Reliance on Algorithmic Estimates: The Joint Influence of Algorithm Adaptability and Measurement Uncertainty

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December 2023

Acknowledgments: We thank Chris Agoglia, Urton Anderson, Josh Beckmann, Bradley Bennett, Monika Causholli, Igor Cunha, Jeff Hales, Blake Holman, Erin Hamilton, Steve Glover, David Piercey, Aaron Roeschley, Aaron Saiewitz, and Jason Smith for their helpful comments and suggestions. We are also grateful for feedback we received from participants at the 2019 AAA/Deloitte Foundation/J. Michael Cook Doctoral Consortium, University of Illinois at Urbana-Champaign, University of Kentucky, University of Massachusetts Amherst, University of Nevada – Las Vegas, and University of Texas – el Paso. We gratefully acknowledge support of an Access to Audit Personnel (AAP) grant from the Center for Audit Quality (CAQ), support from University of Nevada – Las Vegas, and financial support provided by the Von Allmen School of Accountancy and the Gatton College of Business and Economics. The views expressed in the paper are those of the authors alone and not those of the CAQ.

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A B S T R A C T

Measurement uncertainty can exacerbate the challenges associated with developing and evaluating complex accounting estimates. Companies, including public accounting firms, are developing systems that use advanced algorithms to help accounting professionals deal with this uncertainty. We conduct two experiments to examine whether and how accounting professionals' reliance on an algorithmic system's output is jointly influenced by the degree of measurement uncertainty and the system's ability to adapt. In Experiment 1, we find that auditors are more willing to rely on advice from learning algorithms than static algorithms when measurement uncertainty is relatively high. In Experiment 2, we replicate this result in a general accounting context where preparers develop their own accounting estimates. Our findings demonstrate that accounting professionals' reliance on algorithms is contextually dependent, and highlights algorithm adaptability as an important technological feature that can promote advice utilization, particularly when adaptability is important to the judgment context (e.g., heightened measurement uncertainty).

Keywords: accounting, algorithm adaptability, audit adjustments, complex estimates, measurement uncertainty

JEL codes: M40; M41; M42; O30; O32; O33

1. Introduction

Measurement uncertainty arises when the valuation of a financial statement item is not directly observable and, therefore, requires significant judgment and estimation (SEC 2011; Bratten, Gaynor, McDaniel, Montague, and Sierra 2013; FASB 2016; FASB 2019). Measurement uncertainty can make it challenging for financial statement preparers to develop reliable accounting estimates and difficult for auditors to evaluate these estimates as they often include assumptions and inputs that are subjective, forward-looking, and unverifiable (Christensen, Glover, and Wood 2012; Glover, Taylor, and Wu 2017). Furthermore, macroeconomic factors can exacerbate the challenges associated with measurement uncertainty which ultimately could lead to lower financial reporting and audit quality (Deloitte 2022).

As a means of confronting these uncertainties, companies are increasing their use of artificial intelligence (AI) to improve forecasts and operational decisions (McKinsey 2020a; McKinsey 2020b; Deloitte 2021b). Likewise, audit firms and financial service companies report that they are investing significant resources in developing advanced systems to help accounting professionals produce and evaluate complex accounting estimates (Deloitte 2018b; Bloomberg Tax 2020; KPMG 2020a). Although the use of AI can improve accounting judgments (Ding, Lev, Peng, Sun, and Varsarhelyi 2020), recent findings demonstrate that accounting professionals can be hesitant to rely fully on output from AI-based systems (e.g., Commerford, Dennis, Joe, Ulla 2022), which could hamper the benefits realized from using AI in this setting. Accountants and auditors may be hesitant to rely on AI-generated estimates due to the accounting profession's heavy focus on evidence and process documentation (SEC 2003) as well as their tendency to use a verification framework (Griffith, Hammersley, and Kadous 2015). Relatedly, regulators cite a lack of trust in AI due to concerns regarding AI's process opacity and "black box problem" as the "biggest challenge to the…adoption of AI tools" (CPA Canada and AICPA 2020, 6; PCAOB 2023). Therefore, it is important to identify factors affecting accountants' reliance on system output. In this study, we examine whether and how accountants' reliance on output from an algorithmic system is jointly influenced by the degree of measurement uncertainty, as well as the system's ability to adapt.

In general, individuals are averse to uncertainty and attempt to reduce uncertainty in a variety of ways, including seeking advice from others (Sniezek and Van Swol 2001). Specifically, advice-taking literature finds that when individuals face tasks that exhibit greater uncertainty and difficulty, they are more likely to solicit and utilize advice from other individuals (Schrah, Dalal, and Sniezek 2006; Gino and Moore 2007). Consistent with this, accounting professionals are encouraged to seek advice from others to improve the quality of their judgments, especially those involving complex tasks that require expertise (e.g., asset valuations) (Ranzilla, Chevalier, Herrmann, Glover, and Prawitt 2011; PCAOB 2016). This suggests that as measurement uncertainty increases, accounting professionals should become more willing to incorporate advice from others into their judgments.

In addition, the advice-taking literature demonstrates that advice reliance is influenced by characteristics of the advisor (Bonaccio and Dalal 2006). In particular, a key component in advice utilization is whether individuals believe the advisor possesses the necessary skillset or competencies to assist with a given task (Birnbaum and Stegner 1979; Mayer, Davis, and Schoorman 1995; Harvey and Fischer 1997; Van Swol and Sniezek 2005; Pornpitakpan 2004). Relevant to our study, there is evidence that the relation between uncertainty and advice reliance differs when the advisor is an algorithm instead of a human. Specifically, Dietvorst and Bharti (2020) find that individuals become more resistant to relying on algorithmic advisors as uncertainty increases. Importantly though, Dietvorst and Bharti (2020, 1303) argue that "an algorithm's general approach to forecasting is constant, whereas human judges can change their approach at will." This implies individuals believe that, to perform well, advisors should have the ability to adapt in times of high uncertainty, and that algorithms lack this ability. While some algorithms use a fixed set of factors and weights that remain constant, it is increasingly common for algorithmic systems to use AI that enables the system to adapt and learn over time (e.g., machine learning). Therefore, accountants and auditors will likely encounter systems that vary in the degree to which they can adapt (i.e., learning algorithms versus static algorithms).

We propose that when there is significant uncertainty, accountants' reliance on algorithmic advice will depend on whether the algorithm is one that can adapt to new information (i.e., a learning algorithm) or one that cannot (i.e., a static algorithm). We expect that in environments with relatively higher uncertainty, accountants will believe that a learning algorithm's ability to adapt makes it better equipped to handle uncertainty relative to a static algorithm (Deloitte 2014; KPMG 2020c). Accordingly, we predict that accounting professionals will rely more heavily on advice provided by a learning algorithm relative to advice from a static algorithm, particularly when measurement uncertainty is higher versus lower.

To test our prediction, we conduct two experiments. In our first experiment, we examine whether and how our prediction manifests in auditor judgments. We use a 2 × 2 between-subjects design, manipulating the degree of measurement uncertainty (higher versus lower) and the adaptability of the algorithmic advisor (learning algorithm capable of adapting versus static algorithm not capable of adapting). Auditor participants assume the role of an in-charge auditor on a financial statement audit and are tasked with evaluating the client's impairment testing for an intangible asset (i.e., patent). Participants receive audit evidence from their firm's algorithmic system, which is designed to provide auditors with independent estimates for asset valuations. To manipulate algorithm adaptability, we inform auditors that their firm's algorithm is either a learning algorithm or a static algorithm. Next, all participants receive the client's fair value estimate for the patent and the algorithm's fair value estimate, which differ from each other, as well as relevant macroeconomic information to assist with their assessment. To manipulate measurement uncertainty, auditors are provided with macroeconomic information indicating either higher or lower uncertainty around a key input for estimating the patent's fair value. Auditors' proposed audit adjustments serve as our dependent measure, as they reflect auditors' relative weighting of the competing evidence, such that greater reliance on the algorithm's estimate results in larger adjustments. Consistent with our theory-based expectations, we find that higher measurement uncertainty causes auditors to more heavily weight advice from a learning algorithm relative to a static algorithm, resulting in relatively larger proposed adjustments. We also find evidence that higher measurement uncertainty causes auditors to reduce their reliance on the advice of a static algorithm, which is consistent with Dietvorst and Bharti (2020). That said, we find no evidence of this effect when the advice comes from a learning algorithm instead of a static algorithm. Thus, auditors seem to appreciate an algorithm's ability to adapt when uncertainty is heightened.

In Experiment 2, we replicate our Experiment 1 findings in a non-audit setting where participants assume the role of an accounting manager and are asked to help with intangible asset impairment testing by estimating the fair value of a patent. In Experiment 2, participants provide an initial fair value estimate and then receive a fair value estimate from their company's algorithmic software system. We then measure the degree to which participants adjust their estimate to be in accordance with the algorithm's recommended fair value (i.e., a weight of advice measure). Consistent with Experiment 1, we manipulate the degree of measurement uncertainty (higher versus lower uncertainty) and the adaptability of the algorithm (learning versus static algorithm). Again, we demonstrate that when there is higher measurement uncertainty, individuals rely more heavily on advice from learning algorithms relative to advice from a static algorithm. Supplemental analyses reveal that as measurement uncertainty rises, participants' willingness to trust learning algorithm increases, which then leads to greater reliance on a learning algorithm's advice. However, we find no evidence of this indirect effect when participants receive advice from a static algorithm. Thus, when there is greater uncertainty managers' trust in the algorithm is conditional upon the algorithm's ability to adapt.

