increases.

> *HYPOTHESIS 4:* The indirect effect of drafting method on switching intentions through suspicion of AI authorship will be stronger among clients with greater AI familiarity.

III. METHODOLOGY

Design

We test our hypotheses using a 2×1 between-subjects experiment. Our study's sole manipulation (*Drafting Method*) varied the presence of AI-assistance in the tax professional's email, with participants randomly assigned to receive either a human-authored email with no AI-assistance (*No AI-Assistance*) or an email refined with AI (*AI-Assistance*). In both conditions, the email, described in detail below, advised the participant, acting as a hypothetical taxpayer, against reclassifying personal expenses as business expenses.

Participants

Participants were taxpayers from the United States recruited through Prolific. Participants were paid a flat wage of $2.00 for completion of the task with a median time of completion of ten minutes and fifty-two seconds. We required participants had completed at least 1,000 previous Prolific submissions with at least a 95% approval rate. Furthermore, participants were required to successfully complete our screening questions indicating they were at least 21 years of age, citizens of the United States, and hold an employment status of either currently full-time or part-time.[1] Our final sample included 145 participants, after excluding five responses who did not complete the experiment in its entirety. Descriptive statistics for relevant demographic measures are presented in Table 1.

Experimental Procedures and Task

We adapted the experimental scenario from Kaszak et al. (2024). Participants were presented with a hypothetical tax accountant–client interaction case in Qualtrics, in which they assumed the role of Kelly, a self-employed professional photographer. In preparing Kelly's annual tax return, participants learned that the tax liability was unexpectedly high, creating financial strain and jeopardizing an important personal goal (a rare opportunity to take a vacation with a spouse). Friends and colleagues suggested that Kelly could reduce this liability by reclassifying several personal trips taken during the year as primarily business-related, thereby claiming the associated expenses as deductible. Importantly, participants were explicitly informed that this type of expense reclassification is illegal, as travel expenses are deductible only to the extent that they are incurred for business purposes.

The case then introduced Taylor, Kelly's tax advisor and return preparer, who would provide advice about the reclassification decision. Background information about Taylor was held constant across all conditions. Specifically, Taylor was described as a reputable certified public accountant with expertise in taxation and twelve years of experience at a hypothetical professional

[1] At the time of data collection, we were unable to include a custom screening question that would directly assess participants' taxpaying experience (e.g., "how many times have you filed a U.S federal income tax return?"). That said, we did collect that information in our PEQ and can formally note that only 4.1% of our participants indicated that have not filed a tax return, and that these differences do not significantly vary between experimental conditions nor correlate with our process or dependent measures. Interpretations of our moderated mediation model also do not significantly differ if these participants are excluded from the final sample. Thus, we retain these participants for our final analyses.

services firm, SPG. Taylor was consistently referred to in the third person, with no additional demographic details provided.

Participants were then shown an email message from Taylor addressing the deductibility of Kelly's travel expenses. Participants were randomly assigned to receive one of two versions of this email (*No AI-Assistance* or *AI-Assistance*). After reviewing the email, participants completed the dependent measures (e.g., intentions to shop for alternatives and switch preparers), process measures (e.g., perceptions of the email), and demographic questions. We further discuss our manipulated variable and response measures below.

Independent Variable

In both the *No AI-Assistance* and *AI-Assistance* conditions, the email communicated the same substantive conclusion: Taylor advised Kelly not to deduct the travel expenses, emphasizing that such reclassification would be improper under tax law and could result in IRS penalties. The emails were matched in content, length, and overall tone, ensuring that any observed effects could be attributed to perceptions of the drafting method rather than to differences in the underlying message. In the human-authored condition, the email that participants read was completely written by a human (a co-author of this study), with no assistance from AI. Notably, AI detection tools (e.g., Grammarly's AI detector) found that zero percent of this email appeared to be written by AI. The specific email was adapted from the materials of Kaszak et al. (2024), and reads as follows:

> Hi Kelly,
>
> Thanks for your question. Sadly, we can't deduct your personal travel expenses as business expenses. Tax law requires that these expenses be primarily (if not totally) for business purposes. Reclassifying personal items as business expenses is a classic practice that the IRS looks for. If we don't have evidence of business purposes and you get audited, you'll certainly be penalized and fined. It's just not worth it. Let me know if you have any other questions.

