Individual Tax Preparation Fees and the Effects of Artificial Intelligence Offerings

Paul W. Black
Auburn University
pwb0013@auburn.edu

Kerry Inger
Auburn University
kki0001@auburn.edu

Isaiah Messer
University of Tennessee
imesser@vols.utk.edu

January 2025

We are grateful for helpful comments and suggestions received from Paige Csere, Eric Negangard, Jason Schwebke, and Jeff Williams, as well as workshop participants from Auburn University, the BYU Accounting Research Symposium, and reviewers for the ATA Midyear meeting. We also gratefully acknowledge funding provided by Auburn University.

Individual Tax Preparation Fees and the Effects of Artificial Intelligence Offerings

ABSTRACT

While artificial intelligence (AI) offers great possibilities for accounting firms to provide tax services at low cost, it is important to consider how taxpayers will react to such service offerings. We examine whether taxpayer willingness to pay for tax preparation services provided by AI or humans varies depending on how the service offering is *framed*: a search for errors or a search for savings. Using an experiment with taxpayer participants, we find that taxpayers are more willing to pay for humans to search for errors relative to AI, whereas we find no difference in willingness to pay for a search for tax savings. Our theory suggests this occurs because a search for errors (savings) induces a prevention (promotion) regulatory focus and thus reduced (increased) risk appetite resulting in stronger (weaker) preference for humans over AI. Results have important implications for theory and inform service providers considering investments in AI.

Keywords: Artificial Intelligence, Willingness to pay for tax services, Savings, Errors, regulatory focus theory; prevention v. promotion focus

I. INTRODUCTION

Recent advancements in generative artificial intelligence (hereafter AI) are prompting businesses, including those providing individual tax preparation services, to reexamine the tools they employ in providing services to customers (Morel 2023; Thomson Reuters 2023; Uzialko 2024). A recent survey found that 77 percent of respondents in tax related professions believed that generative AI could be applied in their industry, however widespread usage has yet to occur with many still in the adoption consideration phase (Thomson Reuters 2024a). Consistent with other new technologies, AI offers great potential to improve efficiency and reduce service-related costs, yet it also faces challenges as the technology is still developing and, in particular, as users become comfortable adopting the new technology (Davis 1985; Venkatesh, Morris, Davis, G. and Davis, F. 2003; Morel 2023; Steinhardt 2024). As tax firms consider investments in technologies, one consideration is whether, and if so, how they can recoup initial investment costs. Many tax professionals believe they will pass at least some of the costs of AI adoption along to customers through increases in fees (Thomson Reuters 2024a). Conversely, recent roll outs of AI tools by leading tax software providers received negative press feedback (Fowler 2024), calling into question taxpayers' appetite for tax preparation services provided by AI. In this study we experimentally consider individual taxpayers' willingness to pay for tax services, and in particular, we examine whether preferences for AI versus human service providers varies depending on how the service offering is *framed*.

Tax service firms have developed and marketed *software* for individual tax preparation for many years. These software offerings effectively translate the tax code into a series of algorithm-based questions and automatically fill out tax forms based on taxpayer responses. Recent developments in *generative AI*, however, offer potential to leverage data in specific and intelligent ways that go beyond a simple algorithmic application of the tax code. Such AI tax insight might compare to tax advice that has previously been provided only by humans.

With the technology behind AI advancing at a rapid pace and companies investing heavily in its development (Goldman Sachs 2023), our focus in this study is on taxpayers' willingness to pay for services provided by AI. This is important because even with advanced technology, humans are the decision makers who chose whether and how to apply the technology. Accordingly, the impact of AI will presumably be governed by human's decisions. Tax preparation companies will benefit from a better understanding of human users' willingness to pay for AI related services as such information will have implications for these companies' ability to recoup AI development costs, human resource planning, and future firm profitability. Accordingly, we study psychological factors underlying willingness to pay for tax related services provided by AI versus humans.

Companies providing tax services for individual taxpayers might frame their offerings in different ways, including reviewing the tax return for potential errors (e.g. mistakes or misapplication of tax laws), which could help reduce the likelihood and consequences of being audited by the tax authority and incurring penalties and interest, or searching the return for potential additional tax savings (e.g., searching for additional credits or deductions which might be available). Either framing of the service (searching for errors or for additional savings) highlights potential benefits that could be provided by humans or by AI. Importantly, however, taxpayers' *appetite* for who provides the service (AI versus human) could vary depending on how the service is framed.

We develop theory predicting that taxpayers will be willing to pay more to have humans relative to AI provide a service framed as searching for errors, but that the difference will be diminished when the service is framed as searching for additional savings. In developing our predictions, we leverage regulatory focus theory (Higgins 1997; 1998), which suggests that individuals can adopt a prevention focus or a promotion focus as they self-regulate. A promotion focus caters to the need for accomplishments, aspirations, and the achievement of positive outcomes, while a prevention focus caters to the need to be responsible and fulfil obligations and duties. Prior research suggests that regulatory focus can be situationally induced (Crowe and Higgins 1997), and that a promotion focus is associated with greater risk appetite while a prevention focus is associated with a reduced risk appetite (Friedman and Forster 2001; Gino and Margolis 2011). Building off these findings, we argue that a "search for errors" framing will induce a relative prevention focus while a "search for savings" framing will induce a relative promotion focus. Accordingly, when the service is framed in a prevention focused way (i.e., searching for errors) we expect greater risk aversion and thus more trust in the known mode of service (i.e., humans) relative to the lesser known mode of service (i.e., AI) . Conversely, when the service is framed as searching for savings, we expect a greater promotion focus will temper risk aversion and distrust of the less known mode of service and reduce the difference in preference between human and AI. In summary, we predict that the mode of service (human versus AI) will matter more when the service is framed in a prevention focused relative to promotion focused way.

We test our predictions using a 2 × 2 experimental design in which we manipulate how the service offering is framed (a search for errors which we expect will induce a relative prevention focus or a search for savings which we expect will induce a relative promotion focus) and the mode of service (human versus AI). Online participants who are U.S. taxpayers are asked to imagine they are preparing their tax return for the most recent year and are told that they are using a basic software called ABC Tax Preparation. The software prepares tax forms based on information provided but provides no other tax advice or support. Participants are provided high level information about their financial/tax situation and are told that they are nearly finished inputting their tax information into the basic software. The software informs them that they are due a refund and then a message pops up offering an additional service which is manipulated according to the participant's condition. Specifically, the message informs participants that ABC Tax Preparation has a(n) "AI Assistant" ("group of tax professionals") that can search their tax return for possible "errors" ("additional tax savings"). Participants are then asked how likely they would be to pay more for the service described.

Results are consistent with our theory. We first validate our proposition that framing the service as a search for savings (errors) induces a relative promotion (prevention) focus using textual analysis of participants' open responses. We then find an interaction such that participants are willing to pay more for a service framed as searching for errors when humans are performing the search (relative to AI), however this difference diminishes when the service is framed as searching for savings such that we find no difference in willingness to pay between humans and AI. This result is strengthened when controlling for participant risk preferences. Follow up analysis suggests that participants trust humans more than they trust AI to search for errors, but we find no difference in trust when the framing suggests a search for additional savings. This is consistent with our theory which suggests that the framing of the task induces a relative promotion or prevention focus and that this in turn leads to differences in risk appetites and thus trust toward better known or less known modes of service.

Our paper contributes to the literature and to practice in several ways. The provision of tax services is changing with the introduction of AI. Tax service providers are continually looking to reduce the cost of labor and provide additional services including through the investment in and use of AI. These potential services can be advertised in different ways which may lead taxpayers to adopt more of a prevention or promotion focus. AI provides accounting firms a way to alleviate current shortages of tax professionals (e.g., Hamilton 2023) and allow staff to focus on higher level activities requiring judgement and strategic thinking. While prior research has studied technology use and adoption in general (e.g., Davis, 1985; Venkatesh et al., 2003; Puntoni, Reczek, Giesler, and Botti 2021; Horowitz and Kahn, 2021; De Freitas Agarwal, Schmitt, and Haslam 2023) and in accounting and tax specifically (Cooper, Holderness, Sorensen, and Wood 2019; Brink and Hansen 2020; LaMothe and Bobek 2020; Rosenthal, Brown, Higgs, and Rupert 2023), our study extends beyond this research in multiple ways. First, we consider willingness to pay for the service, which is a relevant factor for firms considering investments in AI and/or human workforce staffing. Our findings are important given that tax professionals' expectations regarding how using AI will impact service fees may not align with client expectations. Specifically, in a survey of tax professionals whose firms have adopted AI, Thomson Reuters (2024a) finds 40% (42%) believe the use of AI would increase (not change) their fees. Conversely, implementation of AI tools by leading tax software providers received negative press feedback (Fowler 2024), calling into question customers' willingness to pay for tax services provided by AI.

