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RELIANCE ON ALGORITHMIC EVIDENCE: THE JOINT INFLUENCE OF MEASUREMENT UNCERTAINTY AND ALGORITHM ADAPTABILITY

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RELIANCE ON ALGORITHMIC EVIDENCE: THE JOINT INFLUENCE OF MEASUREMENT UNCERTAINTY AND ALGORITHM ADAPTABILITY

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics At the University of Kentucky

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ABSTRACT OF DISSERTATION

RELIANCE ON ALGORITHMIC EVIDENCE: THE JOINT INFLUENCE OF MEASUREMENT UNCERTAINTY AND ALGORITHM ADAPTABILITY

Artificial intelligence (AI) systems' capability is rapidly expanding to perform complex tasks once reserved only for humans. With machine learning algorithms, AI can learn and adapt as it encounters more data, which has enabled these systems to improve the quality of accounting estimates that traditionally have been more difficult for humans. Although AI systems' capability to adapt has potential benefits, these systems also have become increasingly complex, making it difficult for individuals to understand the processes or algorithms these systems use to produce advice. Practitioners worry that when algorithms behave like "black boxes" this opacity may lead to a lack of reliance on evidence provided by these systems. This study seeks to examine and understand whether the degree of measurement uncertainty within a complex estimate influences the weight individuals will place on advice provided by an algorithm and whether that relationship depends on the algorithm's capability of adapting. I experimentally demonstrate that higher levels of measurement uncertainty increase individuals' reliance on advice provided by an algorithm, but only if that advice is produced by an algorithm capable of adapting (versus an algorithm not capable of adapting). I also find that this joint effect of measurement uncertainty and algorithm adaptability on individual's advice utilization operates indirectly through individuals' willingness to trust the algorithm. This study provides important insights to firms that are planning to deploy AI systems that will assist accounting professionals with developing and evaluating complex estimates.

KEYWORDS: Algorithm, adaptability, uncertainty, accounting, advice taking, judgment and decision making

Jenny W. Ulla

April 21, 2021

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I would like to dedicate this dissertation to my amazing husband,

Tor Aleksander Ulla.

With you by my side, I can accomplish anything.

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CHAPTER 1

INTRODUCTION

Companies (e.g., audit firms, financial service firms) are investing significant resources in developing artificial intelligence (AI) systems capable of assisting accounting professionals with complex business and financial decision-making (Deloitte 2018c; KPMG 2018; Bloomberg Tax 2020; KPMG 2020a).[1] With recent advancements in AI's capability, such as the ability to learn and adapt overtime, firms are keen on implementing these systems in areas that have traditionally proven difficult for accountants (CPA Canada and AICPA 2020). For example, financial service companies have begun developing AI technology to provide managers with financial forecast estimates such as future cash flow (Deloitte 2019a). While companies continue to encourage accounting professionals to seek and utilize advice to improve the quality of developing and evaluating judgment-based tasks, such as complex estimates (Ranzilla, Chevalier, Herrmann, Glover, and Prawitt 2011; PCAOB 2016; Deloitte 2019d), literature suggests that accounting professionals may not be willing to rely on an AI system, and as a consequence may place less weight on advice provided by the system (Dietvorst, Simmons, and Massey 2015; Dietvorst 2016; Commerford, Dennis, Joe, Ulla 2021). Likewise, practitioners have expressed concerns that characteristics of these advanced technology, such as lack of interpretability and transparency, could lead to a loss of trust in these systems (EY 2018; KPMG 2018; CPA Canada and AICPA 2019, 13; KPMG 2019a). Consequently, accounting practitioners'

[1] Following the Brookings Institution (e.g., West and Allen 2018), I define AI as a network of algorithms that are capable of performing actions traditionally considered only possible by humans, such as creatively solving problems or completing complex tasks. The AI technology that I consider in this paper is "narrow" AI, which performs one specified, narrow task, as opposed to a general AI that is able to perform any task that a human can do (Bughin, Chui, and McCarthy 2017).

reluctance in utilizing advice provided by an AI system may lead to lower quality accounting estimates and companies may not capitalize on their investments in these advanced technologies. Given the increasing prevalence and magnitude of complex estimates in financial statements (Christensen, Glover, and Wood 2012; PCAOB 2014), it is important to understand factors affecting accounting professionals' willingness to utilize evidence produced by algorithms.

Accounting practitioners experience many challenges when developing and evaluating complex estimates due to the extreme measurement uncertainty and the inherent subjectivity in predicting future outcomes (Christensen et al. 2012; Bratten, Gaynor, McDaniel, Montague, and Sierra 2013; Glover, Taylor, and Wu 2017).[2] Individuals are averse to uncertainty, and to reduce uncertainty they tend to seek out 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 another person (Schrah, Dalal, and Sniezek 2006; Gino and Moore 2007). Importantly, uncertainty has been identified as a key antecedent for the development of an individual's need to seek out and utilize advice because if a situation is certain then there is no need to seek out advice (Van Swol and Sniezek 2005). These findings suggest that accounting practitioners might be relatively more willing to incorporate advice from an algorithm when facing higher degrees of measurement uncertainty.

[2] Measurement uncertainty is defined as the "ambiguity in the valuation of an item (e.g., financial instrument)" (Bratten et al. 2013, 10). For example, measurement uncertainty can arise from uncertainty surrounding the model inputs and the model selected to value a financial item.

Although individuals may be more willing to utilize advice when facing higher uncertainty regarding a decision, literature has found that another key component in advice utilization is whether individuals believe the advisor possesses the necessary skillset or competencies to assist with the task (Mayer, Davis, and Schoorman 1995; Van Swol and Sniezek 2005). Specifically, individuals tend to weight others' advice proportional to the expertise or level of knowledge attributed to that source such that greater emphasis is placed on recommendations provided by more capable sources (Birnbaum and Stegner 1979; Harvey and Fischer 1997; Pornpitakpan 2004). Furthermore, certain advisor characteristics, such as adaptability, may be more highly valued depending on the specific environmental characteristics of the task at hand. For example, firms note that they seek out leadership that will undertake an adaptive business strategy because firms view this approach is more sustainable in an uncertain and rapidly changing business environment (Reeves and Deimler 2011). In another example, firms have noted that in volatile times, as a means of "confronting uncertainty intelligently", they have leveraged their advanced technology to "adaptively navigate (during) evolving conditions" (Deloitte 2021). Collectively, these examples suggest that when facing environments that exhibit relatively high uncertainty, individuals may increasingly value algorithms that can adapt as a means of confronting uncertainty. This has important implications in an accounting setting where accountants will likely encounter technologies that vary in the degree to which they can adapt. For example, some systems utilize static algorithms that function on defined rules that are not capable of adapting, while other more capable systems utilize learning algorithms that can *adapt* to improve the prediction models (Schatsky, Muraskin, and

Gurumurthy 2015; Deloitte 2018a; EY 2018; Deloitte 2019a).[3] Although there are concerns regarding lack of transparency in these learning algorithms leading to lower reliance on their output, advice-taking literature suggests that accounting practitioners may weight algorithmic advice proportional to the algorithm's capability, where greater weight is placed on algorithms capable of adapting. Accordingly, I predict that as individuals face higher measurement uncertainty, they will place heavier weight on advice especially if the advice is provided by an algorithm that exhibits learning capabilities rather than if the algorithm does not exhibit learning capabilities.

To test my predictions, I conduct an experiment using a 2 × 2 between-subjects design, manipulating measurement uncertainty surrounding the inputs to generate an estimate (higher versus lower future uncertainty) and capability of an algorithm (more versus less capable). Participants are asked to help with intangible asset impairment testing by estimating the fair value of a patent related to natural gas drilling. Participants receive macroeconomic information to assist them with developing their estimate. To manipulate measurement uncertainty, I provide participants with a graph of natural gas price forecasts and analysts quotes that exhibit either higher or lower uncertainty in future natural gas prices. Next, participants provide their initial patent fair value estimate. Before providing their final estimate, participants receive an estimate developed by a proprietary software system called the E-Val system, which recommends a lower patent fair value than the participant's initial estimate. To manipulate algorithm capability, I inform participants that the E-Val system utilizes learning algorithms that can adapt and improve (i.e., more

[3] The statement that a learning algorithm is more capable than a static algorithm is based on the assumption that the technology has been properly developed and trained on a sufficient amount of dataset, which is consistent with how firms are currently developing these technologies (Deloitte 2018a).

capable algorithm) or static algorithms (i.e., less capable algorithm) that are fixed and do not adapt. My dependent variable measures the degree to which individuals incorporate the algorithm's recommended fair value into their final estimate.