Our study has both theoretical and practical contributions. First, practitioners continue to voice concerns that as technologies' capability continues to increase, its processes behave more like a "black box" which prevents individuals from understanding how the algorithm developed its output (EY 2018; CPA Canada and AICPA 2019; KPMG 2019). These concerns suggest that accounting professionals might be particularly hesitant to rely on learning algorithms, due to concerns about a lack of transparency. Contrary to these practitioner concerns, we find that under higher levels of uncertainty, both auditors and accounting managers rely more heavily on advice provided by learning algorithms compared to static algorithms. Thus, despite the black box concern, accounting professionals exhibit a preference for learning algorithms over static algorithms when the context is fitting (i.e., heightened measurement uncertainty). Our study suggests that there are settings in which it can be beneficial to highlight an algorithm's adaptability. The results of our study should also help inform organizations' considerations of how and when to implement systems that utilize advanced algorithms with varying abilities to adapt.

Secondly, we contribute to the growing literature around measurement uncertainty within complex accounting estimates. As demonstrated by recent global events (e.g., COVID-19 pandemic, international conflicts, worldwide supply chain disruptions, rising inflation, and bank failures), it is important that accounting professionals are prepared to respond to uncertain conditions. Nevertheless, high measurement uncertainty remains a challenge for accounting professionals (Cannon and Bedard 2017; PCAOB 2017; Mard 2018; Griffith 2020; Pinello 2020). For example, research suggests that under greater uncertainty, auditors are less likely to adjust management's estimates (Nelson, Elliott, and Tarpley 2002; Cannon and Bedard 2017), which raises the concern that measurement uncertainty enables audit clients to opportunistically achieve their preferred reporting outcomes. Consistent with this, we find that measurement uncertainty can cause auditors to propose smaller adjustments to clients' estimates, but only when firm-provided contradictory evidence comes from an algorithm that is unable to adapt. In contrast, auditors are relatively more willing to adjust client estimates in highly uncertain settings with evidence from learning algorithms. In this way, our study demonstrates how the implementation of audit tools with adaptive capabilities might improve the quality of auditor judgments and lead to higher financial reporting quality.

Lastly, we contribute to research examining human interactions with algorithms. Studies have shown that individuals are averse to relying on algorithms across various factors and decision domains (Dietvorst, Simmons, and Massey 2015; Dietvorst, Simmons, and Massey 2016; Castelo, Bos, and Lehmann 2019). Results suggest that individuals may be reluctant to rely on algorithmic advice in part due to concerns that algorithms lack the necessary level of expertise or capability (Castelo et al. 2019; Commerford et al. 2022). In addition, prior research suggests that reliance on algorithmic advice decreases as uncertainty increases (Dietvorst and Bharti 2020). However, our study finds that algorithm adaptability is an important factor that can influence the weight individuals will place on algorithmic evidence in uncertain conditions. Overall, we demonstrate that reliance on algorithmic advice is contextually dependent, and that algorithm adaptability is an important technological feature that influences advice utilization, particularly when that capability is important to the judgment context (i.e., elevated uncertainty).

2. Hypothesis Development

2.1 Accounting Estimates and Algorithms

Many accounting estimates require practitioners to make subjective, forward-looking assumptions in order to value and record financial statement balances (Bratten et al. 2013). For example, when determining the value for an intangible asset (e.g., a patent), one typically forecasts the future cash flows that the asset is expected to generate and then discounts those future cash flows into a present value at an assumed rate (KPMG 2017; Cavanaugh 2022). The inherent subjectivity and uncertainty involved in choosing inputs and predicting future outcomes can make it difficult to develop reliable accounting estimates (Bratten et al. 2013; Ding et al. 2020). Furthermore, even small changes to these assumptions can result in materially different valuations (Christensen et al. 2012). Likewise, it is challenging to evaluate the reasonableness of such estimates, as the "correct" value is often ambiguous or unknowable (Bratten et al. 2013; Griffith, Hammersley, Kadous, and Young 2015; Glover et al. 2017).

To confront these challenges, companies and public accounting firms are developing and acquiring technologies that have the potential to help professionals manage uncertain economic conditions (Bloomberg Tax 2020; Apedo-Amah et al. 2021; Deloitte 2021b). For example, to deal with supply chain uncertainties associated with the COVID-19 pandemic, organizations across many industries adopted AI technology to synthesize macroeconomic information to better forecast demand patterns and provide more relevant information (McKinsey 2020b). Similarly, financial service companies are developing AI technology capable of forecasting financial estimates, such as future cash flows (Deloitte 2019a). Relatedly, audit firms are also investing substantial resources into developing AI systems to assist auditors with the evaluation of complex accounting estimates (KPMG 2016; Shandwick 2016; Bughin, Chui, and McCarthy 2017; Deloitte 2021c; Commerford et al. 2022). For instance, Deloitte has developed Omnia DNAV, an AI platform that uses advanced algorithms to help auditors evaluate investment funds by identifying areas of high risk, verifying key inputs, and producing independent valuations (Deloitte 2021a, 3; 2021c, 19). Thus, accountants are (or soon will be) receiving input from systems that use advanced algorithms to provide recommendations and evidence around accounting estimates.

2.2 Advice-taking and Uncertainty

It is not uncommon for accounting professionals to seek advice from individuals who possess specialized knowledge and expertise (e.g., valuation specialists) when making judgments around complex estimates (Church and Shefchik 2012; Deloitte 2015; Griffith et al. 2015; Cannon and Bedard 2017; Griffith 2018; PCAOB 2017, 2020a, 2020b, 2020c, 2020d). Incorporating the advice of others is a rational approach when making difficult judgments, as advice-taking has been shown to increase judgment quality (Bonaccio and Dalal 2006). Importantly though, a growing body of research finds that individuals respond to algorithmic advisors and human advisors differently. Individuals are often hesitant to rely fully on the advice of algorithms (Promberger and Baron 2006; Yeomans, Shah, Mullainathan, and Kleinberg 2018; Dietvorst et al. 2015). This aversion to algorithmic advice has been demonstrated in a variety of judgment contexts (Burton, Stein, and Jensen 2020), including the accounting context. For example, Commerford et al. (2022)

find that, on average, auditors propose smaller adjustments to their client's biased estimates when they receive contradictory evidence from an AI system instead of a human specialist.

Furthermore, recent findings suggest this aversion to algorithmic advice is more pronounced in settings with high uncertainty. Specifically, Dietvorst and Bharti (2020) demonstrate that as uncertainty increases, individuals become even more resistant to relying on algorithmic advisors. This is in stark contrast to prior research showing that individuals become more willing to seek and utilize advice from others as tasks become more uncertain and difficult (Sniezek and Van Swol 2001; Gino and Moore 2007). Therefore, although emerging technologies have the potential to improve accounting judgments around uncertain estimates, practitioners' hesitancy to incorporate algorithmic advice into their judgments (particularly when there is high uncertainty) might limit the realized benefits from this technology.

2.3 Algorithm Adaptability

Importantly though, Dietvorst and Bharti (2020) only consider individuals' reliance on "static" algorithms, which are algorithms that remain constant and do not adapt. For instance, Dietvorst and Bharti (2020, 1303) state that "an algorithm's general approach to forecasting is constant, whereas human judges can change their approach at will." While many systems utilize static algorithms that function on defined rules that do not change, it is increasingly common for algorithms to possess the ability to adapt (Schatsky, Muraskin, and Gurumurthy 2015; Deloitte 2017a; Deloitte 2018a; CPA Canada and AICPA 2019; Deloitte 2019a; Deloitte 2019b). For example, machine learning is a type of artificial intelligence that involves building algorithms and models that can automatically learn and improve from experience or data. It uses statistical and mathematical techniques to find patterns and relationships in data, and then uses these patterns to make predictions or decisions about new data. Machine learning algorithms can develop models that contain millions of parameters or rules without human intervention or explicit instructions on how to perform a task (Bleicher 2017; EY 2018; Deloitte 2019a). Companies are eager to integrate AI technology into their processes not only for potential operational efficiencies, but also for the technology's ability to enhance the quality of accounting information (Raschke, Saiewitz, Kachroo, and Lennard 2018; Ding et al. 2020; KPMG 2020a; KPMG 2020b). Thus, accountants are likely to encounter algorithms that vary in their ability to adapt to new data and environments.

Advice utilization is often a function of whether individuals perceive the advisor to be capable of completing the task (Mayer et al. 1995; Van Swol and Sniezek 2005; Bonaccio and Dalal 2006). For example, individuals are more willing to rely on advice from others when they have greater task-relevant expertise and knowledge (Birnbaum and Stegner 1979). An algorithm's ability to adapt is a characteristic that might influence accounting professionals' willingness to rely on algorithmic advice. On one hand, the accounting setting is one in which there is a heightened need to justify, verify, and document information (Koonce, Anderson, and Marchant 1995; Peecher 1996; FASB 2018). For example, auditors are required to document procedures performed and the evidence obtained in sufficient detail to provide a clear understanding of the conclusions reached (PCAOB 2022). As such, accounting professionals might prefer to use static algorithms over learning algorithms, as static algorithms operate in a consistent and predictable manner, offering greater ease of documentation (CPA Canada and AICPA 2020). On the other hand, accounting professionals might believe a learning algorithm's adaptability to be a favorable characteristic as this allows the algorithm to incorporate new information and improve over time, thereby enhancing the quality of the evidence obtained.