Second, we directly manipulate the framing of the tax related service that is offered and in so doing highlight that appetite for technology adoption may vary depending on how it is framed. That is, in our tax setting, we find that participants are less willing to pay for AI relative to humans when the service is framed as searching the tax return for possible errors. However, we find no difference in willingness to pay between human preparers and AI when the service is framed as searching for additional tax savings. As such, our findings contribute to practice and suggest that companies concerned with consumer technology adoption should consider how they frame the services they wish to provide using AI. Our findings also provide insight into the types of services that are more worthwhile for AI technology investment. Our results suggest that when the framing of the service is likely to induce a promotion focus, consumers may be more willing to accept new technology performing the service, but that this may not be the case when the framing of the service induces a prevention focus.

II. BACKGROUND AND HYPOTHESES DEVELOPMENT

Artificial Intelligence and Tax Services

Artificial intelligence or AI has evolved since the 1950s when Alan Turing cracked the enigma code used throughout World War II (Anyoha, 2020). Since that time, AI has progressed along with computing power of the 21st century. AI is "the ability of a computer… to perform tasks that are commonly associated with the intellectual processes characteristic of humans" (Britannica 2024) and is usually accomplished through computer algorithms that are able to learn from available data. Today, large language models (LLMs) ingest large volumes of data to provide a wide array of valuable services that were provided by humans in the past. For the purposes of our study, we focus on AI services that resemble generative AI offerings which utilize large language models.

The financial sector relies on information technology to handle and process an intense amount of information (Tan and Teo, 2000). This information rich environment where IT innovation and technology thrive produced the "fintech revolution" in the mid-2010s (Gomber, Kauffman, Parker, and Weber 2018) and transformation of the way that financial companies provide services through AI, big data, and robo-advisors (Sangwan, Harshita, Prakash, and Singh

2019). Accounting has long been a regulatory backbone of the financial sector with audited financial statements, tax returns, internal accounting of operations and myriad other data generating endeavors. This creates a rich setting for AI applications to improve processes and make work more efficient.

The field of tax practice provides an abundance of opportunity for AI enabled service provision, from tax compliance to research functions. Thomson Reuters (2024b) reports that AI has become an integral part of streamlining tax and accounting professionals' processes through automation of routine tasks, enhanced data analysis, and ensuring compliance with ever changing regulations. Additionally, AI-powered software can offer custom solutions to clients based on their financial and personal situation. Recently, AI tax preparation services and tools have become available, including AITax (https://www.aitax.com/), Black Ore (https://www.blackore.ai/*)*, and April (https://www.getapril.com/).

The IRS Data Book shows that in 2023 90.6% of individual income tax returns were filed electronically (IRS 2023). This represents an increase in the share of individuals choosing electronic filing over the past decade from 82.9% in 2013 (IRS 2023).[1] With few taxpayers preparing a return on paper, AI could have a large impact on the tax return preparation environment going forward, both for software and paid preparers. Individuals choosing to pay for software to prepare their own returns is also increasing, (41.3% in 2023 which is up from 33.4% in 2013) while the use of paid tax practitioners has declined (56.8% in 2023 which is down from 63.3% in 2013) (IRS 2023). Our study involves examining United States taxpayers who utilize software to file their taxes such as H&R Block or TurboTax. Software providers such

[1] Individual taxpayer preparation data come from the IRS Data Book (https://www.irs.gov/statistics/soi-tax-stats-irs-data-book) 'Table 3 Number of Returns Filed, by Type of Return and State' and 'Table 4 Number of Returns Filed Electronically, by Type of Return and State', for fiscal years 2023 and 2013.

as these have been increasing their efforts to include AI services such as TurboTax's AI-powered Intuit Assist and H&R Block's AI Tax.

Tax preparation service choice

A long line of literature finds the use of tax preparation services is generally associated with three choice-based factors: (1) tax savings, (2) uncertainty protection, and (3) time savings (e.g. Fleischman and Stephenson 2012; Frischman and Frees 1999; among others).[2] In a study examining demand for tax preparation services using tax return data, Frischman and Frees (1999) find that taxpayers choose to use paid tax return preparers for both uncertainty protection and time savings. In their model, a taxpayer's purchase of uncertainty protection is a combination of (1) the inherent risk that the IRS will select their tax return for audit and propose an adjustment and (2) the taxpayer's attitudes towards risk. Under this model, a service framed as a search for errors should be perceived to reduce the risk of a negative tax outcome. The purchase of uncertainty protection in regard to the reduction of potential errors on a tax return is consistent with the demand for insurance contracts, where the only utility of the contract is protection against potential unforeseen losses. Prior literature supports uncertainty protection as a primary driver for the purchase of tax preparation services (Fleischman and Stephenson 2012, Sakurai and Braithwaite 2003; Collins, Milliron, and Toy 1990; Hite and McGill 1992).

Prior literature also finds that the purchase of tax preparation services is associated with the generation of tax savings (Long and Claudill 1987; DeBacker, Heim, Tran and Yuskavage 2024) and that taxpayers purchase services with the intent to reduce their tax liability

[2] Some studies (i.e. Stephenson 2010; Fleischman and Stephenson 2012) include four factors: tax savings, time savings, legal compliance, and protection from the tax authority. We include legal compliance and protection from the tax authority as one construct, uncertainty protection, following Fischmann and Frees (1999) because error detection could result in both legal compliance and protection from the tax authority. While prior literature supports time savings as a choice-factor (Long and Claudill 1987; Frischman and Frees 1999; Fleischman and Stephenson 2012; among others), we hold time savings consistent in our study in order to focus on tax savings and uncertainty protection.

(Yankelovich, Skelly, and White, Inc. 1984; Fleischman and Stephenson 2012; Stephenson, Fleishman and Peterson 2017). Frischman and Frees (1999) find that the fees paid for tax preparation services are associated with both tax savings and time savings.

Many studies examine the association between the choice to use tax preparation services and taxpayers' characteristics, including the types and level of income, complexity, age, gender, and opportunity cost of time. (See Rosenthal et al. 2023 Table 1 for a review of this literature). Important to our study, Dubin et al. (1992) and Long and Caudill (1993) find increased audit rates and potential penalties are associated with an increased likelihood of using a paid preparer, suggesting taxpayers place trust in preparers to reduce the risk associated with potential tax return errors. This literature generally focuses on measurable characteristics from tax return data or demographic questionnaires. We build upon this literature by examining the psychological underpinnings of taxpayer decision-making.

Technology and modes of tax preparation

As the adoption of technology has evolved, research has examined new ways that tax preparers provide services (e.g. Rosenthal et al. 2023; Hunt and Iyer 2018; Brink and Lee 2015*)*. Recent research has examined the use of tax return preparation software, finding that the mode of service delivery affects taxpayer behavior (Brink and Hansen 2020; LaMothe and Bobek 2020). For example, Brink and Hansen (2020) find compliance is higher when using software developed by the IRS compared to commercial software and LaMothe and Bobek (2020) find taxpayers were less compliant when using software compared to a paid preparer. In a survey of taxpayers examining the choice between a human paid preparer and tax return preparation software, Rosenthal et al. (2023) find taxpayers choosing a paid preparer rated accuracy as the single most important factor in tax preparation mode selection, whereas taxpayers choosing tax software rated minimizing taxes paid as the single more important selection factor. This research suggests that preferences for the mode of service delivery vary with the type of service desired.

An emerging mode of service delivery is the provision of tax preparation services through the use of AI. Relative to humans, we expect taxpayers to view AI as less known, and to perceive that using AI for tax related services involves more risk, which will have important implications for their willingness to pay for tax services provided by AI. Importantly, we predict that this effect on willingness to pay will differ depending on the framing of the service.