Consistent with my theory-based expectations, I find that higher future uncertainty causes individuals to more heavily weight advice but only if the advice is provided by a learning algorithm rather than a static algorithm. Furthermore, results indicate that when facing lower future uncertainty, individuals do not differentially weight advice provided by a learning or static algorithm. Supplemental mediation analyses reveal that individuals' willingness to trust in an algorithm mediates the positive relation between future uncertainty and utilization of advice, but that this mediation indirect effect is conditional upon the capability of the algorithm. Specifically, I find that the indirect effect of measurement uncertainty on advice utilization through willingness to trust in an algorithm is significant when individuals receive advice from a learning algorithm but that the indirect effect is not significant when individuals receive advice from a static algorithm. This is consistent with literature, which identifies advisor's capability as a key factor in the development of an individual's willingness to trust in others. Collectively, these findings suggest that although higher uncertainty may increase the degree to which individuals incorporate advice into their final estimate, advice utilization also depends on the capability of the algorithm.

In a second study, I further validate my findings in Experiment 1 in a different financial setting. Specifically, in Experiment 2, I examine whether individuals will more heavily weight advice provided by an algorithm capable of adapting relative to an algorithm not capable of adapting when completing a task that contains high uncertainty regarding the task solution. Participants are tasked with forecasting a stock's future price. Similar to Experiment 1, participants provide their initial forecast and then are provided with the algorithm's estimate before finalizing their forecast. I use a 1 × 2 between-participants design, manipulating the adaptive capability of the algorithm that provides advice to the participant as an algorithm capable of adapting or not capable of adapting (i.e., learning versus static algorithm). Consistent with my Experiment 1 findings, Experiment 2's results reveal that when tasks that contain high uncertainty, individuals weigh advice provided by a learning algorithm relative to a static algorithm.

My study has both theoretical and practical contributions. First, my study contributes to the growing literature around complex accounting estimates. High degree of measurement uncertainty and subjectivity remains a challenge for accounting practitioners (Cannon and Bedard 2017; PCAOB 2017; Griffith 2020). For example, financial institution managers are experiencing difficulties with developing forward looking estimates such as current expected credit loss (CECL) estimates in part due to macroeconomic uncertainty (Mard 2018; Pinello 2020). Furthermore, recent literature suggests that under greater uncertainty, auditors are less able to negotiate a downward fair value estimate adjustment (Cannon and Bedard 2017). I contribute to this literature by providing direct evidence on how measurement uncertainty influences the degree to which accounting practitioners willingly incorporate advice into their accounting estimate. Specifically, my results reveal that overall, individuals are more willing to incorporate algorithmic evidence into their final estimate when facing higher uncertainty, which is of importance to practitioners given that they intend to deploy advanced technologies in these more challenging areas. I also demonstrate that reliance on algorithmic advice is contextually dependent and that algorithm adaptability is an important technological feature that influences advice utilization.

Secondly, I contribute to psychology literature regarding human and algorithm interaction. Studies have shown that individuals are averse to relying on algorithms across various factors and decision domains (Dietvorst et al. 2015; Dietvorst, Simmons, and Massey 2016; Burton, Stein, and Jensen 2020; 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. 2021). My study finds that algorithm adaptability is an important factor that can influence the weight individuals will place on algorithmic evidence under certain settings. Additionally, my study suggests that there may be benefits in highlighting an algorithm's advanced capability. Overall, this study helps identify the contexts in which accounting practitioners might be more willing to rely on algorithms.

Lastly, 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. This lack of transparency may reduce an individuals' willingness to trust output provided by learning algorithms. Contrary to these practitioner concerns, I find that under higher levels of uncertainty, accounting practitioners are quite willing to rely on a learning algorithm (relative to a static algorithm) despite the lack of ability to understand its decision processes. The results of my study should be of interest to businesses employing algorithm-based technology. Furthermore, my study's results suggests that potential advantages of combining human and algorithmic advisors' insights may not be realized if individuals are unwilling to incorporate algorithmic advice into their judgment and decisions.

The remainder of this dissertation is organized as follows. In Chapter 2, I provide background and discuss psychology theory relevant to the development of my hypothesis. In Chapter 3, I describe the research design and results for my two studies. Chapter 4 reports the results of additional analyses. In Chapter 5, I draw conclusions about the results of my dissertation and discuss the implications of the findings for accounting research.

CHAPTER 2

BACKGROUND AND HYPOTHESIS DEVELOPMENT

Artificial Intelligence: The Moving Target

The term "artificial intelligence' (AI) was first coined in 1955 and defined as machines that can simulate or imitate human intelligence (McCarthy, Minskey, Rochester, and Shannon 1955). A more current and generally accepted definition of artificial intelligence is the theory and development of machines (i.e., computer systems) able to complete tasks that normally require human intelligence (Deloitte 2014, 2; CPA Canada and AICPA 2019). However, human intelligence-required tasks that qualify systems to be labeled as "AI" continuously changes – a phenomenon termed the 'AI Effect' (Hofstadter 1980). For example, in the 1960s chatbots that simulate and process human conversation were once considered intelligent systems (Shum, He, and Li 2018). As technology's capability to conversate with humans became more widely adopted or diffused as a common part of daily life, the AI effect occurs and general population cease to view chatbots as AI (Deloitte 2014). In another example, technology capable of face recognition was once labeled as AI (Think Automation 2020). However, as this function became a widespread technological application, face recognition was no longer a defining capability that classified technology as artificially intelligent. Thus, the label of "AI" continuously evolves and is concisely stated as "AI is whatever hasn't been done yet" (Hofstadter 1980, 608).

A Brief History of Technology in Accounting Settings: Decision Aids and Expert Systems

Decision aids are tools that provide assistance to decision makers in "gathering, processing, or analyzing information for a decision" (Brown and Eining 1997, 164). Decision aids utilized in the accounting setting ranged from simple checklists and statistical models to more complex expert systems (Ashton 1990; Kachelmeier and Messier 1990; Eining, Jones, and Loebbecke 1997; Bonner 2008, 342). Decision aids were designed to improve accountants' judgment and decision-making quality by reducing the negative effect of certain task-specific characteristics, such as task complexity (Bonner 2008). For example, a management fraud decision aid checklist can improve auditors' performance of multi-cue judgments by focusing auditors on a set of information or cues which reduces task complexity by decreasing the volume of information the auditor (Bonner 2008). Given these benefits decision aids provide, firms began to invest in and develop more advanced decision aids, such as statistical models and expert systems, that were capable of assisting accountants with judgment-laden tasks such as predicting likelihood of going concern (Brown and Jones 1998; Davis 1996), forecasting earnings (Ghosh and Whitecotton 1987; Whitecotton 1996), or assessing likelihood of management fraud (Boatsman, Moeckel, and Pei 1997; Arnold and Sutton 1998).

Expert systems gained prominence in the 1980s and were designed to perform tasks in a narrow or specific decision domain and were once the latest advancement in the field of AI (Turban and Watkins 1986; Brown 1991; EY 2019). Designers held high hopes for expert systems to not only assist humans with complex tasks but also to potentially replace people or experts. Expert systems were developed to replicate an expert's knowledge base for a specific problem domain and to mimic a human expert's decision processes, reasoning, and behavior in a decision-making task (Enslow 1989).[4] Accounting firms used expert systems to assist with a range of task in their tax, audit, and consulting practices. For example, these systems were capable of assisting tax accountants in selecting accounting methods and structuring transactions to minimize federal and state income taxes (Brown 1991). Specific to audit, firms developed a variety of expert systems that could assist auditors with selecting testing procedures and determining sample sizes (Brown 1991; Eining et al. 1997), establishing materiality thresholds (O'Leary and Watkins 1989), and conducting fraud risk assessments (Lombardi 2012). Although expert systems were meant to replace human specialists and experts, these systems failed to reach expectations and were used in a more advisory role (Bonner 2008). Firms realized that unlike a human specialist, the expert system was unable to draw on past experiences to solve an unusual or new case and as a result, the expert system was only capable of solving "rudimentary problems" (EY 2019). Furthermore, decision aids and expert systems are both more akin to passive machines that are mechanical in nature and as such, are poor tools for handling uncertainty, an "ubiquitous fact of life' (Deloitte 2014; West 2018). Several factors contributed to expert system's limited success: mounting costs of maintaining these large systems, difficulty of capturing experts' tacit knowledge and reasoning capabilities, and lack of data availability (Turban and Watkins 1986; Deloitte 2014; Deloitte 2019c). Given these shortcomings, interest in expert systems declined and firms ceased funding the development of these systems (EY 2019).