Best,

Taylor Jones, CPA

In the AI-authored condition, the email that participants read was refined and updated by ChatGPT 4, a popular Generative AI platform. Specifically, the solely human-authored email (above) was entered into ChatGPT 4 with the prompt ‘Can you clean this email up for me?’. We made this design choice as this is how professionals use AI to draft emails, not to compose entirely new messages but to polish and formalize an existing message. Grammarly’s AI detector found that approximately fifty percent of the *AI-Assisted* email appeared to be AI-generated. This assessment is important for experimental realism. A score approaching 100 percent would overstate the presence of AI cues, reducing believability and potentially introducing demand effects. Conversely, a very low score (e.g., under 50 percent) would limit our ability to claim that participants are responding to meaningful indicators of AI authorship. Positioning the stimulus near the midpoint therefore enhances the plausibility of our treatment, ensuring that participants’ reactions reflect genuine perceptions of potential AI-assistance rather than artifacts of stimulus design. The wording of the specific email is below.

Dear Kelly,

Thank you for your inquiry. Regrettably, we are unable to deduct your personal travel expenses as business expenses. Tax regulations mandate that such deductions primarily (if not entirely) serve business purposes. Reclassifying personal expenses as business expenses is a common practice that the Internal Revenue Service (IRS) scrutinizes. In the absence of substantial evidence demonstrating business purposes, as audit may result in significant penalties and fines. Therefore, it is advisable to refrain from attempting this maneuver.

Please do not hesitate to contact me if you have any further questions.

Best regards,

Taylor Jones, CPA

Dependent Variables

Suspicion of AI-Assistance

We asked participants several questions regarding their perceptions of the communication from their tax professional, focusing both on the email itself and on the advice conveyed. A confirmatory factor analysis with Varimax rotation revealed that the three items concerning suspicion of AI-assistance in refining the email and the three items concerning perceptions of AI-assistance in formulating the professional's advice loaded on two distinct factors. The AI-assistance in email refinement items were: (1) *In your opinion, did Taylor use a Generative Artificial Intelligence (AI) application (e.g., ChatGPT or Microsoft Copilot) to write that email?* (2) *In your opinion, what are the chances that Taylor used a Generative AI application to write that email?* and (3) *In your opinion, how much of that email was generated by a Generative AI application?* Item #1 is a binary measure, whereas items #2 and #3 are continuous measures measured on an 11-point Likert-type scale. These items loaded strongly on a single factor (*Suspicion of AI-Assistance*; factor loadings = 0.859, 0.852, 0.836; Cronbach's α = 0.705). Finally, the factor score for *Suspicion of AI-Assistance* was retained for subsequent analyses as our main mediating variable.

The AI-advice perception items were: (1) *In your opinion, did Taylor use a Generative AI application to come up with that advice?* (2) *In your opinion, what are the chances that Taylor used a Generative AI application to come up with that advice?* and (3) *In your opinion, how much of the advice in the email was generated by a Generative AI application?* These items also loaded strongly on a distinct factor (factor loadings = 0.822, 0.889. 0.830; Cronbach's α = 0.705).

Together, these results provide evidence of discriminant validity: participants distinguished AI-assistance in the drafting the email communication itself from AI-involvement in formulating the professional advice. Importantly, subsequent analyses reveal that only perceptions of AI-assistance in drafting method, not perceptions of advice formulating, significantly influence client retention intentions.

Opinion Shopping and Preparer Switching Intentions

To capture clients' behavioral intentions, we measured participants' likelihood to *opinion shop* for a second tax professional and to *switch* to a new preparer or preparation service. The first two items were adapted from Kaszak et al. (2024) and are measured on an 11-point Likert-type scale, while the final two items were created to capture other modern options that taxpayers have to file their tax return.

1. *Given you have plenty of time before the tax filing deadline, how likely are you to ask another tax professional for a second opinion regarding your personal travel expense deduction?*

2. *Given you have plenty of time before the tax filing deadline, how likely would you be to switch to the new tax professional for your tax needs?*

3. *Given you have plenty of time before the tax filing deadline, how likely would you be to switch to a tax filing software application (i.e., TurboTax) for your tax needs?*

4. *Given you have plenty of time before the tax filing deadline, how likely would you be to switch to a tax filing software application with Generative AI features and capabilities for your tax needs?*

Responses were recorded on an 11-point Likert scale ranging from 0 (*not at all likely*) to 100 (*extremely likely*), with increments of ten for each scale point. The items were highly correlated and loaded on a single factor (*Client Switching Intentions*; factor loadings = 0.868, 0.879, 0.823, and 0.836; Cronbach's α = 0.873). The factor score was retained as the main dependent variable for subsequent analyses, with higher values on this factor score indicate a greater likelihood of client opinion shopping and switching behavior.