Regulatory focus theory

Regulatory focus theory (Higgins 1997,1998) proposes that individuals approach goal-setting and self-regulation through different regulatory systems ("focuses") based on different psychological and emotional needs. A promotion focus caters to the need for accomplishments, aspirations, and the achievement of positive outcomes. A prevention focus caters to the need to be responsible and fulfil obligations and duties. Prevention focus draws upon an individual's need for security rather than the more risk-taking position of achievement of promotion focus (Lanaj, Chang, and Johnson 2012). Promotion focus involves *striving toward* desired states while prevention focus involves *avoiding* conditions that pull away from desired states (Lanaj et al., 2012).

In a tax context, studies examine how the regulatory focus of individual taxpayers interacts with the regulatory focus of tax authority messaging ("regulatory fit") (Leder, Mannetti, Holzl, and Kirchler 2010; Holler, Hoelzl, Kirchler, Leder and Mannetti 2008). Bauman, Impink, Mayberry and McGill (2023) find that firms led by promotion-focused executives engage in higher levels of tax avoidance, an inherently risky activity, relative to firms led by prevention-focused executives. This result suggests that a promotion-focus is associated with a higher tolerance for tax risk, with executives exhibiting tolerance for potential penalties and impaired reputation that are inherently associated with tax avoidance. In contrast, the result suggests a prevention-focus is associated with a lower tolerance for tax risk, with executives behaving more cautiously to prevent mistakes and avoid the potential costs of tax avoidance.

Prior research (Friedman and Forster 2001; Gino and Margolis 2011) provide evidence that a regulatory focus induced or primed by situational cues results in powerful behavioral responses. Crowe and Higgins (1997) propose that a promotion focus leads to a riskier processing style. Friedman and Forster (2001) test this proposal in an experiment and confirm that the cued promotion focused participants had risker response tendencies than the cued prevention focused participants.[3] Gino and Margolis (2011) find that participants in a primed-promotion focused condition reported feeling more risk-taking than those in the primed-prevention focused condition.[4] In summary, this research suggests that a promotion-focus is positively associated with risk-seeking tendencies, while a prevention-focus is associated with greater risk aversion.

Hypotheses

We focus in this paper on how a service is framed based on two common tax related services which could be provided by either a human or by AI: a search for potential savings or for potential errors. Linking back to our discussion of regulatory focus, we argue that a service offering framed as searching for potential savings is likely to induce a greater promotion focus relative to searching for potential errors. The reason is that searching for savings is likely to

---

[3] In study 3, Friedman and Forster (2001) use a maze where a trapped cartoon mouse is encouraged with a piece of cheese at the end of the maze (promotion focus) or frightened by an owl hovering about the maze (prevention focus).

[4] In study 3, Gino and Margolis (2011) use an essay writing exercise to prime promotion and prevention focus. Specifically, in the promotion-focus condition, students were asked to consider and write about their hopes, aspirations, and dreams. In the prevention-focus condition, students were asked to consider and write about their duties, obligations and responsibilities.

induce a mindset of accomplishment, achievement, and focus on positive outcomes consistent with a promotion focus. Conversely, we argue that a service framed as searching for potential errors is likely to induce a greater prevention focus relative to searching for potential savings. This is because searching for errors is inherently associated with avoiding mistakes and fulfilling obligations and duties consistent with a prevention focus. Consistent with these notions, prior research finds that performing different tasks prime different types of regulatory foci, with tasks requiring identification of errors activating the prevention focus, whereas tasks requiring identification of new ideas activate the promotion focus (Van Dijk and Kluger 2011). Borges and Gomez (2015) find that the type of product induces a consumer's regulatory focus, with sunscreen inducing a prevention focus and orange juice inducing a promotion focus. Similarly, we expect framing a service as searching for additional tax savings will induce a promotion focus, while framing the service as a search for potential errors will induce a prevention focus.

As described above, prior research suggests a promotion focus is associated with greater risk seeking behavior while a prevention focus is associated with greater risk aversion. In our context, this suggests that when the service is framed as searching for errors, taxpayers will exhibit risk aversion, which will result in them trusting humans more relative to AI. Conversely, when the service is framed as searching for savings, we predict taxpayers will have a relatively greater appetite for risk. This suggests that individuals will be more comfortable with AI, and thus, the preference for human over AI will diminish.[5] Together these predictions suggest that taxpayers' willingness to pay for a human versus AI to perform a tax related service depends on the framing of the service being offered. If the framing of the service induces a prevention focus,

[5] Note that having a relative increase in risk appetite does not of itself imply that an unfamiliar mode of service will be perceived as superior unless there are other factors making it such. As such, we do not necessarily expect a preference for AI, but rather, that the risk driven aversion to AI will be diminished.

as in a search for errors in the tax return, taxpayers will exhibit more risk aversion and have a preference for the known mode of service (humans). However, if the framing of the service induces a promotion focus, as in a search for savings, the mode of service will be less important. We formally state our predictions as follows:

Hypothesis 1: When the framing of the tax related offering induces a prevention focus, individuals will be willing to pay more for humans (versus AI) to provide the service.

Hypothesis 2: When the framing of the tax related offering induces a promotion focus, the mode of service (human versus AI) will be less important in individuals' willingness to pay.

III. METHOD

We use a 2 × 2 between-subjects experimental design where we manipulate how the service offered is framed (a search for potential *errors* or additional *savings*) and the mode of service (either *human* or *AI*). Participants work through the instrument using Qualtrics and must indicate on the first screen that they had previously filed taxes to be allowed to continue with the study.

Participants are asked to imagine they are preparing their tax return for the most recent year and are told that they are using a basic software called ABC Tax Preparation. Participants learn that they own a small business, have a small investment portfolio, and purchased an electric vehicle this year. Participants also learn that "The software version you are using is very basic in that it provides general prompts for your financial/tax-related information and prepares tax forms based on the information you input but provides no other tax advice or support." This information is then reinforced as participants respond to two open-ended questions asking them to describe their financial situation as it relates to their taxes and to describe the software they are using. By emphasizing the basic nature of the software and the moderately complex tax situation participants face, we create a setting where additional tax help would likely be beneficial, but it is not certain that it is essential. Participants then learn that as they are finishing their taxes, they find they should receive a refund of $2,753.[6] At this point participants read that the software pops up with a message offering additional tax services. The message contains our manipulations as described further below. Participants then respond to dependent and process related measures before completing demographic information and finishing the study.

Independent Variables

Both of our manipulations (i.e., the *service framing*: *errors* versus *savings;* and the *mode*: *human* versus *AI*) are embedded in the paragraph participants read about the additional service offered. The manipulation read as follows:

> You are almost finished! We here at ABC Tax Preparation want you to have the best experience possible filing your taxes. To help with this, we have a group of tax professionals [an AI Assistant] that can search your tax return for possible additional tax savings (and could potentially increase the size of your refund) [errors (and could reduce your risk of a costly audit by the IRS)]. The service is fairly quick, and you should have results back by the end of the day tomorrow.[7]

Dependent Variable

We measure our primary dependent variable using the following question, "How likely would you be to pay more for the service described above?" (on a 7-point scale with endpoints 1

[6] This amount was chosen because it is consistent with average U.S. tax return amounts in recent years (see https://www.irs.gov/newsroom/filing-season-statistics-for-week-ending-april-21-2023). We chose to put participants in a refund position because this is common in practice and thus speaks to an externally valid setting. While this design choice may induce a "gain" frame, such a setting is, again, common in practice, and therefore important to study. We discuss the potential to further explore other starting tax positions further in the Conclusion.
[7] We include the expected time to complete the service such that it is held constant between *human* and *AI*. This strengthens our ability to attribute differences between these conditions to our theoretical explanations rather than merely to any expected difference in the amount of time each might take. We discuss this design choice further in the conclusion.

= “Extremely unlikely” and 7 = “Extremely likely”). This question immediately follows our explanation of the service offered which differs by condition as explained above, and captures participants willingness to pay for the tax service described.

IV. RESULTS

Our sample consists of 318 United States taxpayer participants recruited from Connect (Hartman et al. 2023).[8] Demographic information for our participants in shown in Table 1 and summary information is reported here.[9] The average age of participants is 39.8 years old, 54.1 percent are female, median work experience is 15 years, and 62.6 percent have completed at a bachelor’s degree or higher. Compared to U.S. Census data, our sample is younger and more educated compared to the U.S. population. Ninety-two percent indicated they have usually e-filed their taxes, consistent with IRS data that 91% of individual taxpayers e-file.[10] Seventy-two percent indicated that they have usually used a program such as TurboTax or similar that walked them through what information to input, which is higher than IRS data that reports 41% of taxpayers prepare their own taxes using a computer program. Only nineteen percent report using a paid tax preparer, whereas IRS data reports 56%. Given the use of Connect to reach our participants through the internet, it is reasonable that our sample would be skewed towards those more likely to also use the internet or downloaded software to prepare their return. Participants completed the study via a Qualtrics link and received $1.50 for completing the study.