[4] Another aspect of expert systems that differentiates it from prior decision aids is expert systems contain an explanation and justification capability that provides the user with some explanation of its reasoning (Turban and Watkins 1986).

Artificial Intelligence and Machine Learning

Letting the Machine "Think"

While expert systems, along with other similar decision aids in the past, attempted to model a human expert's thought patterns, current AI systems are developed to perform tasks that require human intelligence rather than to emulate how they think (Deloitte 2014). Alan Turing, the father of AI, stated, "If the man were to try and pretend to be the machine he would clearly make a very poor showing. May not machines carry out something which ought to be described as thinking but which is very different from what a man does" (Turing 1950, 4). Enabling an AI system to develop its own method of "thinking", learning, and reasoning has allowed technology to not only surpass prior technological limitations, but also outperform human experts. For example, the DeepMind for Google (DMG) team developed an AI system named AlphaGo (Stern, Graepel, and MacKay 2004). AlphaGo was designed to play Go, an abstract strategy board game that originated from China and dates back some 4,000 years ago (Holcomb, Porter, Ault, Mao, and Wang 2018). Experts doubted that an AI system could ever defeat a human in Go given the massive amount of possible moves (i.e., large degrees of freedom) players can make and the high uncertainty about the future course of the game (Stern et al. 2004).[5] Furthermore, given the large degrees of freedom in potential moves, Go is associated with imaginative and creative thinking, traits that are not commonly associated with an AI system (Bory 2019). In a stark contrast to prior AI systems that were generally modeled on how an expert or a human would perform a task, DMG's scientists and engineers instead focused their efforts towards developing an "un-humanlike" system that could learn the game with as little human

[5] For example, at the start of the game, each player has an estimated 360 options for placing each stone (Cho 2016). In total, the number of possible arrangements of stones is beyond googol (i.e., 10^{100}).

guidance and interference as possible using machine learning technology (Bory 2019). In 2016, AlphaGo defeated Lee Sedol, the leading Go professional player. AlphaGo demonstrated that AI systems could not only surpass human achievements in highly uncertain and subjective domains, but also exhibit creativity and a new way of thinking that is "un-humanlike".[6]

Currently, AI technology can perform tasks that require human intelligence by seeking patterns, learning and adapting from experience, and updating its output based on situational or environmental awareness (Citibank 2018). One of the methods a system can achieve artificial intelligence is through machine learning algorithms.[7] Similar to how humans learn through experiences, machine learning is an application of artificial intelligence that equips computer systems with the capability to learn and adapt as it interacts with its environment and encounters more data in order to achieve "intelligence" (Deloitte 2019c). Specifically, machine learning refers to a "set of algorithms that enables [a system] to recognize patterns from large datasets and then apply these findings to new data" (Citibank 2018, 20). See Figure 1 for a depiction of the relationship between AI, machine learning, and future machine learning applications such as deep learning.

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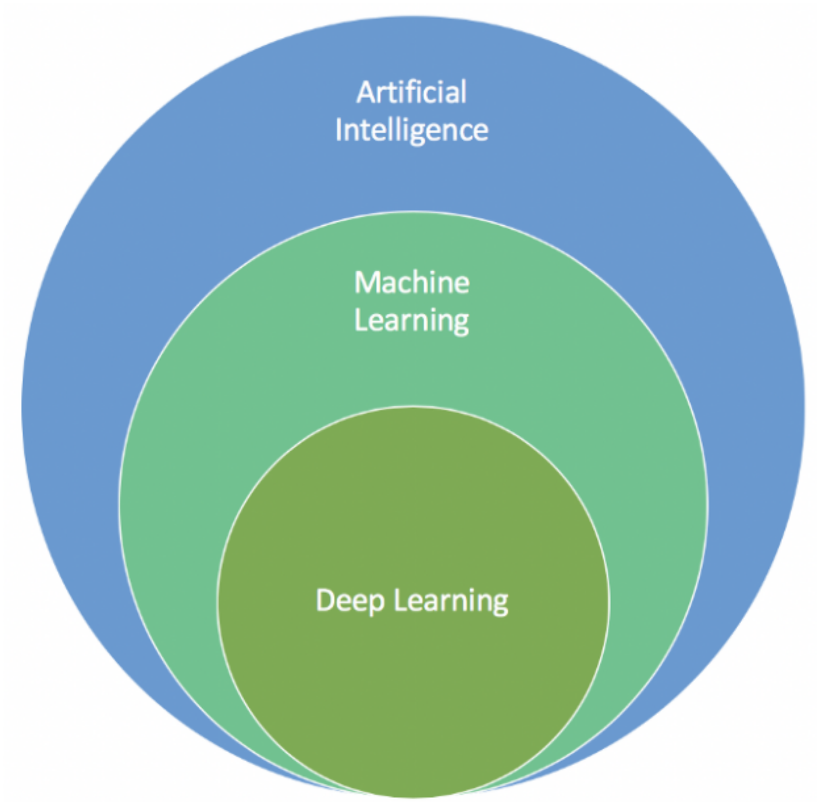
[6] The landmark event that defined the encounter between AlphaGo and Sedol occurred in Game 2 move 37. AlphaGo's move 37 was described as one that "normally humans would never play", "very beautiful" play, and a move never played by a strong player (Bory 2019, 636).

[7] Algorithms are a set of rules or problem-solving operations used to interpret the training data and create a model which will predict an output when given an input (i.e., live data) (EY 2018).

FIGURE 1
Relationship Between Artificial Intelligence, Machine Learning, and Deep Learning

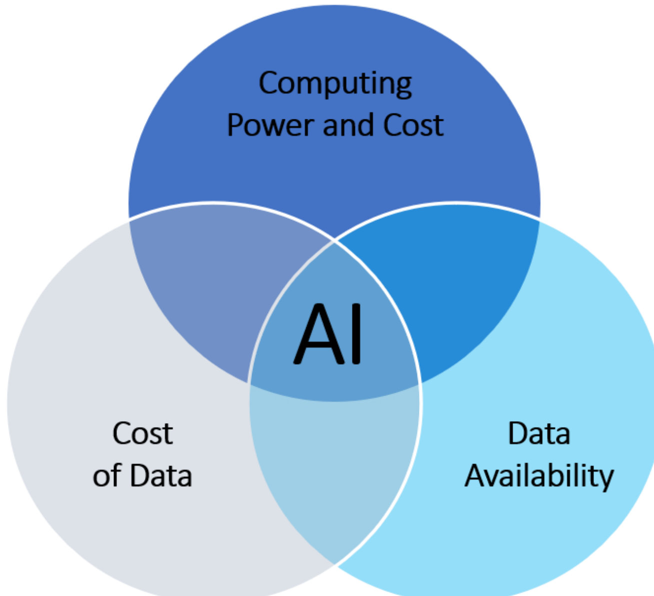


Note: The purpose of Figure 1 is to illustrate the relationship between artificial intelligence (AI), machine learning, and deep learning, which is the next generation of machine learning technology (Oppermann 2019).

Advancements in Artificial Intelligence and Machine Learning – Why Now?

Development of artificial intelligence and machine learning technology began in the 1950s (Alzubi, Nayyar, and Kuma 2018). Although machine learning is not new technology, several barriers prevented widespread adoption of machine learning enabled systems. The unprecedented availability of affordable advanced computing power, massive increase in data availability (i.e., big data), and a reduction in cost of storing and accumulating large amounts of data are three key recent developments that facilitated the recent industrialization of machine learning enabled systems referred to as AI (Citibank 2018; Deloitte 2018b). See Figure 2 for a depiction of the "raw materials" for AI. With these necessary "raw materials" now readily available, AI researchers have begun to capitalize on machine learning technology's practical applications (Jordan and Mitchell 2015).

FIGURE 2
Raw Materials of Artificial Intelligence



Note: The purpose of Figure 2 is to illustrate the three recent developments that have allowed AI to become a practical technology application available for widespread commercial use (Citibank 2018). Current AI systems have surpassed prior technological capabilities in part due to machine learning algorithms.

Machine Learning and Adaptability

Machine learning algorithms equips technology with new capabilities, such as the ability to adapt and learn from its mistakes (i.e., the capability to improve its performance over time) (Deloitte 2017a; CPA Canada and AICPA 2019). Using machine learning technology, algorithm-based models are trained on massive amounts of data and can improve as it continues to encounter more data. For example, a typical process for using machine learning algorithms to develop a credit card fraud detection model capable of identifying potentially fraudulent transactions begins with feeding the model with training data. In the training data, transactions are labeled as fraudulent or non-fraudulent. The model begins to recognize patterns and learns which features should be weighted more or less heavily when delineating between fraudulent and non-fraudulent transactions (Deloitte 2017b). As more data is fed into the model, the machine learning algorithms will update the model by adapting and refining these features' weights to improve its future predictions (Deloitte 2017b; Deloitte 2019c).