Importantly, in settings with high levels of uncertainty, the ability to adapt is a particularly desirable advisor characteristic. For example, firms note that they seek out leadership that will undertake dynamic and adaptive strategies because firms view this approach to be more sustainable in uncertain and volatile business environments. Hence, companies consider a leader's adaptability to be a "competitive advantage" in times of uncertainty (Reeves and Deimler 2011, 137). In the same way, accountants likely believe learning algorithms are better equipped to handle uncertainty than static algorithms (Deloitte 2014; KPMG 2020c). Therefore, we expect the relationship between measurement uncertainty and the degree to which accounting practitioners utilize advice from an algorithm depends on whether the algorithm is capable of adapting. Specifically, we expect that under heightened levels of measurement uncertainty, accounting practitioners will be more likely to exhibit a preference for advice from learning algorithms relative to advice from static algorithms. Accordingly, we propose the following interaction hypothesis:

Hypothesis: Individuals will exhibit a stronger preference for learning over static algorithms when measurement uncertainty is higher versus lower.

3. Experiment One: Audit Setting

3.1 Participants

We obtained participants with the assistance of the Center for Audit Quality ("CAQ") and through the authors' personal contacts.[1] We provided the CAQ with a recruitment email, which invited auditors to participate in the study and included a hyperlink to the online experiment. CAQ personnel forwarded the email to contacts at each of the participating firms. We assured participating auditors that their identity and the identity of their firm would be confidential. We used a similar process when recruiting participants through personal contacts.

[1] Both experiments in this study were approved by the Institutional Review Board (IRB) for Human Participants at the university where administration of the study was completed.

Our final sample includes responses from 100 experienced auditors.[2] As reported in Table 1, participants have an average of 7.49 years of public accounting experience and report they are relatively likely to provide input into decisions regarding proposed audit adjustments (mean of 5.71 on a scale from 1 = "Not at All Likely" to 7 = "Highly Likely"). Participants also report spending approximately 51.05% of their time working on audits of public companies. Thus, these auditors possess an appropriate level of experience for evaluating client estimates (Griffith et al. 2015; Commerford et al. 2022).

[Insert Table 1]

Experimental Design

To test our theory, we conduct a 2 × 2 between-participants experiment, manipulating the degree of measurement uncertainty around a client estimate (i.e., higher versus lower measurement uncertainty). Participants receive relevant audit evidence from their firm's proprietary valuation system, and we manipulate whether that system can adapt (i.e., employs static versus learning algorithms).

Participants are instructed to assume the role of an in-charge auditor on the financial statement audit of Heartland Resource Corporation (HRC), a publicly traded oil and gas company. Auditors learn that HRC acquired a patent for a state-of-the-art drill technology. However, recent changes in the business climate (i.e., competing drill technology being developed) required HRC's management to re-evaluate the patent for possible impairment. After conducting a recoverability test, HRC's management determined that the patent value was impaired and estimated the fair value of the patent to determine the amount of the impairment loss. Ultimately, HRC booked a

[2] We received 122 complete responses. However, we instruct participants to complete the case in one-sitting of uninterrupted time. Consistent with prior literature, we exclude 22 participants who were inattentive and/or distracted (i.e., spent over 15 minutes on a single screen) and did not follow these instructions (Hammersley and Ricci 2021). As a result, our final sample includes responses from 100 auditors.

$13.2 million impairment loss related to the patent. Participants are asked to consider the audit evidence and provide a judgment pertaining to the adequacy of this impairment loss.

Case details indicate that their firm developed a proprietary software system called the E-Val system that assists with complex valuations. Participants are provided with a description of this system and how it was developed. In all conditions, auditors are informed that their firm guidance indicates that the E-Val system is considered an approved source of evidence and that the firm has invested significant resources developing and testing the system. Furthermore, the firm has partnered with a large international technology company with leading experts in developing prediction models to help develop the system.[3] Participants in the learning algorithm condition are informed that the E-Val system utilizes algorithms that can adapt and improve over time. The use of learning algorithms allows the E-Val system to discover new predictors and identify different predictor weights to improve the model. In contrast, auditors in the static algorithm condition read that the E-Val system utilizes algorithms that are fixed and stay constant when developing fair value estimates. See Appendix A which presents the experimental manipulation of algorithm adaptability.

Auditors learn that differences between the E-Val system's and HRC's estimate of the patent impairment loss indicate a potential material audit difference that would reduce earnings by $10.5 million. Case details indicate that the discrepancy is primarily attributed to differences in projected patent revenue growth rates which affect future cash flow generated from royalty payments. Specifically, the E-Val system expects slower economic growth over the next 10 years

[3] When describing the algorithm, we include statements in all conditions to equalize the quality and acceptability of the algorithm as to not manipulate the learning algorithm as simply a "better" algorithm relative to the static algorithm. For example, in both static and learning algorithm conditions we inform participants that their firm partnered with a large international technology company with leading experts to develop the algorithm. Additionally, participants learn that their firm gathered input from valuation specialists with expertise in determining fair value of assets and liabilities and that their firm has invested significant resources developing and testing the algorithm. In both conditions, participants are told explicitly that the algorithm is an approved source of audit evidence.

resulting in lower revenue growth rates than what HRC's management projected. Auditors receive HRC's discounted cash flow analysis along with a summary of differences between the E-Val system's key inputs into the discounted cash flow model and HRC's key inputs.

Auditors are also provided with additional evidence to assist them with assessing the reasonableness of projected revenue growth rates. Specifically, auditors are presented with natural gas price projections for the next ten years along with analyst comments. Auditors are informed that forecasted natural gas price is a major macroeconomic input that is a good indicator for projected patent-related sales revenues and the related estimated fair value of the patent. To manipulate measurement uncertainty, we provide auditors with a graph of natural gas price forecasts and corresponding analysts' quotes that exhibit either higher or lower uncertainty around future natural gas prices. Specifically, the forecast graph contains four price indices' projections of future natural gas prices. In the higher future uncertainty condition, the four price indices exhibit higher volatility and divergence in price projections. In the lower future uncertainty condition, the four price indices exhibit lower future volatility and price projections exhibit a more linear pattern.[4] See Appendix B which presents the experimental manipulation for measurement uncertainty.

After reading the case, auditors recommend a proposed adjustment to HRC's patent value and impairment loss. Larger (smaller) proposed adjustments indicate greater (lower) reliance on evidence provided by their firm's E-Val system (Commerford et al. 2022). Lastly, auditors complete a post-experimental questionnaire, which includes demographic information.

[4]Although the price indices exhibit different patterns between the two conditions, the *average* natural gas price projection each year is the same across conditions. For example, the average natural gas price for 2022 for both higher and lower uncertainty conditions is $2.84. Additionally, the average projected growth rate per year is equal across conditions (i.e., average price increase from year 2022 to 2023 is 1.4% for both conditions).

3.2 Results

3.2.1 Manipulation Checks

To evaluate whether we successfully manipulated measurement uncertainty, we ask auditors to assess, "how certain or uncertain are future natural gas prices" (1 = "Very Certain" to 7 = "Very Uncertain"). Auditors in the higher uncertainty conditions (mean = 5.71) assessed future natural gas prices as more uncertain than participants in the less uncertain condition (mean = 3.38; $t_{98} = 9.50$, $p < 0.01$, untabulated), indicating that our manipulation of uncertainty was effective.[5] To assess whether we successfully manipulated the algorithm adaptability, we asked participants to rate "which description best describes your company's E-Val system" (1 – "static algorithms and prediction methods that are fixed and do not adapt over time" and 7 – "learning algorithms and prediction methods that adapt and improve over time"). Participant responses in the learning algorithm condition (mean = 5.79) were higher than those in the static algorithm condition (mean = 2.58; $t_{98} = 8.94$, $p < 0.01$, untabulated).

3.2.2 Test of Hypothesis

To test our hypothesis, we estimate a 2 × 2 ANCOVA with adaptability of the algorithm and degree of uncertainty as independent variables and proposed adjustments as the dependent variable. We also include how closely participants followed natural gas prices as a covariate in the model.[6] Table 2, Panel A provides descriptive statistics by experimental condition, Figure 1 graphs these cell means, and Table 2, Panel B reports the results of the ANCOVA model.

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[5] Consistent with our directional prediction, all reported *p*-values are one-tailed equivalents, unless otherwise noted.
[6] Data collection occurred throughout 2021. However, in the summer of 2021, global natural gas prices began to rise rapidly, which was widely reported in news outlets. Thus, there was a significant change in relevant macroeconomic conditions that occurred during our data collection, which could add variation and noise to our results. Controlling for the degree to which individuals followed natural gas prices allows us to control for a source of variation on our dependent measure and better examine our hypothesized effects (Piercey 2023). To control for this, we include a covariate in the model capturing how closely participants follow natural gas prices. Specifically, we ask participants how closely they have tracked natural gas prices in the past 12 months on a scale from 1 = "Not Closely at All" to 7 = "Extremely Closely."