Other Variables

We measured participants' perceptions of and familiarity with artificial intelligence (AI). Specifically, participants responded to three items: (1) *How familiar are you with artificial intelligence?* (2) *How knowledgeable are you about artificial intelligence?* and (3) *How often do you use artificial intelligence*? These items were measured on a five-point Likert type scale. A factor analysis indicated that these items loaded strongly on a single construct (*AI Familiarity*; factor loadings = 0.933, 0.926, and 0.871; Cronbach's α = 0.806). This factor score was retained for subsequent analyses as the moderating variable, with higher values reflecting greater familiarity, knowledge, and frequency of AI use.

We also measured participants' perceptions of the hypothetical tax professional's source credibility, as well as several items related to their satisfaction with the professional's services. In addition, demographic information was collected. None of these variables were significant in our theoretical model, nor did they differ significantly across experimental conditions. Accordingly, they are not discussed further.

IV. RESULTS

Manipulation Check and Preliminary Analysis

A primary goal of this study is to examine the extent to which tax clients can detect their tax professional's utilization of AI-refinement tools in email communications. We asked several questions pertaining to this research question, which serve the dual purpose of evaluating the effectiveness of our *AI-Assistance* experimental treatment as well as formally testing H1. While we provide our formal analysis of H1 in the next section, we offer some preliminary analysis of the effectiveness of the *AI-Assistance* treatment below.

When responding to the binary AI-assistance perception question, 93 out of 145 participants believed that their email was solely authored by their tax professional (i.e., written by a human), while only 52 participants believed that their email was refined by AI. That is the case although only 78 participants were in the *No AI-Assistance* condition and 67 participants were in the *AI-Assistance* condition. In the *No AI-Assistance* condition, 70.5 percent of participants correctly identified the email as solely human-authored, while 29.5 percent misclassified it as AI-assisted. In contrast, in the *AI-Assistance* condition, only 43.3 percent of participants correctly identified the email as AI-refined, whereas 56.7 percent misclassified it as solely human-authored. This initial pattern is consistent with the manner in which the *AI-Assistance* email was constructed: the AI condition involved refining the human-authored email, rather than fully generating a unique piece of communication. As such, many of the human stylistic cues remained intact, making the AI-refined message more difficult to fully distinguish from the human-authored message.

Analysis of the composite measure of the two continuous AI-likeness suspicion items provides strong evidence that participants were able to detect AI assistance. Unlike the binary classification above, which forced a categorical judgment, the 11-point Likert-type scale allowed participants to express gradations in their perceptions. This flexibility revealed that although the AI-refined email retained some artifacts of human authorship, it also contained linguistic cues more closely associated with AI. Results of an untabulated one-way ANOVA indicate that participants were able to pick up on those cues when given the opportunity to respond with greater nuance. Participants in the human-authorship condition responded significantly lower ($M = 67.05$) than those in the AI-authorship condition ($M = 85.22$; $F = 4.415$; $p = 0.037$) to a composite measure of the two continuous AI-likeness suspicion items (see the Methodology section for definitions of these two items). Overall, these preliminary results indicate that the *AI-Assistance* treatment functioned as intended: although participants responded imperfectly to the binary classification question (as expected, given the design of the AI-assisted email), their responses to the continuous measures revealed significant gradations in the predicted direction.

Hypothesis Testing

See Table 2. We first predicted that participants would be able to detect emails refined by AI (H1), such that emails refined with AI would be suspected as more AI-assisted than substantively identical emails written solely by a human tax professional. Building on this, we expected that greater suspicion of AI assistance would be associated with stronger intentions to shop for alternatives and switch preparation services (H2). We further anticipated that this positive relationship would not be uniform across clients but rather amplified among those with greater familiarity with AI (H3). Finally, we predicted a moderated mediation effect, such that the indirect effect of AI assistance on switching intentions, operating through suspicion of AI assistance, would be stronger for AI-familiar clients than for those less familiar with AI (H4).