Machine learning algorithms have drastically improved technology's ability to recognize patterns and forecast or predict future events (Deloitte 2019b). In the past with expert systems, data scientists would create models by coding each rule by hand. However, machine learning algorithms can develop higher quality models that contain millions of parameters or rules without human intervention (Bleicher 2017). With advancements in storage systems along with improvement in processing speeds and analytic techniques, algorithms are now capable of conducting complex analyses and decision-making that could exceed beyond human capabilities (West 2018; Ding, Lev, Peng, Sun, and Varsarhelyi 2020).[8] For example, financial investment algorithms are able to manage large volumes of transactions in multiple markets, learn and adapt to real-time data, and execute market transactions that take advantage of information extracted from the data (Cao, Jiang, Yang, and Zhang 2020).[9] Some other examples of practical applications of machine

[8] For example, Kensho used machine learning algorithms to develop a google-style platform that allows investors to ask complex questions and provide answers by analyzing millions of market data points to find correlations and arbitrage opportunities (Gara 2018). For example, investors can ask Kensho "What stocks go up the most when a Category 3 hurricane hits Florida?" or "How do the big banks trade the day after the Federal Reserve's stress test results are released?" (CNBC 2015; Citibank 2018).

[9] The Man Group, a hedge fund group, manages 45 percent of its $96 billion in assets through quantitative trading using machine learning (CNBC 2017). The advantage of quantitative trading is that the algorithms do most of the work and develops newer technology where the computer systems do not need to be told what and when to trade – the systems identify patterns and arbitrage opportunities on their own and put their own buy and sell orders based on its own research (Man Institute 2021).

learning algorithms include investment recommendations, language translation, image recognition, and predictive analytics (Deloitte 2017b).

A defining feature that delineates machine learning technology from prior decision aid technology is that current AI systems have the capability to learn from prior experience (West and Allen 2018). While prior technology operated in a "mechanistic" manner, machine learning enabled technology can adapt as it encounters real-time external data just as humans can gain more knowledge through experience. Although the capability of adapting is highly beneficial when dealing with uncertainties and instability in the external world, it could erode a decision maker's trust in the model (KPMG 2019b). Specifically, it could cause concerns that as AI integrates changes in its models, the decision processes and rules that guide the model's decision making may become opaque or a "black box" (Bleicher 2017; CPA Canada and AICPA 2019). While adaptability is a new feature of technology that can provide comfort to firms deploying these systems in uncertain environments, this new capability may not always be viewed as beneficial.

Machine Learning Applications in Accounting Settings

Accounting firms have begun to implement AI technology that rely on algorithms to perform judgment-based tasks once reserved for humans, such as developing and evaluating complex estimates (i.e., an estimate that contains a predictive input or element) (KPMG 2016; Deloitte 2017a; West and Allen 2018; CPA Canada and AICPA 2019).[10] For example, financial service companies are developing AI technology capable of forecasting financial estimates, such as future cash flows (Deloitte 2019a). Similarly, audit

[10] In a survey of 250 senior executives, a third of respondents are developing systems to support better human judgement and decision making by using advanced technology to provide predictions based on analyzing structured and unstructured data (Deloitte 2017a).

firms are also investing substantial resources into developing AI systems to assist auditors with the evaluation of complex accounting estimates (e.g., commercial loan grades; KPMG 2016) (Shandwick 2016; Bughin et al. 2017; Commerford et al. 2021).

Organizations are rapidly integrating advanced technology into their business strategy as a tool for generating value (McKinsey Analytics 2020).[11] Specifically, firms are keen on integrating AI technology into their processes not only for potential operational efficiencies (i.e., cost savings), 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). For example, Ding et al. (2020) developed AI technology using machine learning algorithms that produced more accurate valuations of insurance companies' loss reserves (i.e., estimates of future claims expenditures) compared to managers' actual estimate of the reserves reported in the financial statements. Accordingly, AI technology can help improve accounting practitioners' judgment and decision making on some of the more challenging tasks, such as estimating and evaluating complex estimates (KPMG 2016; Murphy 2017; Deloitte 2019a; Commerford et al. 2021). However, practitioners have voiced concerns regarding whether these advanced technologies' lack of interpretability and transparency could potentially lead to a "lack of trust" in these systems (CPA Canada and AICPA 2019, 13). Given the increasing significance and magnitude of complex estimates in financial statements (Christensen et al. 2012; PCAOB 2014), it is important to understand factors affecting accounting professionals' willingness to rely on evidence produced by these AI-based systems.

[11] While firm value is a very broad term, recently firms cited that AI adoption has generated firm value in the form of increasing revenue while also at the same time decreasing expenses (McKinsey Analytics 2020). However, other forms of value that AI adoption could yield is streamlining processes and higher quality decision making.

Measurement Uncertainty and Complex Estimates

Many accounting estimates involve a forward-looking element (e.g., allowance for loan loss provision, projected benefits obligation) (Spiceland, Nelson, and Thomas 2018). For example, when determining the value to record for an intangible asset such as a patent, accountants can utilize a discounted cash flow method which involves predicting the future cash flow that the patent will likely generate. The inherent subjectivity in predicting future outcomes, along with the potential of extreme measurement uncertainty, makes estimating and evaluating complex accountings estimates (hereafter complex estimates) particularly problematic for accounting practitioners (Christensen et al. 2012; Bratten et al. 2013; Glover et al. 2017; Ding et al. 2020). Measurement uncertainty is defined as the "ambiguity in the valuation of an item" (Bratten et al. 2013, 10). Some of the difficulty related to measurement uncertainty can be attributed to market volatility, which further adds to the challenges of developing reasonable and accurate model inputs (e.g., future cash flows for a discounted cash flow model valuation) (Bratten et al. 2013). Consistent with the notion that accountants struggle with developing complex estimates, PCAOB inspection reports continue to identify audit deficiencies related to the evaluation of complex estimates (Church and Shefchik 2012; PCAOB 2017, 2020a, 2020b, 2020c, 2020d). Given the challenges with developing and evaluating complex estimates, accounting practitioners generally involve valuation specialists to provide advice and to assist with the assessment of these estimates (Martin, Rich, and Wilks 2006; Deloitte 2015; Griffith, Hammersley, Kadous, and Young 2015; Cannon and Bedard 2017; Griffith 2018). As technology continues to evolve and improve, firms are moving towards implementing AI specialist systems to develop and evaluate complex estimates (Commerford et al. 2021).

One of the key findings in advice-taking literature is that individuals tend to discount advice (Yaniv and Kleinberger 2000; Yaniv 2004; Bonaccio and Dalal 2006). According to the egocentric bias explanation, individuals view themselves as superior to others and consequently prefer their own opinions over opinions or recommendations received from advisors (Kruger 1999; Gino and Moore 2007). However, evidence suggests that while people view themselves as superior to others on less complex tasks, they tend to believe they are worse than others on difficult or more complex tasks (Kruger 1999). As a result, when individuals face tasks with greater difficulty or involving higher uncertainty (i.e., uncertainty about the solution to the task), they are more willing to trust in others and also utilize advice as a means to reduce that uncertainty (Sniezek and Van Swol 2001; Gino and Moore 2007). For example, in a study where participants were asked to estimate the weight of a person in a photo, participants more heavily relied on advice when examining a blurry photo (i.e., more uncertainty) than a clear photo (i.e., less uncertainty) (Gino and Moore 2007). Collectively, these studies suggest that when accountants are developing a complex estimate that exhibits higher measurement uncertainty, they may view themselves as less capable of developing the estimate and as a result, are more likely to utilize advice provided by others.

Although individuals may exhibit greater reliance on advice when completing tasks with higher uncertainty, the degree advice utilization also depends on whether individuals perceive the advisor of being capable of completing the task (Mayer et al. 1995; Van Swol and Sniezek 2005). Specifically, literature finds that individuals weight other sources' advice proportional to the expertise or level of knowledge attributed to that source, such that higher emphasis is placed on information provided by more capable and competent sources (Birnbaum and Stegner 1979; Harvey and Fischer 1997; Pornpitakpan 2004; Bonaccio and Dalal 2006). For example, in an experiment where participants were presented with selecting a hypothetical medical treatment, participants more heavily weighted advice from an advisor who was a trained counselor (i.e., higher expertise) compared to advice from a friend (i.e., lower expertise) (Jungermann and Fischer 2005). Advice-taking literature suggests that increasing the perceived capability of the advisor, such as an algorithm, could increase reliance on that algorithm's advice. These findings have implications when applied to an accounting setting because accounting practitioners will likely encounter technologies that vary in the degree to which they can adapt. For example, some systems utilize static algorithms that function on defined rules that do not adapt, while other more capable systems utilize algorithms that can *adapt* to improve performance (i.e., learning algorithms) (Schatsky et al. 2015; Deloitte 2018a; Deloitte 2019a). With the application of machine learning algorithms, systems are capable of learning and adapting without being given explicit instructions on how to perform a task (EY 2018; Deloitte 2019a). Overall, theory suggests that an algorithm characteristic, such as adaptability, may be an important factor that influences the degree to which individuals will rely on its output.