[Insert Figure 1 and Table 2]

Our hypothesis predicts that accounting practitioners are more likely to exhibit a preference for advice from learning algorithms relative to advice from static algorithms when measurement uncertainty is higher versus lower. Consistent with our hypothesis, we find a significant interaction between algorithm adaptability and measurement uncertainty ($F_{1,95} = 2.96$; $p = 0.04$). We perform follow-up simple effects (Table 2, Panel C) to further test the nature of the interaction. Results show that, when measurement uncertainty is higher, participants proposed larger audit adjustments when audit evidence comes from a system using learning algorithms relative to system that uses static algorithms (6.59 versus 4.97 million; $t_{1,95} = 1.56$, $p = 0.06$). However, when measurement uncertainty is lower, the effect of algorithm adaptability is nonsignificant (5.74 million versus 6.73 million; $t_{1,95} = 0.91$, $p = 0.37$, two-tailed). These results are consistent with the notion that higher uncertainty, auditors exhibit a preference for evidence from learning algorithms over evidence from static algorithms. In contrast, we find no evidence that algorithm adaptability affects auditors' reliance in low measurement uncertainty environments.

Interestingly, we also observe that when measurement uncertainty increases, auditors rely less on the evidence from static algorithms and propose smaller audit adjustments (6.73 million versus 4.97 million; $t_{1,95} = 1.68$, $p = 0.10$, two-tailed). This is consistent with prior research indicating that aversion to algorithmic advice increases as uncertainty increases (Dietvorst and Bharti 2020). However, increased measurement uncertainty does not lead to smaller adjustments in the learning algorithm condition (5.74 million versus 6.59 million; $t_{1,95} = 0.78$, $p = 0.44$, two-tailed). Our results suggest auditors believe that as measurement uncertainty increases, static algorithms become less acceptable source of advice, while learning algorithms are viewed as suitable for both degrees of uncertainty. Collectively, these results provide strong support for our hypothesis.

4. Experiment Two: General Accounting Setting

The purpose of our second experiment is to test the generalizability of our findings and to use a more direct measure of reliance on algorithmic advice. In Experiment 1, we examine our theory in an audit context and we infer reliance on algorithmic advice through participants' proposed adjustments. In Experiment 2, we examine whether we can replicate our findings in a more general accounting setting where individuals are developing and reporting their own accounting estimate rather than deciding how to weight contradictory information from two competing sources, as is often the case in audit contexts (Commerford et al. 2022).

One of the key findings in advice-taking literature is that individuals tend to discount advice, especially if they are psychologically tied to their estimate (Yaniv and Kleinberger 2000; Yaniv 2004; Bonaccio and Dalal 2006; Baer and Brown 2012). Notably, Experiment 1 participants are not explicitly asked to develop their own estimate prior to receiving advice, which could possibly have increased their willingness to incorporate algorithmic advice. In contrast, we ask all Experiment 2 participants to make an estimate prior to receiving any algorithmic advice. Then, after receiving advice from an algorithm, participants are given an opportunity to revise their estimate. This allows us to observe a more direct measure of reliance on algorithmic advice compared to the dependent measure utilized in Experiment 1 (i.e., proposed adjustments).

4.1 Participants

We recruited participants through Prolific, an online crowdsourcing platform, and our final dataset contains 145 responses.[7] At a minimum, participants are required to have an undergraduate

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[7] Given that participants were compensated for their completion of the survey, our concern in regard to inattentiveness is that participants would complete the materials too quickly and not attend to the information presented. Thus, we

business degree. In exchange for completing this study, we paid each participant a fixed wage of $1.75. Participants had a reasonable understanding of accounting and finance as, on average, they completed four accounting and finance courses. Furthermore, all participants have an undergraduate degree in the field of business or economics. See Table 3 for demographic information for the final sample. On average, participants are 29.43 years old, have some experience with making financial forecasts, and are comfortable relying on technology.

[Insert Table 3]

Prolific workers with general business experience are appropriate participants for our study because we are examining a psychological phenomenon that does not necessarily require extensive prior knowledge or expertise. Although the experimental task involves estimating the fair value of a patent, the task is simplified by asking participants to estimate sales forecasts related to the patent (i.e., a key input in a discounted cash flow model).[8,9] Thus, given that a basic familiarity with accounting and business was required, we believe the knowledge base of our participants matches the requirement of the task and the goals of this research (Libby, Bloomfield, and Nelson 2002).

develop a minimum 9-minute cutoff as a conservative estimate of how long participants should have taken if they were reading the case details. For silent reading of non-fiction, most adults fall in the range of 175-300 words per minute (wpm) (Andrews 2010; Brysbaert 2019). We use a conservative estimate of 300 wpm as the "fastest" rate at which individuals can read case information while attending to the case details. On average, there are 2,689 words in each condition, which should take the participant approximately 9 minutes to read (i.e., 2,689 words divided by 300 wpm). Participants who did not meet the 9 minutes minimum criteria were excluded, resulting in 35 participants being excluded. Retained participants spent a median of 14 minutes on the case, yielding an effective hourly wage of $7.48.

[8] Participants are provided a discounted cash flow Microsoft Excel spreadsheet to assist with the calculation of the patent fair value (see Appendix C, Panel A). The discount rate and useful life of the patent were already determined and prepopulated in the spreadsheet. Additionally, once participants entered their future cash flow predictions into the cells, the spreadsheet automatically discounted the cash flow to its present value and provided the participant with their fair value estimate of the patent based on their cash flow predictions (see Appendix C, Panel B).

[9] We are primarily interested in participants' willingness to rely on algorithmic advice under different conditions. To the extent that participants are not familiar with this task, this should only serve to shift participants' advice reliance upward in all conditions (Logg, Minson, and Moore 2019).

4.2 Experimental Design

In Experiment 2, participants are instructed to assume the role of a manager at Heartland Resource Corporation (HRC). Case details inform participants that HRC's CFO tasked them with helping estimate the fair value of the patent as part of testing that intangible asset for impairment. Specifically, manager participants are asked to project patent-related sales revenue, a key input for estimating the fair value of a patent using a discounted cash flow model. Next, participants are provided with additional information to assist with the projection of patent-related sales revenue. Consistent with Experiment 1, participants are presented with natural gas price projections for the next ten years along with analyst comments, which contain our measurement uncertainty manipulation. Following this, participants are provided a discounted cash flow spreadsheet where they submit their projections of patent-related sales revenue cash flow for each year of the patent's useful life. See Appendix C, Panel A for the spreadsheet provided to all participants to assist with the discounted cash flow calculation. Participants enter in their projected future cash flows by typing their estimates into the empty yellow boxes in the spreadsheet. The spreadsheet automatically calculates the fair value of the patent by discounting the participant's projected future cash flows. See Appendix C, Panel B for an example of the spreadsheet's calculation of the patent fair value. At this point, participants submit their initial estimate of the patent value.

Next, all participants learn that their firm has developed a proprietary software system (i.e., the E-Val system) to assist with complex valuations. Similar to Experiment 1, the description of the algorithm contains our algorithm adaptability manipulation.[10] Following this, participants receive the E-Val system's estimate of the patent fair value. To ensure the system's estimate differs meaningfully from the participants' estimate in the same direction in all conditions, the system

[10] Similar to Experiment 1, all participants are informed that their company considers the E-Val system to be an approved source of information and its models are reviewed by the company.

estimate provided to participants is always 20% less than the participant's initial fair value estimate.[11] After reviewing the advice, participants submit their final estimate (i.e., adjusted estimate) of the patent value and complete a post-experiment questionnaire.

Our primary dependent variable is advice utilization, which is calculated as weight of advice (WOA) (e.g., Önkal et al. 2009; Kadous, Leiby, and Peecher 2013). Expressed mathematically:

$$WOA = \frac{\textit{(Initial estimate – Final estimate)}}{\textit{(Initial estimate – E-Val system's estimate)}}$$

WOA captures the extent to which an individual incorporates the E-Val system's estimate into their final estimate. WOA values can range from 0 to 1.[12] If participants' final estimate is equal to their initial estimate, then WOA would equal 0 and represents no weighting and a complete discounting of the E-Val system's advice. In contrast, if there is a complete shift of the initial estimate to the E-Val system's estimate, WOA would equal 1, which represents full weighting of the E-Val system's advice. Partial reliance on the E-Val system's estimate results in intermediate values ranging between 0 and 1. For example, a WOA of 0.50 reflects situations where participants average the E-Val system's estimate with their initial estimate.

[11] Prior advice-taking literature has found that weight placed on advice decreases as the distance between the advice and initial opinion increases (Yaniv 2004). Additionally, research has found that individuals are more willing to take advice when that advice puts individuals in a more favorable position or supports their initial advice (Schmidt 2001; Wheeler and Arunachalam 2008). To control for these effects, we keep the relative distance equal in all conditions, by setting the E-Val system's estimate as 20% less than the participant's initial fair value estimate.

[12] Following previous research, we truncate the WOA value to 1 if the participant "overshoots" the advice (i.e., participants' final estimate is less than the E-Val system's estimate) (Gino and Moore 2007; Gino, Shang, and Croson 2008).

4.3 Results

4.3.1 Manipulation Checks

To evaluate whether we successfully manipulated measurement uncertainty and algorithm adaptability, we ask participants the same questions used in Experiment 1. Participants in the higher uncertainty conditions (mean = 5.83) assessed future natural gas prices as more uncertain than participants in the less uncertain condition (mean = 3.11; $t_{143} = 12.00$, $p < 0.01$, untabulated). We also asked participants to characterize the E-Val system's use of algorithms and adaptability on a seven-point scale (1= "static algorithms and prediction methods that are fixed and do not adapt over time" and 7 = "learning algorithms and prediction methods that adapt and improve over time"). Participant responses are higher in the learning algorithm condition (mean = 6.01) than in the static algorithm condition (mean = 2.16; $t_{143} = 15.25$, $p < 0.01$, untabulated). Results indicate our manipulations of measurement uncertainty and algorithm adaptability were effective.