[Insert Table 1 about here]

[8] We originally had 394 completed instances, however 76 (19%) were removed because they missed an attention check asking them what mode and service had been offered to them (72 participants missed this question) or because they reported they were a different age between the beginning and end of the survey (this occurred with 5 participants, one of whom was already eliminated for missing the attention check). Primary results are mostly consistent but become statistically weaker in some cases if all participants are included.
[9] Untabulated one-way ANOVA tests find there are no significant differences in any of our demographic variables between our experimental conditions (all $p > 0.30$, two-tailed)
[10] Individual taxpayer preparation data come from the IRS Data Book (https://www.irs.gov/statistics/soi-tax-stats-irs-data-book) and U.S. population data are from the U.S. Census Bureau 2020 Census (see: https://data.census.gov).

Manipulation check – promotion and prevention focus in open responses

Our theoretical predictions are based on the premise that search for errors framing induces a prevention focus while search for savings framing induces a promotion focus. To provide credence to this proposition we analyze participants' responses to an open question which was posed on the screen following our primary dependent variable and read as follows: "In one or two sentences, please explain why you would or would not be willing to pay more for the service described on the previous page." Prior research uses textual analyses, including counts of specific terms used, as evidence of regulatory focus (Gamache, McNamara, Mannor, and Johnson 2015; Kanze, Huang, Conley, and Higgins 2018; Bauman, Impink, Mayberry, and McGill 2023). To analyze the open responses, we use an adapted list of prevention and promotion focused words validated by Gamache et al. (2015) (see Gamache et al. 2015 for a full explanation of the validation process and their Table 1 for a complete list of prevention and promotion words).

In our analysis, we began by searching participants' open response for a base version of each of the words listed in Gamache et al. (2015). For example, if the word were "accuracy" we searched for the base of "accura" as this would allow for iterations such as "accurate" which have a similar meaning/purpose in a sentence. Table 2, Panel A, contains a list of words we found (note that we searched for all of the promotion and prevention words used in Gamache et al. 2015, however, Table 2 only includes words which we identified in our dataset). As shown in Table 2, there was a total of 16 promotion words used in the *Savings* condition which is greater than the 8 promotion words in the *Errors* condition ($t = 1.54$, $p = 0.062$, one-tailed). Conversely there was a total of 33 prevention words used in the *Errors* condition which is greater than the 13 error words used in the *Savings* condition ($t = -3.30$, $p < 0.001$, one-tailed). Together these findings support our proposition that a search for saving induces a promotion focus while a search for errors induces a prevention focus and helps to validate the theoretical underpinnings of our study.

[Insert Table 2 about here]

Test of Hypotheses

Descriptive statistics for our primary dependent variable, *likelihood to pay more*, are reported in Table 3, Panel A and are graphically depicted in Figure 1. Hypothesis 1 predicts that, when the framing of the tax related offering induces a prevention focus, individuals will be willing to pay more for humans (versus AI) to provide the service. Hypothesis 2 predicts that, when the framing of the tax related offering induces a promotion focus, the mode of service (human versus AI) will be less important in individuals' willingness to pay. Jointly, these two hypotheses predict an interaction such that there will be a larger difference in *likelihood to pay more* between *Human* and *AI* when the service framing is *Errors* relative to when the service framing is *Savings*.

As shown in Figure 1, we find a pattern consistent with this expectation. As direct support for our predicted pattern, in Table 3, Panel B, we first find a statistical interaction between the *Service framing* and the *Mode* of service using an ANOVA ($F = 2.45$; $p = 0.059$, one-tailed equivalent).[11] Given our theory, individual risk preferences are likely important as variation in risk preferences could affect willingness to try services provided by AI. We measure risk preferences using the following question, "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" (on a 7-point scale

[11] As this single-degree-of-freedom *F*-statistic corresponds to a significant *t*-test with directional predictions, the presented *p*-value is the one-tailed equivalent of the corresponding *t*-test (e.g., Piercey 2023; Pickerd and Piercey 2021).

with endpoints 1 = "Unwilling to take risks" and 7 = "Fully prepared to take risks"). As a further test of the robustness of the interaction identified above, we run an ANCOVA using this measure of risk preferences as a covariate and find in Table 3, Panel C, that our interaction between *Mode* and *Service framing* becomes more significant (F = 3.03; p = 0.042, one-tailed equivalent). To more directly test Hypothesis 1, as reported in Table 3, Panel D, within the *Errors* condition (i.e., the condition where we expect participants to be relatively prevention focused) we find that taxpayer's *likelihood to pay more* is significantly higher when the mode is *Human* (mean = 4.55) than when the mode is *AI* (mean = 3.82) (t = 2.23, p = 0.014, one-tailed). Further, while our primary test of Hypothesis 2 is derived from the interaction reported above, we also find that within the *Savings* condition (i.e., the condition where we expect participants to be relatively promotion focused) there is no significant difference in *likelihood to pay more* when the mode is *Human* (mean = 4.05) versus when the mode is *AI* (mean = 4.04) (t = 0.05, p = 0.961, two-tailed) consistent with our expectation. Overall, results provide support for our theoretical predictions.[12]

[Insert Table 3 and Figure 1 about here]

Supplemental Analysis - Trust

Our theory suggests that taxpayers presented with an offering framed in a relatively prevention focused way (avoiding errors) will be less willing to try an unknown mode and instead rely on known modes of service. More specifically, in terms of our setting, we expect taxpayers to trust humans more than AI when thinking about searching for errors. To better understand participant's *trust*, we asked them the following question, "How much do you trust

[12] We also ask participants how much more they would be willing to pay for the service described in dollars (on a slider scale from $0-$100). The only significant effect we observe with this dependent variable is a main effect of *Mode*, suggesting that the amount taxpayers are willing to pay is higher when a *Human* provides the service relative to when *AI* provides the service (F = 37.02, p < 0.001). One possible explanation for this finding is that taxpayers believe *Human* services cost more and are therefore willing to pay a higher amount for them.

that the service offered by ABC Tax Preparation would result in the desired outcome?" (measured on a 7-point scale with endpoints, 1 = "Extremely distrustful" and 7 = "Extremely trustful"). Consistent with expectations, within the *Errors* condition, we find that taxpayers *trust* humans more than they trust AI ($t = 2.17$, $p = 0.016$, one-tailed). Further, using a mediation model following Hayes (2022) (Model 4), with 5000 bootstrapped samples and a 95% confidence level, we find that *trust* significantly mediates the relation between *Mode* (*Human* vs *AI*) and *likelihood to pay more* (lower bound = -0.510; upper bound -0.018) as reported in Table 4. Finally, in the *Savings* condition we do not find a significant difference between trust toward humans versus AI ($t = 0.46$, $p = 0.645$, two-tailed), nor do we find significant mediation (lower bound = -0.428; upper bound = 0.253). Overall, our results are consistent with our theory which suggests that taxpayers' willingness to trust humans versus AI is dependent on the framing of the service offered. Specifically, we find no significant difference in trust when the service is framed as searching for additional savings, however, we find taxpayers are more willing to trust humans than AI when the service is framed as searching for errors.