However, literature also finds that the value individuals place on certain advisor characteristics may depend on environmental factors. For example, Song et al. (2013) find that firms engaging in more complex mergers and acquisitions (M&A) deals are more likely to hire "boutique" banks as their advisors because these banks tend to specialize by industry and have expertise in M&A. However, in less complex M&A deals, firms are less likely to select a boutique advisor and instead will engage in a full-service bank, which tend to have less experience with M&A deals. This is consistent with the notion that certain advisor characteristics, such as capability of adapting, may be more highly valued depending on the specific environmental characteristics of the task.

When facing environments that exhibit relatively high uncertain, individuals may increasingly value algorithms capable of adapting as a means of confronting uncertainty. For example, businesses face growing instability since the 1980s due to globalization of business operations along with the introduction of new technologies that upend the business environment (Reeves and Deimler 2011). Firms note that they seek out leadership that will undertake dynamic and adaptive strategies because firms view this approach is more sustainable in an uncertain and volatile business environment. In other words, adaptability is viewed as a "competitive advantage" and is a highly valued characteristic (Reeves and Deimler 2011, 137). In another example specific to adaptive technology, as a response to the COVID-19 pandemic, organizations have reported increased investment in advanced technology to assist with decision-making during a time of great uncertainty (McKinsey Analytics 2020). These organizations note that AI's capability to adapt to current economic environment has allowed them to develop real-time solutions that they otherwise would not have had. Furthermore, firms have noted that in volatile times, as a means of "confronting uncertainty intelligently", they have leveraged their advanced technology to "adaptively navigate (during) evolving conditions" (Deloitte 2021). Collectively, this is consistent with the notion that individuals view algorithms that are capable of adapting as more equipped to handle uncertainty (Deloitte 2014; KPMG 2020c) and that individuals may value an adaptive algorithm more when facing higher uncertainty relative to lower uncertainty.

Consistent with the theory above, I expect that higher measurement uncertainty in a complex estimate will cause accounting practitioners to more heavily weight advice provided by an algorithm. However, individuals may be reluctant to utilize advice provided by an algorithm, especially a learning algorithm capable of adapting that lacks transparency. Despite this, advice-taking literature suggests that individuals will weigh other sources' advice proportional to how capable they perceive that source. As such, I propose that the relationship between measurement uncertainty and degree to which accounting practitioners utilize advice from an algorithm depends on whether the algorithm is capable of adapting. Specifically, I expect that higher measurement uncertainty will cause accounting practitioners to more heavily weight advice, especially if the advice is provided by a learning algorithm rather than a static algorithm. However, as the degree of measurement uncertainty decreases, individuals place less value on an algorithm's capability of adapting and as a result, an algorithm's adaptive capability will have less of an effect on the weight an individual places on the algorithm's advice. Accordingly, I propose the following interaction hypothesis:

> **Hypothesis:** As measurement uncertainty increases, individuals will more heavily weight algorithmic advice, especially if the advice is provided by an algorithm capable of adapting relative to an algorithm not capable of adapting.

CHAPTER 3

EXPERIMENT I – DESIGN, METHODS, AND RESULTS

Design and Participants – Experiment 1

I use a 2 × 2 between-participants design, manipulating the adaptive capability of the algorithm that provides advice to the participant as an algorithm capable of adapting (i.e., learning algorithm) or not capable of adapting (i.e., static algorithm).[12] I also manipulate the degree of measurement uncertainty related to a complex accounting estimate (i.e., higher versus lower). This design results in four between-participants conditions and I randomly assign participants to one of these four conditions. I recruited participants through Prolific, an online crowdsourcing platform, and my final dataset contains 145 responses.[13,14] At a minimum, participants were required to have an undergraduate business degree. In exchange for completing this study, I paid each participant a fixed wage of $1.75. My 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 1 for demographic information for the final sample. On average,

[12] This experiment was administered in early fall of 2019, well before the COVID-19 pandemic. As such, I do not expect the uncertainty of the COVID-19 pandemic to affect participants' stock price forecast.
[13] 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.
[14] I 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). I 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, which resulted in 35 participants being excluded. Retained participants spent a median of 14 minutes on the case, yielding an effective hourly wage of $7.48.

participants are 29 years old, have some experience with making financial forecasts, and are comfortable relying on technology.

TABLE 1
Demographic Information

Final Sample (n=145)

Variable	N	Mean	Median
FinAcctCourses	145	5.2	4.0
Forecast Experience	145	3.4	3.0
Technology Comfort	145	5.6	6.0
Age	145	29.4	27.0

	N	Percent
Gender (female)	145	43.4%

This table 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);
Age = participant's age*; and*
Gender = female or male.

Prolific workers with general business experience are appropriate participants for my study because I am 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).[15] Thus, given that a *basic* familiarity with accounting and business was required, I believe the knowledge base of my participants matches the requirement of the task and the goals of my research (Libby, Bloomfield, and Nelson 2002).

Materials, Manipulations, and Dependent Measure – Experiment 1

Following advice-taking literature (e.g., Yaniv and Kleinberger 2000; Yaniv 2004; Önkal, Goodwin, Thomson, Gönül, and Pollock 2009), I employ a two-stage design where participants provided their initial estimate and then finalized their estimate after receiving advice from an algorithm. Participants were instructed to assume the role of a manager at Heartland Resource Corporation (HRC), a publicly traded oil and gas company that engages in acquisition, exploration, and production of crude oil and natural gas. HRC recently acquired a patent for a state-of-the-art drill technology that can minimize wasteful natural gas exploration spending. Due to recent changes in the business climate (i.e., competing drill technology being developed), HRC's CFO tasked the manager with estimating the fair value of the patent as part of an intangible asset impairment test. Specifically, manager participants were 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 were provided with additional information to assist with the projection of patent-related sales revenue. Participants were informed that forecasted natural gas price is a major macroeconomic input that is a good indicator for projected

[15] Participants are provided a discounted cash flow Microsoft Excel spreadsheet to assist with the calculation of the patent fair value (see Figure 4, 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 Figure 4, Panel B).

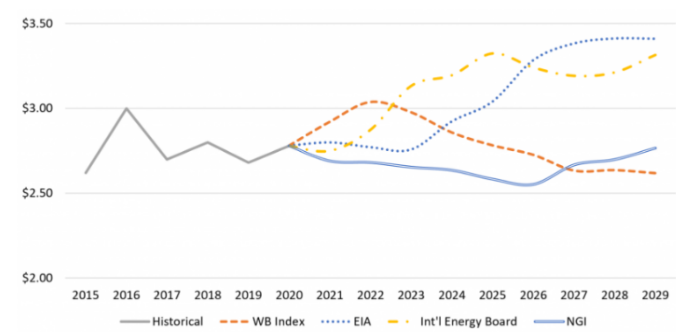
patent-related sales revenues and the related estimated fair value of the patent. To manipulate future uncertainty of the market, I provided participants with a graph of natural gas price forecasts and analysts quotes (i.e., macroeconomic information) that exhibited either higher or lower future uncertainty in future natural gas prices.[16,17] See Figure 3 Panel A and Panel B which presents the experimental manipulation for measurement uncertainty.

[16] 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 projects exhibit a more linear pattern. 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).

[17] The construct of interest is measurement uncertainty, which is defined as the "ambiguity in the valuation of an item" (Bratten et al. 2013, 10). While individuals may feel that the task is more difficult in the higher measurement uncertainty condition than in the less measurement uncertainty condition, the task of developing the fair value of the patent using the discounted cash flow spreadsheet is the same in all conditions.