To further examine whether the adaptive capability of the algorithm manipulation was successful, we ask the participants to assess the degree to which they agree or disagree with the following statement, "The E-Val system responds the same way under the same conditions over time" (1 = "Strongly Disagree" to 7 = "Strongly Agree"). Because learning algorithms have the capability to adapt overtime while static algorithms are fixed and stay constant, we expect individuals in the static algorithm condition to report higher values (i.e., strongly agree) compared to individuals in the learning algorithm condition. We find further evidence of a successful manipulation of algorithm adaptability as participants in the static algorithm condition (mean = 5.42) were more likely to agree that the E-Val system responds the same way over time than participants in the learning algorithm condition (mean = 3.66; $t_{143} = 5.06$, $p < 0.01$, untabulated).

4.3.2 Test of Hypothesis

To test our hypothesis, we estimate a 2 × 2 ANOVA with algorithm adaptability and degree of uncertainty as independent variables and WOA as the dependent variable. Table 4, Panel A provides descriptive statistics by experimental condition, Figure 2 graphs these cell means, and Table 4, Panel B reports the results of the ANOVA model.

[Insert Figure 2 and Table 4]

Consistent with our hypothesis, we find a significant interaction between algorithm adaptability and measurement uncertainty ($F_{1,141} = 3.33$; $p = 0.04$). We perform follow-up simple effects (Table 4, Panel C) and results show that the effect of algorithm adaptability is significant when measurement uncertainty is higher (0.75 versus 0.63 WOA; $t_{1,141} = 2.10$, $p = 0.02$), but not when measurement uncertainty is lower (0.62 versus 0.64 WOA; $t_{1,141} = 0.48$, $p = 0.64$, two-tailed).[13] Consistent with our expectations, and with our findings in Experiment 1, when measurement uncertainty is higher, participants rely on the advice of learning algorithms more heavily than the advice of static algorithms. Thus, participants seem to prefer advice from learning algorithms over static algorithms when there is greater uncertainty.

[13] Our interaction hypothesis predicts that there will be significantly greater reliance on learning algorithms relative to static algorithms when there is higher (versus lower) measurement uncertainty. Thus, our main interest is if and how the simple effect of algorithm adaptability (learnings versus static) varies based on the degree of measurement uncertainty present. Nevertheless, it is interesting that the simple effects relating to measurement uncertainty differ between Experiment 1 and Experiment 2. That is, in Experiment 1, measurement uncertainty reduces auditors' reliance on static algorithms. In contrast, in Experiment 2, measurement uncertainty increases participants reliance on learning algorithms. Importantly, there are contextual and methodological differences across these two experiments that might contribute to this finding. Experiment 1 is set in an audit context where auditors receive contradictory evidence from two different sources. Experiment 2 participants, however, develop their own estimate prior to receiving algorithmic advice. Thus, when creating their estimate, participants may have developed a sense of ownership in the estimate and be more reluctant to accept algorithmic advice, which is only overcome when the algorithm's capabilities are particularly well-matched to the task.

4.3.3 Additional Analysis: Moderated Mediation Analyses

In this section, we explore whether individuals' trust in the algorithm is the mechanism that influences the weight individuals place on algorithmic advice. Prior literature has found that individuals' trust in advisors is positively related to advice-taking (Bonaccio and Dalal 2006; Jungermann and Fischer 2005). Specifically, advice utilization is a decision based on an individual's willingness to trust in others (i.e., a judgment), which is a behavioral intention that reflects a willingness to rely on "the behavior of a person in order to achieve a desired but uncertain objective in a risky situation" (Giffin 1967, 105; Coleman 1990; Moorman, Zaltman, and Deshpande 1992; Mayer et al. 1995). As such, research suggests that for an individual (i.e., the trustor) to exhibit a need and willingness to trust an advisor, there must be some degree of uncertainty involved in the situation or task (Coleman 1990; Sniezek and Van Swol 2001). Although higher uncertainty may increase an individual's willingness to trust others, trust is also dependent on whether the individual perceives the advisor has the necessary capability and skillset to provide assistance (Barber 1983; Mayer et al. 1995; Sniezek and Van Swol 2001). Accordingly, we expect that trust formation is dependent on both the degree of uncertainty of a task as well as whether the advisor possess a skillset capable of handling uncertainty and that greater trust in the advisor has a positive effect on advice utilization.

If results are consistent with theory, we expect a significant positive indirect effect of measurement uncertainty on advice utilization through trust in the algorithm when evidence is provided by a learning algorithm. In contrast, we do not expect this indirect effect to be significant when evidence is provided by a static algorithm. That is, we do not expect accounting professionals to develop trust in an algorithm that is believed to be ill-equipped to handle heightened uncertainty. Collectively, we expect a positive model estimate for our moderated mediation index which quantifies the linear association between the indirect effect and moderator of that effect (Hayes 2022).

Following the procedures described by Hayes (2022), we conduct a moderated mediation analysis using the SPSS PROCESS macro (model 8) with participants' willingness to trust in the algorithm as the mediator.[14] To test for indirect effects, we run 10,000 bootstrapped confidence intervals with resamples of data with replacement. As shown in Figure 3, we find evidence supporting our expectations. First, we find that the index of moderated mediation is significant (95 percent of the bootstrapped estimates are greater than 0.002), which indicates that the indirect effects estimated at the two levels of algorithm adaptability are significantly different from each other. Furthermore, we find that *Trust in Algorithm* mediates the relationship between *Measurement Uncertainty* and *Weight of Advice* in the learning algorithm conditions, but not in the static algorithm conditions (see Figure 3). These results reveal that when auditors receive advice from a learning algorithm, higher future uncertainty causes individuals to exhibit a greater willingness to trust in the learning algorithm, and that greater willingness to trust increases the degree to which individuals incorporate algorithmic advice into their final estimate (i.e., 95 percent of the bootstrapped estimates are greater than 0.003). However, when the algorithm is static, higher future uncertainty does not significantly increase an individual's willingness to trust the algorithm (i.e., the confidence interval includes zero; -0.048 to 0.014). This is consistent with our expectation

[14] We utilize a three-item scale to capture individuals' willingness to trust in the algorithm. Specifically, we ask participants to assess the following three statements: "The E-Val system is trustworthy", "When I am uncertain about a decision, I believe the E-Val system rather than myself", and "I believe advice from the E-Val system even when I don't know for certain that it is correct" on a 7-point scale with endpoints Strongly Disagree (1) to Strongly Agree (7) (Madsen and Gregor 2000). The first item directly assesses participants' perception of the E-Val system's trustworthiness. The second and third items are derived from the human-computer trust scale that Madsen and Gregor (2000) develop to measure faith, which is trust in a system's capability to "perform even in situations where it is untried". We selected these two items they are particularly applicable to a setting in which a system is predicting future outcomes and events, as is the case in our experimental context. The Cronbach's alpha for these three items is 0.69, indicating they reliably measure a single underlying construct (Kline 2016; Field 2018). Therefore, we use the average of the three measures, which we label as *Trust in Algorithm*, as the mediator in our analyses.

that algorithm adaptability is an important factor in the development of one's willingness to rely on algorithmic advice, particularly in highly uncertain environments.

[Insert Figure 3]

5. Conclusion

We provide experimental evidence on how measurement uncertainty and algorithm adaptability affect the weight accounting practitioners place on advice from algorithms. In multiple accounting contexts, we predict and find that when individuals encounter higher measurement uncertainty, they more heavily weight advice from learning algorithms compared to advice from static algorithms. We demonstrate this effect in both an audit context and in a financial reporting context. Furthermore, we also find that individuals' willingness to trust an algorithm mediates the joint effect of measurement uncertainty and algorithm adaptability on advice utilization. Our findings should be informative to companies, including public accounting firms, as they continue to implement emerging technologies in their organizations.

Our study makes several important contributions. First, our study provides insights on relevant factors affecting accounting professionals' reliance on emerging technologies. Although learning algorithms are inherently more capable than static algorithms, practitioners have voiced concerns regarding an inability to trust learning algorithms due to a lack of understanding regarding how these algorithms develop recommendations (i.e., decision making processes), which is commonly referred to as the "black box" concern (CPA Canada and AICPA 2019). Given that documentation and justification for accounting choices are important features of the accounting profession (Koonce et al. 1995; Kadous et al. 2013; Deloitte 2015), accounting professionals might be hesitant to rely on learning algorithms, as they can be more difficult to understand and explain to others. This could lead to a preference for advice from static algorithms, which are arguably less sophisticated than learning algorithms. However, contrary to these practitioner concerns, our results show that in contexts with higher measurement uncertainty, accounting professionals are more willing to rely on advice from learning algorithms compared to static algorithms. Based on our findings, it is somewhat encouraging that accounting professionals demonstrate a willingness to rely on advanced algorithms in contexts where the algorithm is most likely to improve their judgments – when measurement uncertainty is relatively high.

Second, we contribute to the growing literature around measurement uncertainty within complex accounting estimates. High measurement uncertainty continues to be a challenge for accounting professionals (Cannon and Bedard 2017; PCAOB 2017; Mard 2018; Griffith 2020; Pinello 2020). Consistent with research suggesting that increased uncertainty reduces the likelihood that auditors constrain their clients' aggressive estimates (Nelson, Elliott, and Tarpley 2002; Cannon and Bedard 2017), we find that measurement uncertainty can cause auditors to propose smaller adjustments to clients' estimates. Importantly though, we find this relation only when firm-provided contradictory evidence comes from an algorithm that is unable to adapt. In contrast, auditors are relatively more willing to adjust client estimates in highly uncertain settings with evidence from learning algorithms. This demonstrates how the implementation of new audit tools with adaptive capabilities have the potential to improve the quality of auditor judgments, and thus, financial reporting quality.