[Insert Table 4 about here]

Supplemental analysis – Trust of AI in general

An important part of our theoretical development is the assumption that participants view AI as a relatively less known mode of service compared to humans. Recent research suggests that familiarity and trust with AI are strong predictors of general attitudes towards and support for the use of AI (Schepman and Rodway 2020; Horowitz, Kahn, McDonald and Schneider 2024). Flavian, Perez-Rueda, Belanche and Casalo (2022) find that customers' insecurity with AI technology negatively impacts their intentions to use a service. To better understand participants perceptions of AI we asked them the following question, "I trust AI in my day-today life" (on a 7-point scale with 1 = "Strongly disagree", 4 = "Neither agree nor disagree", and 7 = "Strongly agree"). Responses indicate that on average participants neither agree nor disagree with this statement (mean = 3.92; median = 4). We also find that responses to this question do not differ between our experimental conditions (all $p > 0.40$, two-tailed). To further explore whether inherent trust of AI affects our results, we control for responses to this question in our main interaction test and find that overall results are inferentially unchanged ($F = 2.04$; $p = 0.077$, one-tailed equivalent). We also test whether our results are driven by those with relative agreement or disagreement to this question. Specifically, we exclude those at the scale midpoint ("Neither agree nor disagree") and test whether our interactions manifest among those with *at least* some level of disagreement or agreement. We first test our hypothesized interaction among those who disagree that they trust AI and find a significant main effect reflecting a preference for human over AI ($F = 14.73$; $p < 0.001$, one-tailed equivalent) as well as an interaction similar in significance to our main results ($F = 2.44$; $p = 0.061$, one-tailed equivalent). Next, we test effects among those who agreed that they trust AI and do not find a significant interaction ($F = 0.28$; $p = 0.600$, two-tailed). We do, however, find a main effect of mode of service reflecting a preference for AI over human ($F = 3.54$; $p = 0.031$, one-tailed equivalent). Taken together these results suggest that, consistent with our theory, our hypothesized effects are primarily driven by those who are less familiar with (have a relative distrust of) AI. Of note, we also find that those who do report trusting AI actually have a preference (i.e., would be more likely to pay more) for services provided by AI.[13]

[13] As mentioned previously, 72% of our sample indicated that they use a program (such as TurboTax) to prepare their taxes. Taxpayers that choose software to prepare their return may be more open to AI than those using a paid preparer. We test our primary interaction results using just this subsample, and find that results are largely consistent ($p = 0.102$, one-tailed equivalent, or $p = 0.057$ one-tailed equivalent when risk preferences are included as a covariate).

V. CONCLUSION

In this study we examine whether the framing and mode of tax service offering impacts a taxpayer's willingness to pay for the service. We posit that a search for errors service framing elicits a prevention regulatory focus because of the potential reduction in the likelihood of incurring a negative tax outcome, such as an audit or imposition of penalties and interest from the tax authority. In contrast, we posit a search for tax savings service framing elicits a promotion regulatory focus because of the potential to achieve the desired effect of tax savings. We predict that taxpayers in the induced prevention focused search for errors service framing will be more willing to pay for a human relative to AI because of heightened risk aversion due to the prevention focus. In contrast, we predict mode (human versus AI) will be less important when a promotion focus is induced by framing the service as a search for tax savings.

Using an experiment with experienced taxpayers, we find support for our predictions. Taxpayers are willing to pay more for a service framed as searching for errors when the mode of service is human versus AI. Conversely, we find no difference in willingness to pay between human and AI modes of service when the service is framed as a search for additional savings. Follow-up analyses suggest these effects are explainable through differences in trust perceptions consistent with the service framing inducing a prevention or a promotion focus which, in turn, effects risk appetite.

Our paper contributes to both literature and practice. We contribute to prior research on technology adoption (e.g., Davis, 1985; Venkatesh et al., 2003) by showing that the framing of the service offered can have important implications for users' willingness to adopt a new mode of service. Our theory highlights that regulatory focus induced by the framing (or even nature) of different types of tasks is an important variable to consider. We also provide useful implications for practice. As tax firms consider investments in AI an important question is whether and how they will be able to recoup investment costs. Our study suggests that they would do well to consider how they frame a task they are considering passing to AI, or possibly even which tasks they pass to AI, as this can have important implications for taxpayers' willingness to pay for the service. Firms might consider focusing human capital in areas that are likely to induce a prevention focus while investing more heavily in AI to perform more promotion focused tasks. Alternatively, it may be that firms can frame how they market their AI offerings in ways that will reduce the human over AI disparity. For example, by advertising AI offering in ways that are likely to induce a promotion focus (such as by focusing on potential tax savings).

Our study has limitations which offer opportunities for future research. In our study we intentionally hold constant the amount of time to complete the tax service by informing participants in all conditions that the service should be completed by the next day. This allows us to cleanly test our theory (i.e., by ruling out assumed completion time as a potential driver of results), however, in practice AI is often able to complete tasks quicker than humans. Future research might consider whether taxpayers take into account assumed completion times when making decisions, and if so, how this might moderate our results. Our theory assumes taxpayers will inherently be less comfortable with AI relative to humans, however it may be that as generative AI becomes more mainstream that some of our effects could be diminished. We also hold constant that taxpayers are in a refund position. Given prior research finds varying taxpayer behavior dependent on being in a tax due or refund situation due to decision-making frames (Jackson and Hatfield 2005; Brink and Lee 2015), future research could explore whether the regulatory focus of a service offering elicits similar behavior when taxpayers are facing a tax payment rather than a refund or when taxpayers do not yet know their tax position. We use a hypothetical vignette which lacks richness found in the real world. This allows us to cleanly attribute our findings to our experimental manipulations, however future research might consider whether providing additional information moderates our findings. For example, future research might consider whether results are consistent if the presented financial situation were more or less complex or if the taxpayer needed to exert more effort in preparing the tax return. Finally, in our study we require all participants to have at least some experience filing taxes. Future research might consider whether more or less experience filing taxes affects willingness to pay for AI provided tax services.

References

Anyoha, R. (2020). *The History of Artificial intelligence - Science in the News*. Science in the News. https://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/

Appelbaum, D., Kogan, A., and Vasarhelyi, M. A. (2017). Big data and analytics in the modern audit engagement: research needs. Auditing-a Journal of Practice & Theory, 36(4), 1–27. https://doi.org/10.2308/ajpt-51684

Austin, A. A., Carpenter, T., Christ, M. H., and Nielson, C. (2021). The Data Analytics Journey: interactions among auditors, managers, regulation, and technology*. Contemporary Accounting Research, 38(3), 1888–1924. https://doi.org/10.1111/1911-3846.12680

Bar-Gill, S., Brynjolfsson, E., and Hak, N. (2024). Helping Small Businesses Become More Data-Driven: a field experiment on EBay. *Management Science*. https://doi.org/10.1287/mnsc.2021.02026

Bauer, T. (2014). The effects of client identity strength and professional identity salience on auditor judgments. The Accounting Review, 90(1), 95–114. https://doi.org/10.2308/accr-50863

Bauman, E., Impink, J., Mayberry, M. and McGill, G.A., (2023). Executive Regulatory Focus and Tax Avoidance. *Available at SSRN 4627322*.

Bharadwaj, A., Sawy, O. a. E., Pavlou, P. A., and Venkatraman, N. (2013). Digital Business Strategy: Toward a next generation of insights. *Management Information Systems Quarterly*, *37*(2), 471–482. https://doi.org/10.25300/misq/2013/37:2.3

Bobek, D. D., Hatfield, R. C., and Wentzel, K. (2007). An Investigation of Why Taxpayers prefer Refunds: A Theory of Planned Behavior approach. *The Journal of the American Taxation Association*, *29*(1), 93–111. https://doi.org/10.1521/jata.2007.29.1.93

Borges, A. and Gomez, P. (2015), "How products induce regulatory fit: evidence from the health domain", Journal of Consumer Marketing, Vol. 32 No. 6, pp. 441-449. https://doi.org/10.1108/JCM-01-2015-1292

Brink, W. and Lee, L. (2015) The Effect of Tax Preparation Software on Tax Compliance: A Research Note. *Behavioral Research in Accounting* 27 (1): 121–135. https://doi.org/10.2308/bria-50977

Britannica. (2024). Artificial intelligence. Accessed on July 31, 2024 at: https://www.britannica.com/technology/artificial-intelligence

Brynjolfsson, E. and K. McElheran. (2016). "The Rapid Adoption of Data-Driven Decision-Making." American Economic Review, 106 (5): 133-39.

Chen, C., Law, C., and Yang, S. (2009). Managing ERP Implementation Failure: A Project Management Perspective. IEEE Transactions on Engineering Management, 56(1), 157–170. https://doi.org/10.1109/tem.2008.2009802

Collins, J. H., Milliron, V. C., and Toy, D. R. (1990). Factors Associated with Household Demand for Tax Preparers. Journal of the American Taxation Association, 12(1).