Table 2 presents results of the moderated mediation model, analyzed using Hayes' PROCESS Model 14 (Hayes 2022). In this model, the relationship between the independent variable drafting method (X) and dependent variable client switching intentions (Y) is mediated by suspicion of AI assistance (M), and AI familiarity (W) moderates the relationship between participants' suspicion of AI assistance and client switching. Descriptive statistics for the raw are provided in Panel A, while the model is presented in Panel B and the relevant model statistics are presented in Panel C.

Supporting H1, the relationship between tax professionals' utilization of AI-assistance in drafting email communications and client suspicion of AI-assistance is significant ($\beta = 0.34$; $p = 0.04$), such that participants who received the AI-refined communication rated it as more AI-authored than those who received the solely human-authored message. In contrast, the direct path from suspicion of AI-assistance to switching intentions (H2) was not significant ($\beta = 0.10$; $p = 0.25$). However, consistent with H3 ($M \times W$), this relationship was significantly moderated by participants' AI familiarity ($\beta = 0.18$; $p = 0.04$). That is, clients' suspicion of AI assistance increased their switching intentions, but only among those who were more familiar and knowledgeable about AI.

Finally, the index of moderated mediation (0.0599) was significant, with a bootstrap confidence interval entirely above zero (0.0026 to 0.1296). This result provides evidence for H4, indicating that the indirect effect of professionals' use of AI-assistance in email communications on tax client switching intentions, operating through perceptions of authorship, varied as a function of clients' AI familiarity.

V. CONCLUSION

This study examines client responses to tax professionals' use of artificial intelligence (AI) in the drafting of client communications. Through a 2×1 between-subjects experiment administered to 145 experienced taxpayers; we document how the drafting method utilized by a tax professional influences clients' intentions to switch to an alternative tax preparation service. We predict (and find) that taxpayers can accurately assess (i.e., above random chance levels) when an email from their tax professional has been drafted with the assistance of AI. We also show that client suspicions of AI authorship help to explain the effect of their professional's email drafting method on switching intentions. This indirect effect is stronger among clients with greater AI familiarity, who are better equipped to interpret reliance on AI as a violation of professional expectations.

This work contributes to the growing stream of research on AI in the accounting practice. Prior studies have primarily examined the implications of AI for accounting-related outcomes (Sutton, Holt, and Arnold 2016; Kokina and Davenport, 2017; Commerford et al. 2024). Within behavioral tax research, scholars have also investigated how AI-enabled tax preparation platforms shape compliance decisions. For example, Swider (2025) documents that although taxpayers are influenced by AI-provided advice, they are more willing to rely on human (CPA)-provided advice than AI-provided advice when the provided advice was aggressive in its application of tax law to the reporting context. Our findings further extend this understanding of AI in two ways, as we consider the effect of AI-assistance (1) on client communications (rather as an accounting or tax compliance-related tool) and (2) on client retention intentions (rather than an accounting-related outcome, such as tax compliance intentions).

Our study's implications for tax practice and other professional services are significant. AI adoption in accounting is rapidly accelerating: the *State of AI in Accounting Report* (2025) found that 64% of accountants already use AI to draft emails or adjust tone, and the AICPA has highlighted AI's role in 'email triage' to streamline client communication. More broadly, surveys show that knowledge workers across industries are adopting generative AI at high rates, particularly for routine tasks such as email drafting (Relyea, Maor, and Durth, 2024; Sternfels and Atsmon 2025).

Our results temper this optimism by showing that AI involvement in client-facing communication can disconfirm expectations, thereby carrying client retention risks. Taxpayers do not engage professionals solely for technical accuracy or tax minimization (Rosenthal et al. 2023);

they also expect personalized guidance expressed directly through their preparer's communications (Intuit Inc. 2021, 2022). When clients suspect that an email from their professional has been AI-authored or refined, this expectation is disconfirmed, raising doubts about the service's underlying value. Our experiment thus provides behavioral evidence that suspicion of AI in professional communication can introduce relationship risks, even when technical accuracy is not in question.