FIGURE 3
Experimental Manipulation for Measurement Uncertainty

Panel A: Higher Future Uncertainty

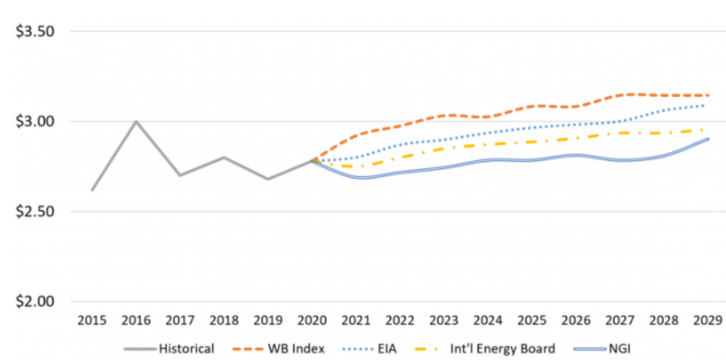


Analyst Quotes

"On average, natural gas prices are expected to increase modestly, but the four national price indices are quite divergent on their projections. The growing uncertainty surrounding the natural gas market makes 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 confident about future natural gas prices." [Analyst B]

Panel B: Lower Future Uncertainty



Analyst Quotes

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

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

Note: The purpose of Figure 3 is to illustrate the information participants were provided in the higher and lower measurement uncertainty conditions.

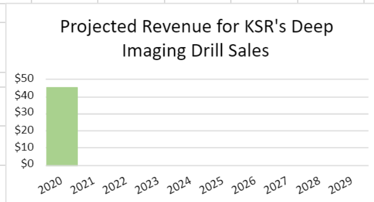
Following this, participants were provided a discounted cash flow spreadsheet where they submitted their projections of patent-related sales revenue cash flow for each year of the patent's useful life. See Figure 4, Panel A for the spreadsheet provided to all participants to assist with the discounted cash flow calculation. Participants entered in their projected future cash flows by typing their estimates into the empty yellow boxes in the spreadsheet. The spreadsheet automatically calculated the fair value of the patent by discounting the participant's projected future cash flows. See Figure 4, Panel B for an example of the spreadsheet's calculation of the patent fair value. The participant's estimated fair value of the patent prepopulates in the blue box. At this point, participants submitted their initial estimate of the patent value.

FIGURE 4
Discounted Cash Flow Spreadsheet
Panel A: Discounted Cash Flow Spreadsheet Provided to All Participants

Royalty Discounted Cash Flow Analysis

ALL NUMBERS ARE IN MILLIONS

2019 Revenue	$ 45.0									
Discount rate:	5%									
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	$ -									

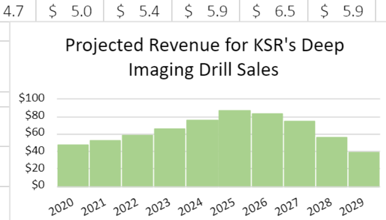


Panel B: Example of Discounted Cash Flow Spreadsheet Filled Out

Royalty Discounted Cash Flow Analysis

ALL NUMBERS ARE IN MILLIONS

2019 Revenue	$ 45.0									
Discount rate:	5%									
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 Figure 4 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.

Next, all participants learn that HRC developed a proprietary software system named the E-Val system that assists with complex valuations. The description of the algorithm is my second manipulation. Specifically, participants in the algorithm capable of adapting condition were informed that the E-Val system utilizes learning algorithms that can adapt and improve. Participants are informed that because the E-Val system uses learning algorithms, it can discover new predictors and identify different predictor weights to improve the model. Participants in the algorithm not capable of adapting condition read that the E-Val system utilizes static algorithms that are fixed and stay constant when developing its fair value estimate. Participants read that because the E-Val system uses static algorithms, the model's predictors and predictor weights are fixed and remain constant (i.e., could not adapt). In all conditions, participants are informed that the HRC firm guidance indicates that the E-Val system is considered an approved source of information and its models are reviewed by the firm. Following this, participants received the E-Val system's estimate of the patent fair value, which is always 20% less than the participant's initial fair value estimate.[18] See Figure 5 which presents the experimental manipulation of algorithm adaptability.

[18] Prior advice-taking literature has found that weight placed on advice decreases as the distance between the advice and initial opinion increases (Yaniv 2004). Therefore, to keep the distance equal in all conditions, I set the E-Val system's estimate as 20% less than the participant's initial fair value estimate.

FIGURE 5
Experimental Manipulation for Algorithm Adaptability

Panel A: Description of Learning Algorithm

The E-Val system utilizes ***learning algorithms*** (i.e., machine learning technology) that can detect patterns in the data and provide assistance with estimates. Learning algorithms are detailed mapping 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 methods ***adapt and improve 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

Panel B: Description of Static Algorithm

The E-Val system utilizes ***static algorithm*** to detect patterns in the data and provide assistance with estimates. Static algorithms are detailed mapping 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 methods are ***fixed and do not adapt over time***.

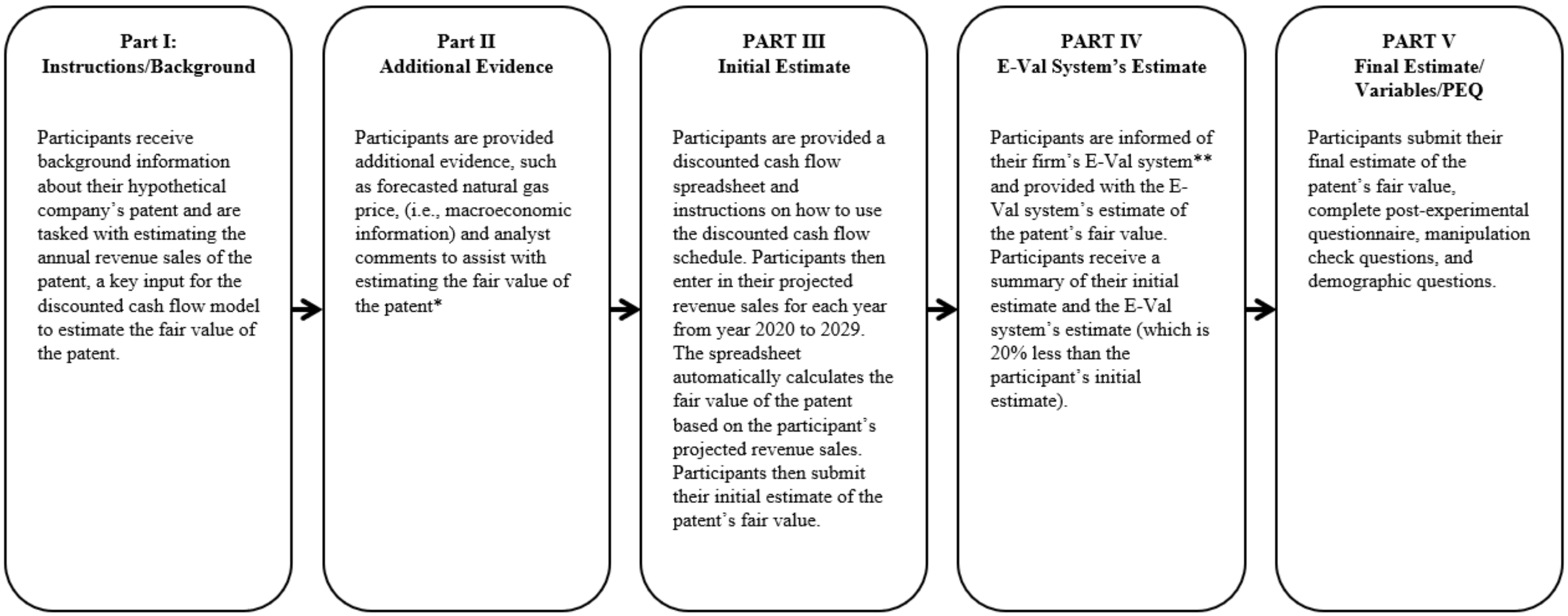
An example of a model used by the E-Val system to estimate a fair value estimate is provided below. Y is the fair value estimate and X's are pieces of information (i.e., predictors) that the model is trained on, such as sizes and trends of the markets in which relevant products are sold, market volatility,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

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

Note: The purpose of Figure 5 is to illustrate the information participants were provided in the learning and static algorithm conditions.

After reviewing the advice, participants submitted their final estimate (i.e., adjusted estimate) of the patent value and completed a post-test questionnaire. See Figure 6 for the sequence of the experimental procedures.

FIGURE 6
Sequence of Experimental Procedures



Note: Figure 6 presents the flow of the experimental design and where the *Measurement Uncertainty* and *Algorithm Adaptability* manipulations occur in the sequence of experimental procedures.

* *Measurement Uncertainty* is manipulated as higher future uncertainty of the market (i.e., natural gas price projections exhibit higher volatility) or lower future uncertainty of the market (i.e., natural gas price projections exhibit lower volatility).