Cooper, L., Holderness, D. K., Sorensen, T. L., and Wood, D. A. (2019). Robotic process automation in public accounting. *Accounting Horizons*, *33*(4), 15–35. https://doi.org/10.2308/acch-52466

Crowe, E. and Higgins, E. (1997). Regulatory Focus and Strategic Inclinations: Promotion and Prevention in Decision-Making, *Organizational Behavior and Human Decision Processes*, (69) 2, 117-132, https://doi.org/10.1006/obhd.1996.2675.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems : theory and results*. http://ci.nii.ac.jp/naid/20001062454

Dagilienė, L., & Klovienė, L. (2019). Motivation to use big data and big data analytics in external auditing. Managerial Auditing Journal, 34(7), 750–782. https://doi.org/10.1108/maj-01-2018-1773

De Freitas, J., Agarwal, S., Schmitt, B. H., & Haslam, N. (2023). Psychological factors underlying attitudes toward AI tools. *Nature Human Behaviour*, *7*(11), 1845–1854. https://doi.org/10.1038/s41562-023-01734-2

DeBacker, J., Heim, B., Tran, A. and Yuskavage A. (2024). Seeking Professional Help: How Paid Preparers Decrease Tax Compliance. *National Tax Journal* (77) 2, 229-261. https://doi.org/10.1086/728928

Dremel, C., Herterich, M. M., Wulf, J., Waizmann, J., and Brenner, W. (2017). How AUDI AG Established Big Data Analytics in its Digital Transformation. *Mis Quarterly Executive*, *16*(2), 3. http://dblp.uni-trier.de/db/journals/misqe/misqe16.html#DremelHWWB17

Dubin, J. A., M. J. Graetz, M. A. Udell, and L. L. Wilde. (1992). The demand for tax return preparation services. The Review of Economics and Statistics 74: 75–82. https://doi.org/10.2307/2109544

Eilifsen, A., Kinserdal, F., Messier, W. F., and McKee, T. E. (2019). An Exploratory Study into the Use of Audit Data Analytics on Audit Engagements. Social Science Research Network. https://doi.org/10.2139/ssrn.3458485

Flavián, C., Pérez-Rueda, A., Belanche, D., and Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*, 33(2), 293-320. https://doi.org/10.1108/JOSM-10-2020-0378

Fleischman, G.M., and Stephenson, T.. (2012); Client Variables Associated with Four Key Determinants of Demand for Tax Preparer Services: An Exploratory Study. *Accounting Horizons* 26 (3): 417–437. https://doi.org/10.2308/acch-50167.

Fowler, G. A. (2024). TurboTax and H&R Block now use AI for tax advice. It's awful. *Washington Post*. https://www.washingtonpost.com/technology/2024/03/04/ai-taxes-turbotax-hrblock-chatbot/

Frischmann, P. J., and Frees, E. W. (1999). Demand for services: Determinants of tax preparation fees. *Journal of the American Taxation Association*, 21(s-1), 1-23. https://doi.org/10.2308/jata.1999.21.s-1.1

Gamache, D.L., McNamara, G., Mannor, M.J. and Johnson, R.E., (2015). Motivated to acquire? The impact of CEO regulatory focus on firm acquisitions. *Academy of Management Journal*, *58*(4), pp.1261-1282.

Goldman Sachs. (2023). AI investment forecast to approach $200 billion globally by 2025. Accessed July 19, 2024 at: https://www.goldmansachs.com/intelligence/pages/ai-investment-forecast-to-approach-200-billion-globally-by-2025.html

Gölzer, P., & Fritzsche, A. (2017). Data-driven operations management: organizational implications of the digital transformation in industrial practice. *Production Planning & Control*, *28*(16), 1332–1343. https://doi.org/10.1080/09537287.2017.1375148

Gomber, P., Kauffman, R. J., Parker, C., and Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. *Journal of Management Information Systems*, *35*(1), 220–265. https://doi.org/10.1080/07421222.2018.1440766

Gepp, A., Linnenluecke, M. K., O'Neill, T., & Smith, T. W. (2018). Big data techniques in auditing research and practice: Current trends and future opportunities. Journal of Accounting Literature, 40(1), 102–115. https://doi.org/10.1016/j.acclit.2017.05.003

Hamilton, B. (2023). So Now There's a Shortage of Tax Accountants? Accessed July 31, 2024 at: https://www.taxnotes.com/featured-analysis/so-now-theres-shortage-tax-accountants/2023/10/19/7hgmq

Hanlon, M., & Heitzman, S. (2010). A review of tax research. Journal of Accounting and Economics, 50(2–3), 127–178. https://doi.org/10.1016/j.jacceco.2010.09.002

Hartman, R., A. J. Moss, S. N. Jaffe, C. Rosenzweig, L. Litman, and J. Robinson. (2023). Introducing Connect by CloudResearch: Advancing Online Participant Recruitment in the Digital Age. https://doi.org/10.31234/osf.io/ksgyr.

Hatfield, R. C., Jackson, S. B., & Schafer, J. (2008). An Investigation of the Relation between Tax Professionals, Tax Refunds, and Fees. *Behavioral Research in Accounting*, *20*(2), 19–35. https://doi.org/10.2308/bria.2008.20.2.19

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach third edition*. New York, NY: Guilford Press.

Hite, P. A., and McGill, G. A. (1992). An Examination of Taxpayer Preference for Aggressive Tax Advice. *National Tax Journal*, *45*(4), 389–403. https://doi.org/10.1086/ntj41788980

Holler, M., Hoelzl, E., Kirchler, E., Leder, S. and Mannetti, L. (2008) Framing of information on the use of public finances, regulatory fit of recipients and tax compliance. *Journal of Economic Psychology,* 29 (4) 597-611, https://doi.org/10.1016/j.joep.2008.01.001.

Horowitz, M. C., and Kahn, L. (2021). What influences attitudes about artificial intelligence adoption: Evidence from U.S. local officials. *PloS One*, *16*(10), e0257732. https://doi.org/10.1371/journal.pone.0257732

Horowitz, M.C., Kahn, L., Macdonald, J. and Schneider, J.. Adopting AI: how familiarity breeds both trust and contempt. *AI & Society* 39, 1721–1735 (2024). https://doi.org/10.1007/s00146-023-01666-5

Hunt, N. and Iyer, G. (2018). The effect of tax position and personal norms: An analysis of taxpayer compliance decisions using paper and software. *Advances in Accounting* 41, 1-6, https://doi.org/10.1016/j.adiac.2018.02.003.

IRS (2023). IRS Data Book. Accessed August 3, 2024. https://www.irs.gov/statistics/soi-tax-stats-irs-data-book

Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research Ideas for Artificial intelligence in Auditing: The Formalization of audit and Workforce Supplementation. Journal of Emerging Technologies in Accounting, 13(2), 1–20. https://doi.org/10.2308/jeta-10511

Jackson, S. and Hatfield, R. (2005). A Note on the Relation between Frames, Perceptions, and Taxpayer Behavior. *Contemporary Accounting Research* 22(1): 145-164. https://doi.org/10.1506/L5LA-L863-CF9K-WEJ5

Jackson, S. B., Shoemaker, P., Barrick, J. A., & Burton, F. (2005). Taxpayers' prepayment positions and tax return preparation fees*. *Contemporary Accounting Research*, *22*(2), 409–447. https://doi.org/10.1506/uu3e-p3yf-px9f-t9tf

Kanze, D., Huang, L., Conley, M. A., & Higgins, E. T. (2018). We ask men to win and women not to lose: Closing the gender gap in startup funding. *Academy of Management Journal*, *61*(2), 586-614.

Kokina, J., & Davenport, T. H. (2017). The Emergence of Artificial Intelligence: How Automation is Changing Auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122. https://doi.org/10.2308/jeta-51730

Lamberton, C., De Neve, J., & Norton, M. I. (2013). Eliciting taxpayer preferences increases tax compliance. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2365751

Lanaj, K., Chang, C.H. and Johnson, R.E., (2012). Regulatory focus and work-related outcomes: a review and meta-analysis. *Psychological bulletin*, *138*(5), p.998.

Leder,S., Mannetti, L., Hölzl, E., and Kirchler, E.. (2010). Regulatory fit effects on perceived fiscal exchange and tax compliance. *The Journal of Socio-Economics*, 39 (22) 271-277, https://doi.org/10.1016/j.socec.2009.12.003.