Lastly, we contribute to the broader literature examining human interactions with algorithms. In general, this literature finds that individuals are averse to relying on algorithms across in a variety of decision domains (Dietvorst et al. 2015; Dietvorst et al. 2016; Casteloet al. 2019). Recent findings suggest that uncertainty can amplify this aversion to algorithmic advice (Dietvorst and Bharti 2020). Consistent with this, we find evidence that measurement uncertainty can reduce auditors' reliance on advice from static algorithms. However, we also find that highlighting an algorithm's ability to adapt mitigates this effect. Thus, the relation between uncertainty and algorithmic reliance appears to be more nuanced than previously suggested by prior findings. Overall, we demonstrate that reliance on algorithmic advice is contextually dependent, influenced by an algorithm's features and capabilities, as well as the context in which the algorithm is being used. This finding is also informative to organizations as they continue to design and implement AI-based systems to assist individuals with judgment-based tasks. Our findings suggest that organizations can promote reliance on their technological investments by highlighting features and characteristics of the systems that are important to the individual task.

APPENDIX A
Experimental Manipulation for Algorithm Adaptability

Panel A: Description of Learning Algorithm

<u>Audit Support from Clark & Miller's E-Val System</u>

This year, your team on the Heartland audit utilized the firm's E-Val system to test the client's Deep Imaging patent and its related Impairment Loss.

Clark & Miller (your audit firm) has developed a proprietary software system, the E-Val system, that audit teams can use to help with testing asset and liability valuations, similar to receiving assistance from a firm valuation specialist. To develop the E-Val system, your firm partnered with a large international technology company with leading experts in developing prediction models. Additionally, the firm gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. The firm has invested significant resources developing and testing the E-Val system.

The E-Val system utilizes ***learning algorithms*** (i.e., machine learning technology) that can detect patterns in the data and provide audit evidence. Learning algorithms are detailed mappings of if-then statements and rules, which are optimized using historical data and ***can continue to improve*** as new data is encountered. The E-Val system uses these algorithms to develop fair value estimates for various assets and liabilities. Because the E-Val system utilizes learning algorithms, the system's prediction model ***adapts and improves over time***.

An example of a model used by the E-Val system to estimate a fair value estimate is provided below. Y is the fair value estimate and X's are pieces of information (i.e., predictors) that the model is trained on, such as sizes and trends of the markets in which relevant products are sold, market volatility, and other relevant financial data. The β is the weight that is applied to the predictors used to estimate the fair value (Y). Because the E-Val system uses ***learning algorithms***, it can ***discover*** new predictors (X_n) and ***identify*** different predictor weights (β_n) to ***improve*** the model.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}$$

New predictors can be identified by the E-Val system

All changes and updates to the model are reviewed and approved by the firm. Your firm has indicated that the overall predictions from the E-Val system are reasonably accurate and reliable and that the E-Val system is ***considered an approved source of audit evidence***. However, while the system aims to make well-calibrated predictions, it will not be perfect because complex estimates are inherently uncertain and difficult to precisely estimate.

Audit tools, such as the E-Val system, are not a substitute for an auditor's own judgment and professional skepticism. Firm guidance indicates that engagement teams can use evidence from the E-Val system to help develop conclusions about account balances. However, auditing standards still require audit teams to use their own professional judgment when evaluating audit evidence provided by the E-Val system.

Panel B: Description of Static Algorithm

<u>**Audit Support from Clark & Miller's E-Val System**</u>

This year, your team on the Heartland audit utilized the firm's E-Val system to test the client's Deep Imaging patent and its related Impairment Loss.

Clark & Miller (your audit firm) has developed a proprietary software system, the E-Val system, that audit teams can use to help with testing asset and liability valuations, similar to receiving assistance from a firm valuation specialist. To develop the E-Val system, your firm partnered with a large international technology company with leading experts in developing prediction models. Additionally, the firm gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. The firm has invested significant resources developing and testing the E-Val system.

The E-Val system utilizes ***static algorithms*** to detect patterns in the data and provide audit evidence. Static algorithms are detailed mappings of if-then statements and rules, which are optimized using historical data. The E-Val system uses these algorithms to develop fair value estimates for various assets and liabilities. Because the E-Val system utilizes static algorithms, the system's prediction model is ***fixed and does not adapt over time***.

An example of a model used by the E-Val system to estimate a fair value estimate is provided below. Y is the fair value estimate and X's are pieces of information (i.e., predictors) that the model is trained on, such as sizes and trends of the markets in which relevant products are sold, market volatility, and other relevant financial data. The β is the weight that is applied to the predictors used to estimate the fair value (Y). Because the E-Val system uses ***static algorithms***, the model's predictors (X) and predictor weights (β) are ***fixed and stay constant***.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

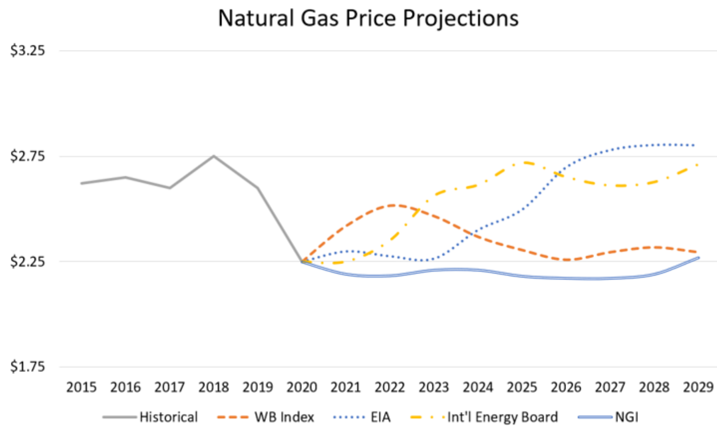
All changes and updates to the model are reviewed and approved by the firm. Your firm has indicated that the overall predictions from the E-Val system are reasonably accurate and reliable and that the E-Val system is ***considered an approved source of audit evidence***. However, while the system aims to make well-calibrated predictions, it will not be perfect because complex estimates are inherently uncertain and difficult to precisely estimate.

Audit tools, such as the E-Val system, are not a substitute for an auditor's own judgment and professional skepticism. Firm guidance indicates that engagement teams can use evidence from the E-Val system to help develop conclusions about account balances. However, auditing standards still require audit teams to use their own professional judgment evaluating audit evidence provided by the E-Val system.

Note: The purpose of Appendix A is to illustrate the information provided to participants in the learning and static algorithm conditions.

APPENDIX B
Experimental Manipulation for Measurement Uncertainty

Panel A: Higher Measurement Uncertainty

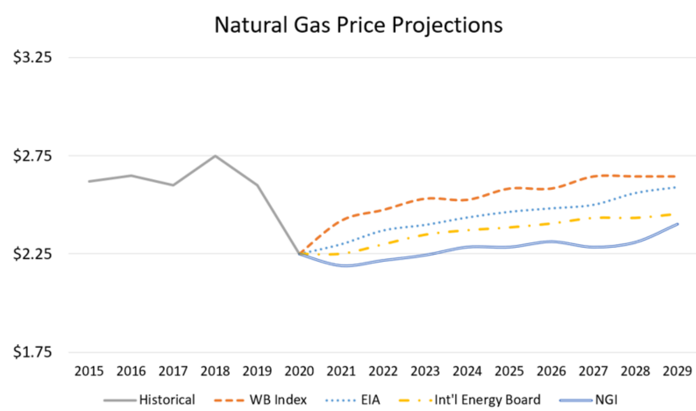


Analyst Quotes

"On average, natural gas prices are expected to increase, but the four national price indices are quite divergent in their projections, making it ***very difficult*** to forecast natural gas prices." [Analyst A]

"There is a lot of uncertainty right now about future natural gas prices. Nobody seems to agree about future natural gas prices." [Analyst B]

Panel B: Lower Measurement Uncertainty



Analyst Quotes

"On average, natural gas prices are expected to increase, and the four national price indices are quite consistent in their projections, making it ***less difficult*** to forecast natural gas prices."
[Analyst A]

"There isn't much uncertainty right now about future natural gas prices. Everybody seems to agree about future natural gas prices." [Analyst B]

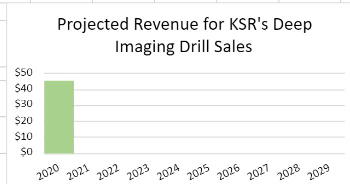
Note: The purpose of Appendix B is to illustrate the information participants were provided in the higher and lower measurement uncertainty conditions.