Our study's results should be interpreted in light of its limitations. First, to maintain proper experimental control, we developed a hypothetical tax communication in a controlled setting, which may not fully capture the complexity of client–preparer interactions or relationships. Future research could consider how the repeated use of AI-assistance in client communications could either bolster its negative effect on client retention. We also simplified the study's setting by holding the aggressiveness of the tax advice conveyed in the email at a low level; the hypothetical CPA disallowed the taxpayer's preferred position. Although this design choice supports internal validity, future research could examine how varying levels of advice aggressiveness moderate the relationship between drafting method and client retention (Swider 2025). Our study sample also reflects the *individual taxpaying public*, and not necessarily business clients, who may make decisions based on a different set of incentives than individual taxpayers or evaluate communications differently from individual taxpayers. Thus, generalization of our findings to corporate taxpayers should be done with caution. Future research could consider this alternate taxpaying population. We also measured participants' intentions rather than actual switching behavior. Future research could use field data or longitudinal designs to assess whether suspicion leads to real client loss over time.

TABLE 1
SAMPLE DEMOGRAPHICS
(n = 145)

Variable	Frequency	Variable	Frequency
Age		*Marital Status*	
21 to 36	57 (39.30%)	Married	97 (66.90%)
37 to 55	71 (49.00%)	Not Married	45 (31.00%)
55 and over	17 (11.70%)	No Response	3 (2.10%)
Gender			
Male	65 (44.80%)		
Female	79 (54.50%)	*Number of Personal Federal Income Tax Returns Filed*	
No Response	1 (0.70%)	Zero	6 (4.10%)
Education		Between one and four	29 (20.00%)
Highschool	11 (7.60%)	Between five and eight	22 (15.2%)
Some College	48 (14.50%)	Between nine and 12	17 (11.70%)
College (Undergraduate)	119 (33.80%)	13 or more	
College (Graduate)	33 (44.10%)		
Income		*Personal Tax Authority Audit History*	
$50,000 or less	42 (29.00%)	Never Audited	113 (77.90%)
$50,000 – $100,000	62 (42.80%)	Audited by IRS	24 (16.60%)
$100,000 – $200,000	33 (22.70%)	Audited by a State Revenue Department	6 (4.10%)
$200,000 or more	8 (5.50%)	Audited by a Foreign Tax Authority	2 (1.40%)

TABLE 2
Moderated Mediation Analysis: Suspicion of AI-Assistance as Mediator (*M*) and AI-Familiarity of Moderator (*W*) of Drafting Method (*X*) and Switching Intentions (*Y*)

Panel A: Descriptive Statistics of Suspicion of AI-Assistance (*M*)

Binary Measure			*Composite Continuous Measure*		
Drafting Method	**Mean (SD)**	**N**	**Drafting Method**	**Mean (SD)**	**N**
No AI-Assistance	1.29 (0.459)	78	No AI-Assistance	67.051 (50.430)	78
AI-Assistance	1.43 (0.499)	67	AI-Assistance	85.224 (53.608)	67
Overall	1.36 (0.481)	145	Overall	75.448 (52.533)	145

Table Notes: Reported means and standard deviations are based on the raw measures of AI-likeness perceptions for interpretability. The binary item asked participants to classify the email as either *"Human-authored"* (coded 1) or *"AI-assisted"* (coded 2). The composite score represents the average of two Likert-type items (0–100 scale) assessing the extent to which the email seemed "AI-like" and the likelihood that it was "AI-generated." These descriptives are presented to provide an intuitive sense of participants' responses. For all PROCESS analyses, a factor score derived from the binary item and the two continuous items was used as the mediator variable.