Morel, D. (2023). The Future Of Work: How Will AI Change Business? *Forbes*. Accessed July 7, 2024 at: https://www.forbes.com/sites/davidmorel/2023/08/31/the-future-of-work-how-will-ai-change-business/

O'Shaughnessy, M., Schiff, D., Varshney, L. R., Rozell, C. J., and Davenport, M. A. (2022). What governs attitudes toward artificial intelligence adoption and governance? *Science and Public Policy/Science & Public Policy*, *50*(2), 161–176. https://doi.org/10.1093/scipol/scac056

Otia, J. E., and Bracci, E. (2022). Digital transformation and the public sector auditing: The SAI's perspective. Financial Accountability and Management, 38(2), 252–280. https://doi.org/10.1111/faam.12317

Pickerd, J., and Piercey, M. D. (2021). The effects of high estimate uncertainty in auditor negligence litigation. Contemporary Accounting Research, 38 (4): 3182–3213. https://doi.org/10.1111/1911-3846.12685.

Piercey, M. D. (2023). "Throw it in as a covariate?" Common problems using measured control variables in experimental research. Auditing: A Journal of Practice & Theory, 42 (2): 183–205. https://doi.org/10.2308/ajpt-2020-011.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. Journal of Marketing, 85(1), 131-151. https://doi.org/10.1177/0022242920953847

Rosenthal, L., Brown, B. L., Higgs, J. L., and Rupert, T. J. (2023). Tax Software versus Paid Preparers: Motivations and Predictors for the Mode of Tax Preparation Assistance. *Accounting Horizons*, *37*(1), 173–191. https://doi.org/10.2308/horizons-2020-083

Sakurai, Y., & Braithwaite, V. (2003). Taxpayers' perceptions of practitioners: finding one who is effective and does the right thing? *Journal of Business Ethics*, *46*, 375–387.

Sangwan, V., Harshita, Prakash, P., & Singh, S. (2019). Financial technology: a review of extant literature. *Studies in Economics and Finance*, *37*(1), 71–88. https://doi.org/10.1108/sef-07-2019-0270

Schepman, A. and Rodway, P. (2020) Initial validation of the general attitudes towards Artificial Intelligence Scale. Computers in Human Behavior Reports, 1: 1-13. https://doi.org/10.1016/j.chbr.2020.100014

Sillamaa, M. (1999). Taxpayer behavior in response to taxation: comment and new experimental evidence. *Journal of Accounting and Public Policy*, *18*(2), 165–177. https://doi.org/10.1016/s0278-4254(99)00005-8

Steinhardt, S.J. (2024). Survey: Half of Taxpayers Distrust AI To Do Their Taxes. *The Trusted Professional. New York State Society of CPA's*. Accessed July 11, 2024 at: https://nysscpa.org/news/publications/the-trusted-professional/article/survey-half-of-taxpayers-distrust-ai-to-do-their-taxes-040424

Stephenson, T. (2010). Measuring taxpayers' motivation to hire tax preparers: The development of a four-construct scale. *Advances in Taxation* 19: 95–121. https://doi.org/10.1108/S1058-7497(2010)0000019006

Stephenson, T., Fleischman, G. and Peterson, M. (2017), Demand for Tax-Preparation Services: An Exploratory Examination of Client Versus Tax-Preparer Expectation Gaps, *Advances in Taxation* 24, 199-231. https://doi.org/10.1108/S1058-749720170000024005

Sun, S., Cegielski, C. G., Jia, L., and Hall, D. J. (2016). Understanding the factors affecting the organizational adoption of big data. *The Journal of Computer Information Systems*, *58*(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891

Tan, M., and Teo, T. (2000). Factors influencing the adoption of internet banking. *Journal of the Association for Information Systems*, *1*(1), 1–44. https://doi.org/10.17705/1jais.00005

Thomson Reuters (2023). How AI will impact the tax profession. Accessed July 11, 2024 at: https://tax.thomsonreuters.com/blog/how-ai-will-impact-the-tax-profession/

Thomson Reuters (2024a). 2024 Generative AI in Professional Services: Perceptions, Usage & Impact on the Future of Work. Accessed July 11, 2024 at: https://www.thomsonreuters.com/en/reports/2024-generative-ai-in-professional-services.html

Thomson Reuters (2024b). How AI transformed the tax and accounting profession in 2023. Accessed July 29 at: https://tax.thomsonreuters.com/blog/how-ai-transformed-the-tax-and-accounting-profession-in-2023/

TurboTax. (n.d.). *All TurboTax® offerings 2023*. https://turbotax.intuit.com/personal-taxes/online/file-your-own-taxes/

Turing, A. (1950). I.—COMPUTING MACHINERY AND INTELLIGENCE. *Mind*, *LIX*(236), 433–460. https://doi.org/10.1093/mind/lix.236.433

Uzialko A. (2024). How Artificial Intelligence Will Transform Businesses. *Business News Daily*. Accessed July 11, 2024 at: https://www.businessnewsdaily.com/9402-artificial-intelligence-business-trends.html

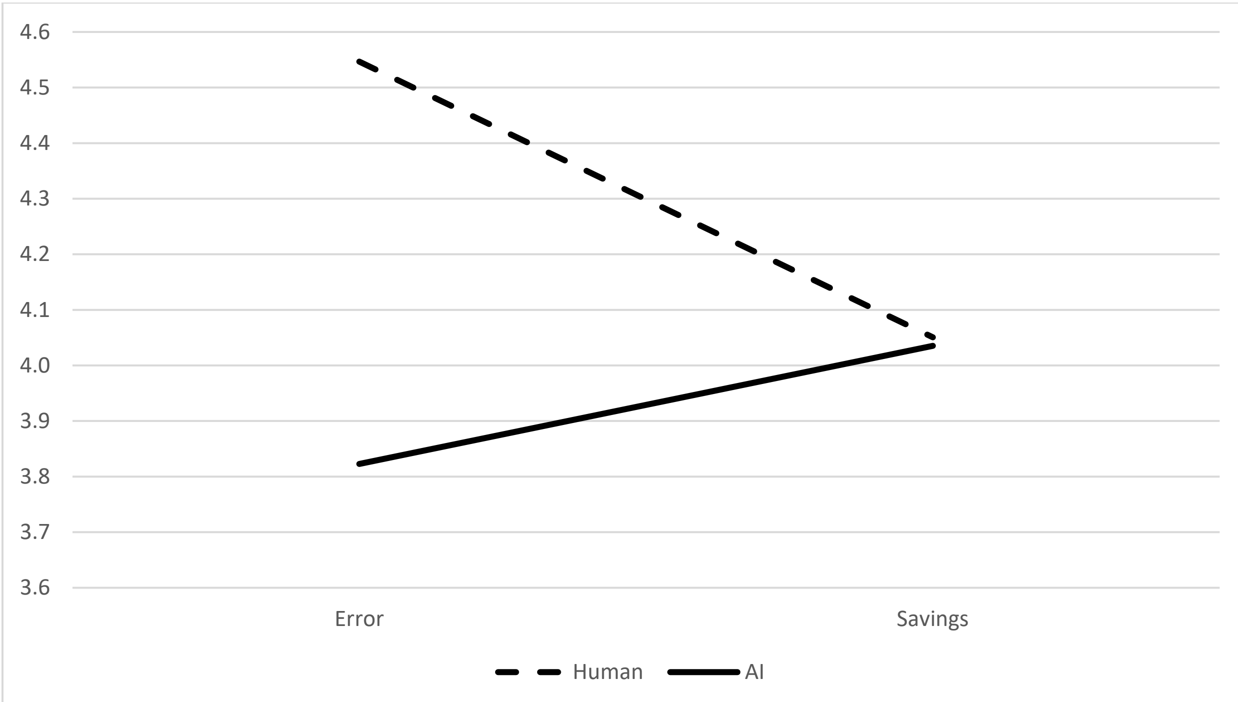
Van Dijk, D. and Kluger, A.N. (2011), Task type as a moderator of positive/negative feedback effects on motivation and performance: A regulatory focus perspective. *Journal of Organizational. Behavior*., 32: 1084-1105. https://doi.org/10.1002/job.725

Venkatesh, V., Morris, M., Davis, G. B., and Davis, F. D. (2003). User acceptance of information Technology: toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Yankelovich, Skelly, and White, Inc. (1984). Survey of taxpayer Attitudes. Report prepared for the Internal Revenue Service. Washington, DC: Department of the Treasury, Internal Revenue Service, Public Affairs Division

Figure 1

Graphical depiction of *likelihood to pay more* by condition



Likelihood to pay more is measured using the following question, "How likely would you be to pay more for the service described above?" (on a 7-point scale with endpoints 1 = "Extremely unlikely" and 7 = "Extremely likely").