** *Algorithm Adaptability* is manipulated as an algorithm capable adapting (i.e., learning algorithm) or an algorithm not capable adapting (i.e., static algorithm).

My 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:

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

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.[19] 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.

Results - Experiment 1

Manipulation Checks

I evaluate whether I successfully manipulated the uncertainty of the market by asking participants to assess, "how certain or uncertain are future natural gas prices" (1 = "Very Certain" and 7 = "Very Uncertain"). Participants in the higher uncertainty conditions (mean = 5.83, standard deviation = 1.22) assessed future natural gas prices as more uncertain than participants in the less uncertain condition (mean = 3.11, standard deviation

[19] Following previous research, I 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).

= 1.50, t_{143} = 12.00, $p < 0.01$, untabulated), suggesting a successful manipulation of market uncertainty.[20] To assess whether I successfully manipulated the adaptive capability of the algorithm, I 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"). [21] Results show that participants in the learning algorithm condition (mean = 6.01, standard deviation = 1.24) responded higher on the scale, which reflects a selection of a description closer to a learning algorithm (i.e., algorithm capable of adapting), while participants in the static algorithm condition (mean = 2.16, standard deviation = 1.78) responded lower on the scale consistent with a description of a static algorithm (t_{143} = 15.25, $p < 0.01$, untabulated).[22]

To further examine whether my adaptive capability of the algorithm manipulation was successful, I 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

---

[20] Consistent with my directional prediction, all reported *p*-values are one-tailed equivalents, unless otherwise noted.

[21] My algorithm manipulation should have only affected the degree to which participants view the adaptive capability of the algorithm. Although I did not intentionally anthropomorphize the algorithm capable of adapting, it is possible that individuals could view the learning algorithm as more human-like compared to the static algorithm. Waytz, Heafner, and Epley (2014) explain that anthropomorphizing a non-human does not simply involve attributing superficial human characteristics, such as a name or a face, to the algorithmic agent. Instead, they find that internal characteristics, such as attributing a human-like mind capable of feeling or thinking, were more effective methods of anthropomorphizing algorithm agents. To provide evidence that I did not manipulate the human-likeness or degree of anthropomorphism that the algorithm exhibited, I asked participant to assess the following statement, "How similar is the E-Val system's decision-making process compared to your decision-making process?" (1 = "Not at All Similar" and 7 = "Very Similar"). Participants' responses in the learning algorithm condition (mean = 3.57, standard deviation = 1.32) did not significantly differ from participants' responses in the static algorithm condition (mean = 3.78, standard deviation = 1.27, t_{143} = 1.01, p = 0.32, two-tailed).

[22] If analyses did not include 12 participants in Lower Uncertainty condition who responded greater than 4 and in Greater Uncertainty condition who responded less than 4 on the scale were excluded from analyses, my main results remain significant (e.g., the predicted interaction effect remains significant at p = 0.05, untabulated).

conditions over time" (1 = "Strongly Disagree" and 7 = "Strongly Agree"). Because learning algorithms have the capability to adapt overtime while static algorithms are fixed and stay constant, I expect that individuals in the static algorithm condition to report higher values (i.e., strongly agree) with the statement compared to individuals in the learning algorithm condition. I find further evidence of a successful manipulation of algorithm adaptability as participants in the static algorithm condition (mean = 5.42, standard deviation = 1.43) 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, standard deviation = 1.80, $t_{143} = 5.06$, $p < 0.01$, untabulated).[23]

Test of Hypothesis

To test my hypothesis, I estimate a 2 × 2 ANOVA with degree of future uncertainty and adaptive capability of algorithm as manipulated variables and WOA (i.e., weight managers placed on advice from the algorithm) as my dependent variable. Table 2, Panel A provides descriptive statistics by experimental condition, Figure 7 graphs these cell means, and Table 2, Panel B reports the results of my Analysis of Variance model.

[23] If analyses did not include 15 participants in Static Algorithm condition who responded greater than 4 and in Learning Algorithm condition who responded less than 4 on the scale were excluded from analyses, my main results remain significant (e.g., the predicted interaction effect remains significant at p = 0.03, untabulated). Additionally, when excluding these 15 participants and the 12 participants in footnote 22, my main results remain significant (e.g., the predicted interaction effect remains significant at p = 0.05, untabulated).

TABLE 2
Weight of Advice

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

Algorithm Adaptability	**Degree of Measurement Uncertainty** *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: Conventional ANOVA

Source	Sum of Squares	*df*	*F*	*p*[a]
Algorithm Adaptability	0.08	1	1.34	0.25[†]
Measurement Uncertainty	0.14	1	2.38	0.06[†]
Algorithm Adaptability × Measurement Uncertainty	0.19	1	3.33	0.04[†]
Error	8.16	141		

Table 2 (continued)

Panel C: Simple Effects Tests

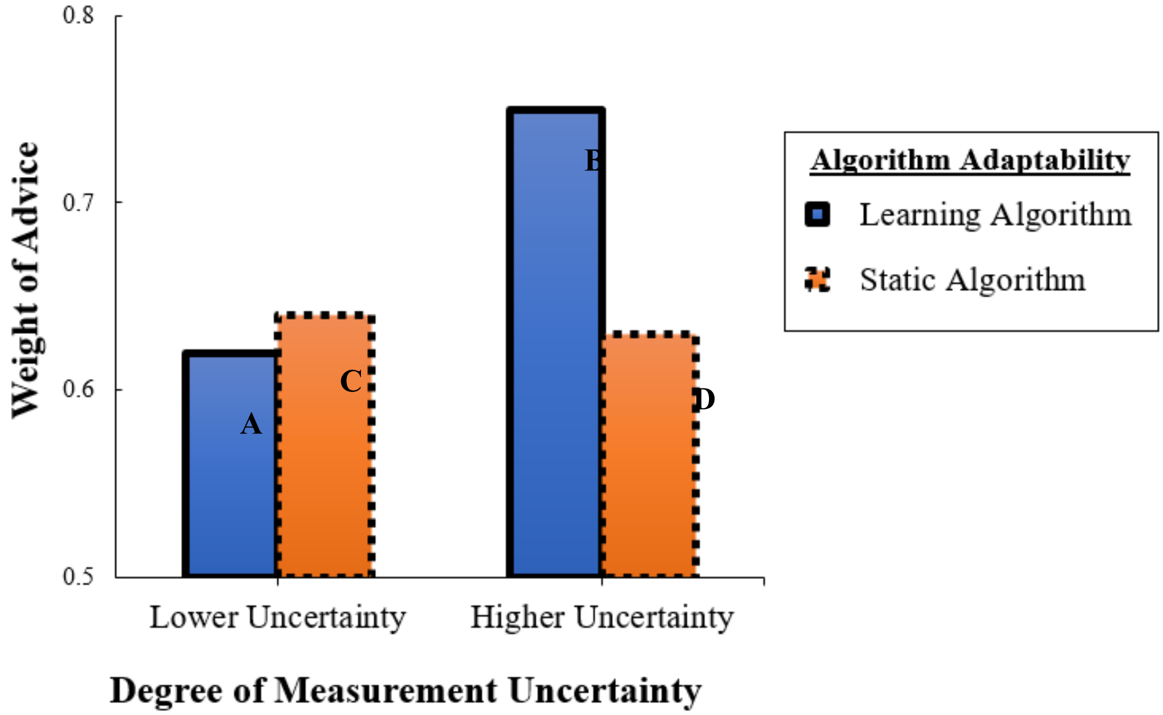
Source	*df*	*t*	*p*
Effect of Algorithm Adaptability given Higher Measurement Uncertainty (B vs D)	1,141	4.23	0.02†
Effect of Algorithm Adaptability given Lower Measurement Uncertainty (A vs C)	1,141	0.23	0.64
Effect of Measurement Uncertainty given Learning Algorithm (A vs B)	1,141	5.96	<0.01†
Effect of Measurement Uncertainty given Static Algorithm (C vs D)	1,141	0.04	0.84

Note: The dependent variable is participants' advice utilization, which is measured as weight of advice (WOA). WOA equals (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). I manipulate algorithm adaptability as static algorithm (i.e., not capable of adapting) versus learning algorithm (i.e., capable adapting), between participants, and the degree of measurement uncertainty as higher future uncertainty versus lower future uncertainty, between participants.

[a] I 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 my directional predictions.

FIGURE 7
Observed Effects of Measurement Uncertainty and Algorithm Adaptability on Participants' Weight of Advice



Note: See notes to Table 2 for descriptions of dependent variable and independent factors. Figure 7 graphs the means for my main dependent variable, WOA, by experimental condition, as reported in Table 2, Panel A.