APPENDIX C
Discounted Cash Flow Spreadsheet

Panel A: Discounted Cash Flow Spreadsheet Provided to All Participants

Royalty Discounted Cash Flow Analysis

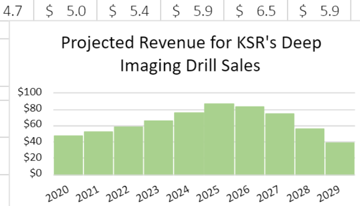
2019 Revenue	$ 45.0									
Discount rate:	5%		ALL NUMBERS ARE IN MILLIONS							
Royalty rate:	10%									
Year	1	2	3	4	5	6	7	8	9	10
Heartland Resource Corp.	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
Projected Revenue Growth Rate Percentage										
Projected Sales Revenue for KSR's Deep Imaging Drill	$ 45.0									
Projected Patent Royalty (10% of Sales Revenue)										
Present Value of Cash Flow from Royalty										
Sum of Present Value of Cash Flow from Royalty: Fair Value of the Patent	$ -									



Panel B: Example of Discounted Cash Flow Spreadsheet Filled Out

Royalty Discounted Cash Flow Analysis

2019 Revenue	$ 45.0									
Discount rate:	5%		ALL NUMBERS ARE IN MILLIONS							
Royalty rate:	10%									
Year	1	2	3	4	5	6	7	8	9	10
Heartland Resource Corp.	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029
Projected Revenue Growth Rate Percentage	5%	10%	12%	13%	15%	15%	-5%	-10%	-25%	-30%
Projected Sales Revenue for KSR's Deep Imaging Drill	$ 47.3	$ 52.0	$ 58.2	$ 65.8	$ 75.6	$ 87.0	$ 82.6	$ 74.4	$ 55.8	$ 39.0
Projected Patent Royalty (10% of Sales Revenue)	$ 4.7	$ 5.2	$ 5.8	$ 6.6	$ 7.6	$ 8.7	$ 8.3	$ 7.4	$ 5.6	$ 3.9
Present Value of Cash Flow from Royalty	$ 4.5	$ 4.7	$ 5.0	$ 5.4	$ 5.9	$ 6.5	$ 5.9	$ 5.0	$ 3.6	$ 2.4
Sum of Present Value of Cash Flow from Royalty: Fair Value of the Patent	$49.0									



Note: The purpose of Appendix C is to illustrate the discounted cash flow spreadsheet that participants filled out to estimate the fair value of the patent. Participants were first provided a spreadsheet where they were instructed to fill in the empty yellow boxes with their projected patent-related sales revenue growth rate each year. When participants finish submitting their projections, the spreadsheet provides the fair value of the patent in the blue box, which is based on their input.

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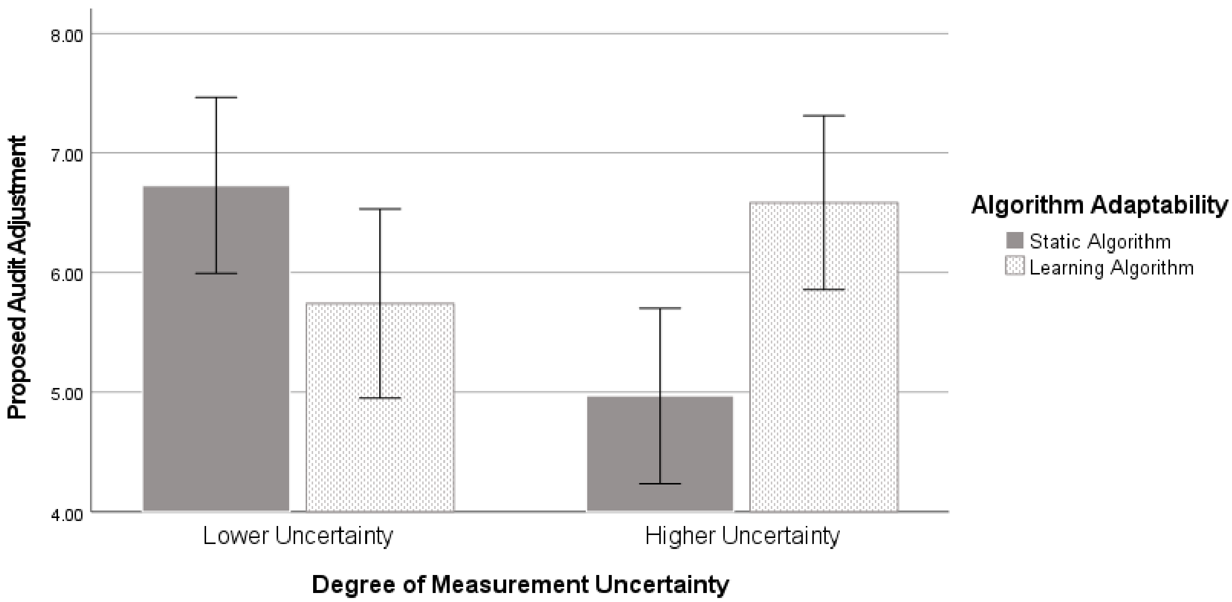
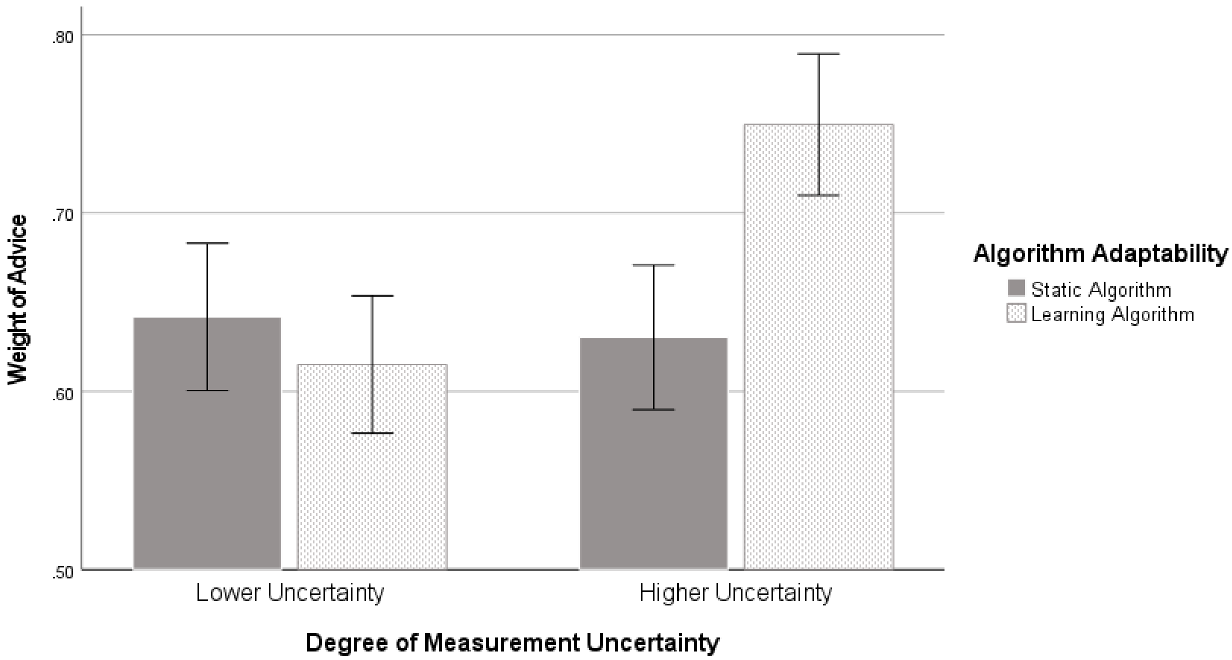
FIGURE 1
Observed Effects of Measurement Uncertainty and Algorithm Adaptability on Participants' Proposed Audit Adjustment



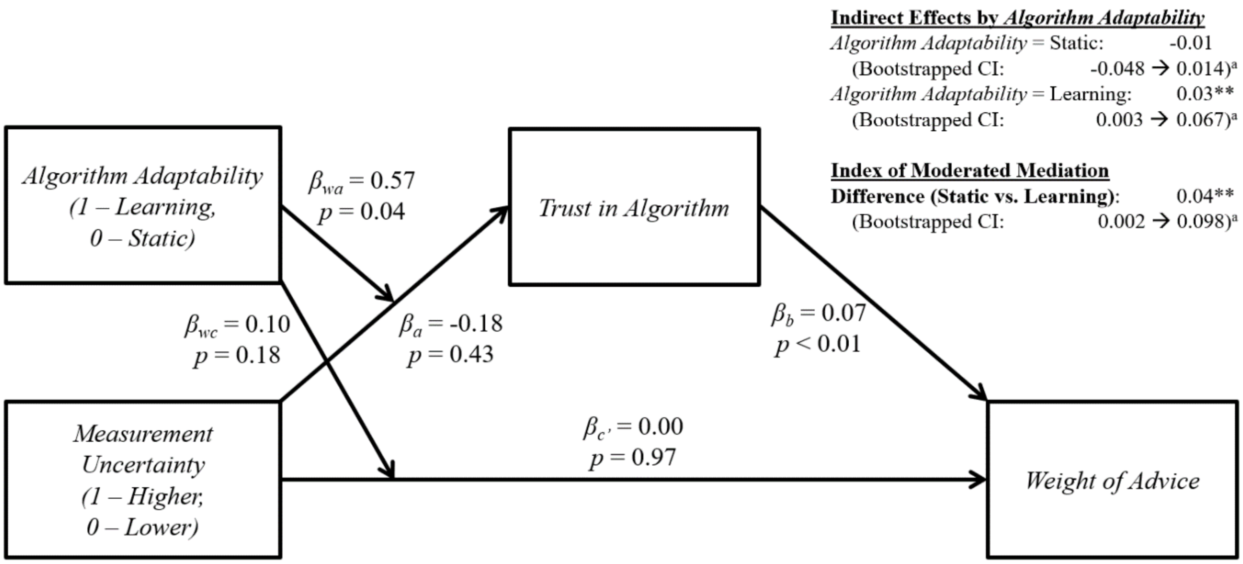
Note: Figure 1 graphs the means for the main dependent variable, proposed audit adjustment, by experimental condition, as reported in Table 2, Panel A. See notes to Table 2 for descriptions of dependent variable and independent factors. Error bars are displayed and indicate one standard error from the mean.