In the *Errors* condition the service offered is to, "search your tax return for possible errors (and could reduce your risk of a costly audit by the IRS)".

In the *Savings* condition the service offered is to, "search your tax return for possible additional tax savings (and could potentially increase the size of your refund)".

In the *Human* condition the mode of service is a "group of tax professionals".

In the *AI* condition the mode of service is an "AI assistant".

Table 1
Demographic Information

	Sample N = 318	U.S. Population
Sex		
Male	45.9%	49.5%
Female	54.1%	50.5%
Age		
20 to 24	3%	6%
25 to 34	34%	14%
35 to 44	33%	13%
45 to 54	15%	12%
55 to 64	12%	13%
65 to 74	2%	10%
75 or older	1%	7%
Education		
Less than high school	<1%	5%
High school	11%	26%
Some college	16%	19%
Associates degree	10%	9%
Bachelor's degree	40%	22%
Advanced degrees	22%	14%
Income		
Less than $25,000	9%	15%
$25,001 to $50,000	20%	17%
$50,001 to $100,000	40%	29%
$100,001 to $150,000	20%	17%
$150,001 or more	10%	22%
Filing method		
Paper file	8%	9%
E-file	92%	91%
Preparation method		
Directly fill out forms (e.g., 1040)	7%	
Use program (e.g., TurboTax)	72%	41%
Use tax professional (not CPA)	9%	
Use CPA	10%	
Total Paid Preparer		56%
Other	2%	
Gender, age, education, and household income for the U.S. population are from the U.S. Census Bureau 2020 Census (see: https://data.census.gov). Age is based on the population over age 20, and education data are based on the population over age 25. Filing method data are from the IRS Data Book (https://www.irs.gov/statistics/soi-tax-stats-irs-data-book).		

Table 2
Evidence of Manipulation Effectiveness

Panel A: Promotion and prevention focused words in participant's open responses by condition

	Number of appearances in each condition	
Promotion focused terms	Savings	Errors
advanc	0	1
earn	1	2
gain	1	2
hop	3	1
increas	10	1
speed	0	1
toward	1	0
Total promotion terms	16	8

Prevention focused terms	Savings	Errors
accura	2	7
afraid	0	2
care	1	2
anxi	0	1
avoid	0	4
fear	0	1
los	2	1
ought	4	1
prevent	0	2
protect	0	1
risk	3	3
safe	0	6
secur	1	2
Total prevention terms	13	33

Panel B: Statistical tests

	t	p-value
Promotion focused: Savings versus Errors	1.54	**0.062**
Prevention focused: Savings versus Errors	-3.30	**<0.001**

Bolded p-values are one-tailed equivalents

Table 3

Descriptive statistics and statistical tests for *likelihood to pay more*

Panel A: Descriptive statistics: mean [standard deviation] of *likelihood to pay more* by condition

	Savings	Errors	Row mean
Human	4.05	4.55	4.29
	[2.08]	[2.02]	[2.05]
	N=79	N=75	N=154
AI	4.04	3.82	3.93
	[1.97]	[2.03]	[1.99]
	N=85	N=79	N=164
Column Mean	4.04	4.18	
	[2.01]	[2.04]	
	N=164	N=154	

Panel B: ANOVA model – test of hypothesis

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**p-value**
Intercept	5371.06	1	5371.06	1318.83	<0.001
Mode (AI vs Human)	10.84	1	10.84	2.66	0.104
Service framing (Savings vs Errors)	1.59	1	1.59	0.39	0.532
Mode × Service	9.96	1	9.96	2.45	**0.059**
Error	1278.80	314	4.07		

Panel C: ANCOVA model – test of hypothesis controlling for risk preferences

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**p-value**
Intercept	466.61	1	466.61	120.26	<0.001
Risk preferences	64.37	1	64.37	16.59	<0.001
Mode (AI vs Human)	11.26	1	11.26	2.90	0.089
Service framing (Savings vs Errors)	2.33	1	2.33	0.60	0.439
Mode × Service	11.76	1	11.76	3.03	**0.041**
Error	1214.43	313	3.88		

Panel D: Simple effects

Comparison	**t**	**p-value**
Effect of Service framing (Errors vs Savings) given Mode is Human	1.51	0.134
Effect of Service framing (Errors vs Savings) given Mode is AI	0.68	0.497
Effect of Mode (Human vs AI) given Service framing is Errors	2.23	**0.014**
Effect of Mode (Human vs AI) given Service framing is Savings	0.05	0.961

Bolded p-values are one-tailed equivalents

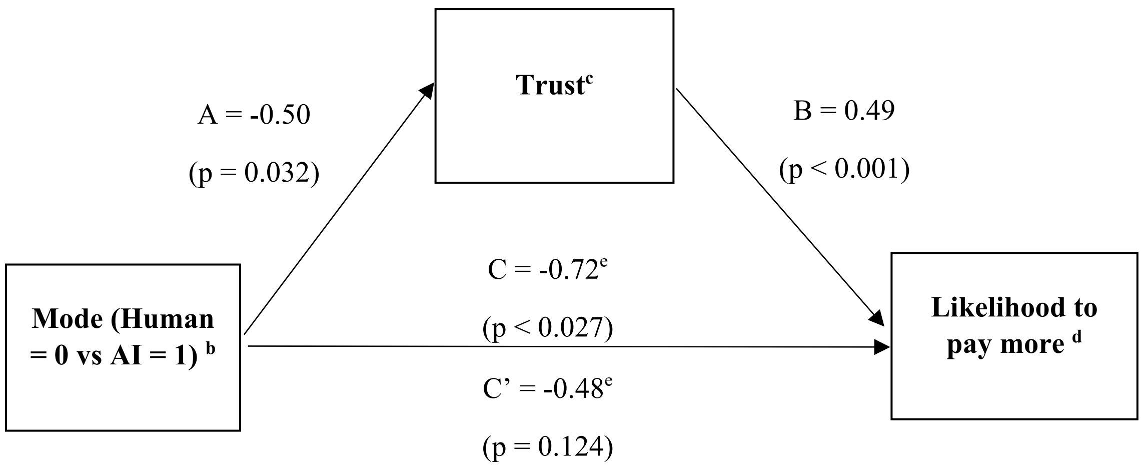
Table 3 (Cont.**)**

Likelihood to pay more is measured using the following question, “How likely would you be to pay more for the service described above?” (on a 7-point scale with endpoints 1 = “Extremely unlikely” and 7 = “Extremely likely”).

Service framing is manipulated as *Errors* or *Savings*. In the *Errors* condition the service offered is to, “search your tax return for possible errors (and could reduce your risk of a costly audit by the IRS)”. In the *Savings* condition the service offered is to, “search your tax return for possible additional tax savings (and could potentially increase the size of your refund)”.

Mode is manipulated as *Human* or *AI*. In the *Human* condition the mode of service is a “group of tax professionals”. In the *AI* condition the mode of service is an “AI assistant”.

Table 4
Mediation through trust (*Errors* conditions only) [a]



Confidence interval for the indirect effect of *Mode* on *likelihood to pay more* through *trust*:

	Lower Bound	Upper Bound
Indirect Effect	-0.510	-0.018*

* Presented confidence interval is based on a 95% confidence level.

---

[a] All tests are two-tailed.
[b] *Mode* is manipulated as *Human* or *AI*. In the *Human* condition the mode of service is a “group of tax professionals”. In the *AI* condition the mode of service is an “AI assistant”. Note that in this test *Human* is coded as 0, while *AI* is coded as 1.
[c] *Trust* is measured using the following question, “How much do you trust that the service offered by ABC Tax Preparation would result in the desired outcome?” (measured on a 7-point scale with endpoints, “Extremely distrustful” and “Extremely trustful”).
[d] *Likelihood to pay more* is measured using the following question, “How likely would you be to pay more for the service described above?” (on a 7-point scale with endpoints 1 = “Extremely unlikely” and 7 = “Extremely likely”).
[e] C represents the total effect of *Mode* on *likelihood to pay more* without considering the effect of the mediating variables. C’ represents the direct effect of *Mode* on *likelihood to pay more* when including the effect of the mediating variables.