Panel B: Main Model

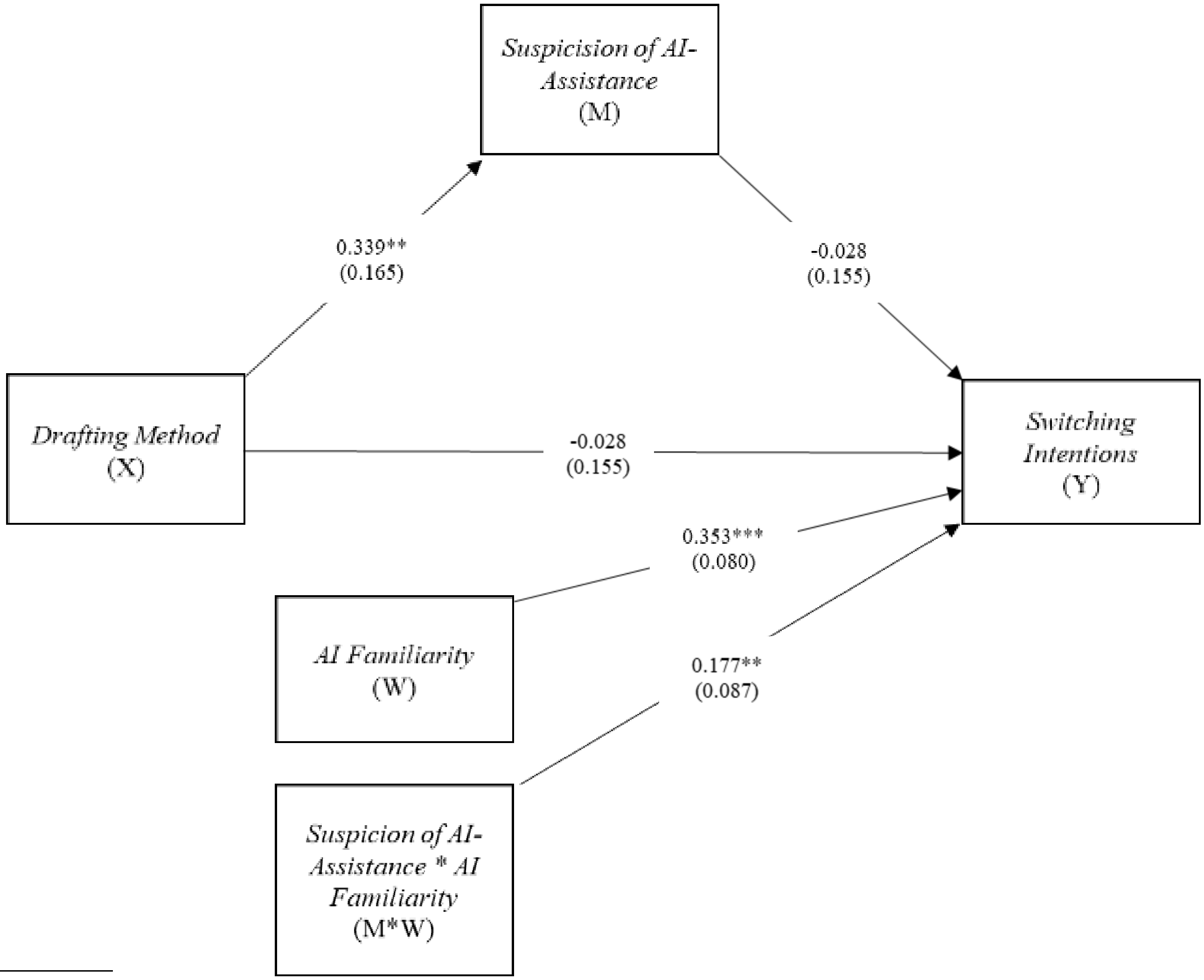

Table Notes: X (Drafting Method): Experimental condition indicating whether the tax professional's email was authored solely by a human (0) or assisted by AI (1), M (Suspicion of AI-Assistance): Participant self-reported perceptions of the extent to which the tax professional's email was generated using AI, W (AI Familiarity): Participant self-reported familiarity, knowledge, and frequency of use of AI applications, Y (Client Switching Intentions): Participant likelihood of seeking a second opinion, switching to another tax professional, or adopting tax software (traditional or AI-enabled). * indicates < 0.10 p-value, ** < 0.05 p-value, and *** < 0.001 p-value.

Panel C: Total Sample Primary Statistical Analysis

	Consequent					
	M *(Perceptions of Email Authorship)*			**Y** *(Retention Intentions)*		
Antecedent	**Coeff.**	**SE**	**p-value**	**Coeff.**	**SE**	**p-value**
X	0.339	0.165	0.041	-0.028	0.155	0.86
M	-	-	-	0.097	0.083	0.246
W	-	-	-	0.353	0.08	< 0.001
M*W	-	-	-	0.177	0.087	0.045
Constant	-0.157	0.112	0.165	-0.035	0.107	0.742
R2		2.87%			18.24%	
F		(1, 144) = 4.225			(4, 141) = 7.806	
p-value		0.0417			< 0.001	

Index of moderated mediation = 0.060 (SE 0.40). A bootstrap confidence interval (90%) based on 5,000 bootstrap samples was entirely above zero (0.0026 to 0.1296), evidence that the moderated mediation model is significant. The conditional effects of AI-assistance on switching intentions through suspicion of AI-assistance vary significantly based on participants' AI familiarity.

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