FIGURE 2
Observed Effects of Measurement Uncertainty and Algorithm Adaptability on Participants' Weight of Advice



Note: Figure 2 graphs the means for the main dependent variable, WOA, by experimental condition, as reported in Table 4, Panel A. See notes to Table 4 for descriptions of dependent variable and independent factors. Error bars are displayed and indicate one standard error from the mean.

FIGURE 3
Moderated Mediation Analysis



Note: The above diagram represents a moderated mediation model (Hayes 2022). We use a Model 8 with one mediator. Specifically, this model depicts the effect of measurement uncertainty and algorithm adaptability on weight placed on algorithm's advice (i.e., Weight of Advice) and that interactive effect is expected to operate through willingness to trust in the algorithm. *Measurement Uncertainty* equals 1 (0) for higher (lower) measurement uncertainty condition. *Algorithm* equals 1 (0) for learning (static) algorithm condition. To capture participants' willingness to trust in the algorithm, we asked participants to assess the following three statements, "When I am uncertain about a decision, I believe the E-Val system rather than myself", "I believe advice from the E-Val system even when I don't know for certain that it is correct", and "The E-Val system is trustworthy" on a 7-point scale with endpoints *Strongly Disagree* (1) to *Strongly Agree* (7). We take the average of these three items to measure an individual's willingness to trust in an algorithm. All continuous variables are mean-centered to facilitate interpretation of the coefficients.

[a] We use 10,000 bootstrapped resamples of data with replacement to estimate the path coefficients and to test the significance of the indirect effects. Given the directional expectation for the indirect effect though *Trust in Algorithm*, we use a one-tailed bootstrapping test, consistent with prior research (Mackinnon 2009; Hayes 2022; Saiewitz and Piercey 2020; Pickerd and Piercey 2021). The overall path is considered statistically significant if at least 95% of the subsamples generate an overall path coefficient *above* zero, as suggested by our theory.

** denotes statistical significance equivalent to $p < 0.05$, one-tailed.

TABLE 1
Demographic Information for Audit Setting Participants

Final Sample (n=100)

Variable	N	Mean
Years in Public Accounting	100	7.49
Fair Value Experience	100	4.71
Input to Adjustments	100	5.71
Technology Comfort	100	5.03
Percent Time on Public Companies	100	51.05%

Note: Table 1 provides descriptive statistics on demographic information of participants in experiment one.

Variable Definitions:
Years in Public Accounting = number of years participant has worked in public accounting;
Fair Value Experience = participants assessed their level of experience with auditing fair value estimates on a 7-point scale with endpoints *No Experience at All* (1) to *Highly Experienced* (7);
Input to Adjustments = participants assessed their likelihood of providing input into decisions related to proposed audit adjustments on a 7-point scale with endpoints *Not at All Likely* (1) to *Highly Likely* (7);
Technology Comfort = participants assessed how comfortable they are relying on technology on a 7-point scale with endpoints *Not at All Comfortable* (1) to *Very Comfortable* (7); and
Percent Time on Public Companies = percent of participants' time spent working on public company audits.

TABLE 2
Proposed Audit Adjustments

Panel A: Descriptive statistics: Estimated Marginal Means (standard error) [n] Cell

	Degree of Measurement Uncertainty		
Algorithm Adaptability	*Lower Measurement Uncertainty*	*Higher Measurement Uncertainty*	Overall
Learning Algorithm	5.74 (0.79) [22] A	6.59 (0.73) [26] B	6.16 (0.54) [48]
Static Algorithm	6.73 (0.74) [26] C	4.97 (0.73) [26] D	5.85 (0.51) [52]
Overall	6.24 (0.54) [48]	5.78 (0.52) [52]	

Panel B: ANCOVA for Proposed Audit Adjustments

Source	Sum of Squares	*df*	*F*	*p*[a]
Algorithm Adaptability	2.46	1	0.18	0.67
Measurement Uncertainty	5.17	1	0.38	0.54
Algorithm Adaptability × Measurement Uncertainty	40.66	1	2.96	0.04†
Follow Gas Price	76.41	1	5.56	0.02
Error		95		

Panel C: Follow-Up Comparisons for Proposed Audit Adjustments

Source	*df*	*t*	*p*
Effect of Algorithm Adaptability given Higher Measurement Uncertainty (B vs D)	1,95	1.56	0.06†
Effect of Algorithm Adaptability given Lower Measurement Uncertainty (A vs C)	1,95	0.91	0.37
Effect of Measurement Uncertainty given Learning Algorithm (A vs B)	1,95	0.78	0.44
Effect of Measurement Uncertainty given Static Algorithm (C vs D)	1,95	1.68	0.10

Note: Table 2 reports the results of Experiment 1. All reported analyses include the covariate (i.e., *Follow Gas Price*). The estimated marginal means in Panel A, also known as adjusted least-squares means, are also adjusted for the effect of the covariate (i.e., *Follow Gas Price*).
Dependent variable:
Proposed Audit Adjustment = the amount of participants' proposed audit adjustments to the Patent Impairment Loss Estimate on a scale from $0 million (no adjustment) to $10.5 million (full adjustment of the difference between the firm's estimate and the client's estimate).
Independent variables and covariate:
Algorithm Adaptability = manipulated as static algorithm (i.e., not capable of adapting) or learning algorithm (i.e., capable adapting).
Measurement Uncertainty = manipulated as higher future uncertainty or lower future uncertainty.
Follow Gas Price = a covariate which measures how closely participants have tracked natural gas prices in the past 12 months on a scale from 1 = "Not Closely at All" to 7 = "Extremely Closely".
[a] We derive the one-tailed equivalent *p*-values in Panel B from the ANCOVA contrast *t*-statistics, which are equivalent to the square roots of the respective *F*-statistics (see, e.g., Kachelmeier and Williamson [2010]; Piercey [2011]; Saiewitz and Kida [2018]).
† *p*-values are equivalent to a one-tailed test, consistent with our directional predictions.

TABLE 3
Demographic Information for Non-Audit Setting Participants

Final Sample (n=145)

Variable	N	Mean
FinAcctCourses	145	9.46
Forecast Experience	145	3.43
Technology Comfort	145	5.55
Age	145	29.43

Note: Table 3 provides descriptive statistics on demographic information of participants.

Variable Definitions:
FinAcctCourses = number of finance and accounting courses participant has taken;
Forecast Experience = participants assessed their level of experience with making projections and forecasts on a 7-point scale with endpoints *No Experience At All* (1) to *Highly Experienced* (7); and
Technology Comfort = participants assessed how comfortable they are relying on technology on a 7-point scale with endpoints *Not At All Comfortable* (1) to *Very Comfortable* (7); and
Age = participant's age.

TABLE 4
Weight of Advice

Panel A: Descriptive statistics: Least squares mean (standard error) [n] Cell

	Degree of Measurement Uncertainty		
Algorithm Adaptability	*Lower Measurement Uncertainty*	*Higher Measurement Uncertainty*	Overall
Learning Algorithm	0.62 (0.04) [39] A	0.75 (0.04) [37] B	0.68 (0.03) [76]
Static Algorithm	0.64 (0.04) [34] C	0.63 (0.04) [35] D	0.64 (0.03) [69]
Overall	0.63 (0.03) [73]	0.69 (0.03) [72]	

Panel B: ANOVA for Weight of Advice

Source	Sum of Squares	*df*	*F*	p^a
Algorithm Adaptability	0.08	1	1.34	0.25
Measurement Uncertainty	0.14	1	2.38	0.13
Algorithm Adaptability × Measurement Uncertainty	0.19	1	3.33	0.04†
Error	8.16	141		

Panel C: Follow-Up Comparisons for Weight of Advice

Source	*df*	*t*	*p*
Effect of Algorithm Adaptability given Higher Measurement Uncertainty (B vs D)	1,141	2.10	0.02†
Effect of Algorithm Adaptability given Lower Measurement Uncertainty (A vs C)	1,141	0.48	0.64
Effect of Measurement Uncertainty given Learning Algorithm (A vs B)	1,141	2.44	0.02
Effect of Measurement Uncertainty given Static Algorithm (C vs D)	1,141	0.20	0.84

Note: Table 4 reports the results of Experiment 2.
Dependent variable:
Weight of Advice (WOA) = participants' advice utilization which is calculated as (initial estimate – final estimate)/(initial estimate – E-Val system's estimate) and ranges from 0 to 1 where larger values of WOA indicates greater weighting of advice provided by the algorithm (i.e., greater reliance on advice).
Independent variables:
Algorithm Adaptability = manipulated as static algorithm (i.e., not capable of adapting) or learning algorithm (i.e., capable adapting).
Measurement Uncertainty = manipulated as higher future uncertainty or lower future uncertainty.
[a] We derive the one-tailed equivalent *p*-values in Panel B from the ANOVA contrast *t*-statistics, which are equivalent to the square roots of the respective *F*-statistics (see, e.g., Kachelmeier and Williamson [2010]; Piercey [2011]; Saiewitz and Kida [2018]).
† *p*-values are equivalent to a one-tailed test, consistent with our directional predictions.