My hypothesis predicts an interaction such that when future uncertainty is higher, managers will weight advice more heavily from a learning algorithm rather than a static algorithm compared to when future uncertainty is lower. Consistent with my hypothesis, I find a significant interaction between algorithm adaptability and measurement uncertainty ($F_{1,141} = 3.33$; $p = 0.04$). I perform follow-up simple effects (Table 2, Panel C) to more directly test the hypothesis. Results show that individuals exhibited greater WOA on estimates provided by a learning algorithm when facing higher future uncertainty compared to lower future uncertainty (0.75 versus 0.62 WOA; $p < 0.01$ one-tailed). Furthermore, when future uncertainty is higher, the effect of algorithm adaptability is significant (0.75 versus 0.63 WOA; p = 0.02), but not when future uncertainty is lower (0.62 versus 0.64 WOA; p = 0.64, two-tailed). These simple effects provide further support for my hypothesis and demonstrate that when individuals face higher future uncertainty, they will weight advice from the algorithm relatively more only if the algorithm exhibits adaptive capabilities. Lastly, results show that under lower future uncertainty, individuals do not differentially weight advice from a learning algorithm compared to a static algorithm. This is consistent with expectations that when measurement uncertainty is lower, individuals will feel less of a need to seek and utilize advice and as a result, algorithm adaptability will have less of an effect on individuals' WOA. Collectively, these results provide strong support for my theory-based predictions.

Moderated Mediation Analyses

In developing my hypothesis, I draw on theory that suggests an individual's degree of advice utilization may be determined by the level of trust in the algorithm (i.e., the advisor). Specifically, advice utilization is a decision and an outcome of an individual's willingness to trust in others (i.e., a judgment). An individual's willingness to trust others is defined as 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).[24] As such, for an individual (i.e., the trustor) to exhibit a need and willingness to *trust* an advisor, there must be some uncertainty involved in the situation or task (Sniezek and Van

[24] This is consistent with judgment and decision-making research which defines a judgment as an idea or opinion about an object and tends to "take the form of predictions about the future or an evaluation of a current state of affairs (Bonner 1999, 385). On the other hand, a decision refers to a course of action that individuals take to perform a task or solve a problem (Bonner 1999; Solomon and Trotman 2003).

Swol 2001). In a most extreme example of a need to place trust in others, a person in an uncertain and desperate situation from which he is unable to free himself from without help is more likely to accept assistance from another (Coleman 1990). 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). In particular, researchers found that individuals developed higher levels of trust in their advisor as the task expertise asymmetry between the individual and the advisor became greater (Sniezek and Van Swol 2001).[25]

In my setting, I expect that when accounting practitioners are completing tasks while facing higher future uncertainty, they will be more willing to trust an algorithm, but only if that algorithm exhibits advanced capabilities suited to handle uncertainty, such as the capability of adapting. I also expect that individuals' willingness to trust the algorithm is the mechanism that influences the weight individuals place on an algorithm's advice such that increase in an individual's willingness to trust an algorithm will cause an individual to more heavily weight advice. If results are consistent with theory, I expect a significant indirect effect of measurement uncertainty on advice utilization through willingness to trust in algorithm when evidence is provided by a learning algorithm but an insignificant indirect effect when evidence is provided by a static algorithm. The model is depicted in Figure 8.

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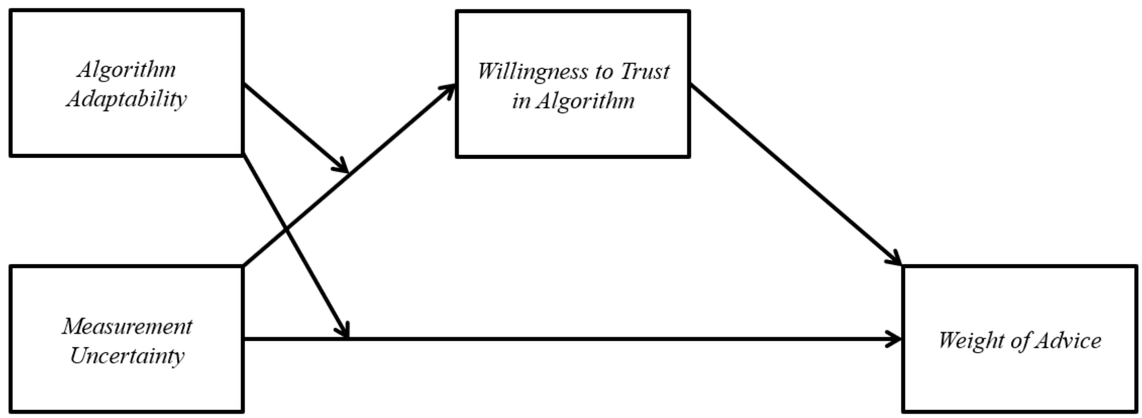
[25] Expertise in this study was defined as "knowledge about a specific domain" and operationalized as computer-knowledge based on an 18-item pre-test where participants who scored higher were considered to exhibit greater expertise and participants who scored lower were considered to exhibit less expertise (Ericsson and Smith 1991; Snizek and Van Swol 2001; Van Swol and Sniezek 2005).

FIGURE 8
Moderated Mediation Model



Note: The above diagram represents a moderated mediation model (Hayes 2018). I 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, I 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). I take the average of these three items to measure an individual's willingness to trust in algorithm.

I measure participants' willingness to trust in an algorithm and examine whether individuals' judgment on the degree to which they are willing to trust an algorithm mediates algorithm adaptability and measurement uncertainty's effect on WOA. I develop a composite measure of an individual's willingness to trust in the algorithm by asking 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).[26] Cronbach's alpha for the three-item measure is 0.69, indicating acceptable reliability (Kline 2016; Field 2018). As the three trust items appear to capture a single underlying construct, I use the average of the three measures as the mediator in my analyses, which I label as willingness to trust in the algorithm.

Following the procedures described by Hayes (2018), I conduct a moderated mediation analysis using the SPSS PROCESS macro (model 8) with participants' willingness to trust in the algorithm as the mediator. To test for indirect effects, I construct 90% confidence intervals with 10,000 bootstrapped resamples of data with replacement. Figure 9, Panel A presents results for the learning algorithm conditions, which reveal results consistent with my expectations. The indirect effect is significant for the learning algorithm conditions (90 percent confidence interval of 0.003 to 0.067, indicating a one-tailed *p*-value less than 0.05). Examining the coefficients reported in the path model provides additional insights into the indirect effect of measurement uncertainty on weight of advice through willingness to trust in algorithm. Measurement uncertainty has a significant positive effect on individuals' willingness to trust in the algorithm ($p < 0.05$) and willingness to trust in the algorithm exhibits a significant positive effect of on weight of advice ($p < 0.01$). These results are consistent with expectations that under learning algorithm conditions, higher measurement uncertainty causes individuals to exhibit a

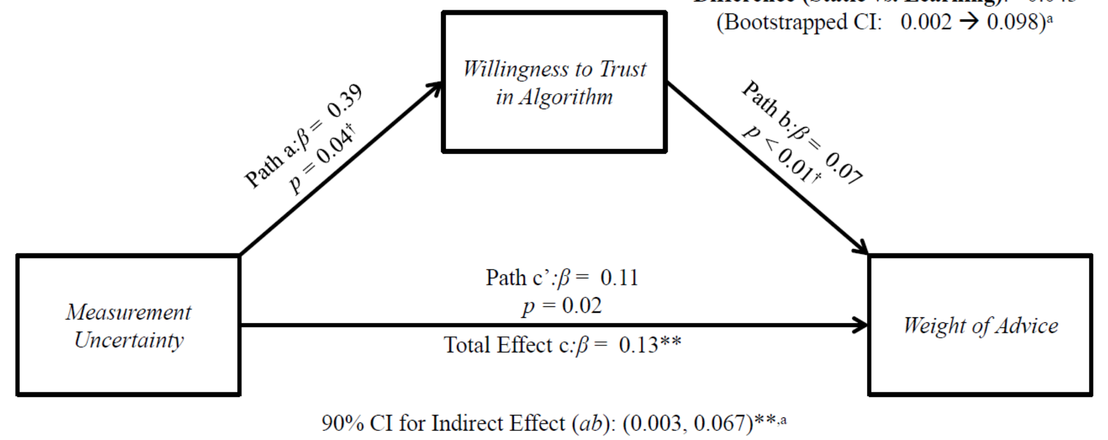
[26] I utilize a three-item scale to capture individuals' willingness to trust in the algorithm. The first item directly assesses participants' perception of the E-Val system's trustworthiness. However, trust is a complex concept that is difficult to measure with one item (Madsen and Gregor 2000). Thus, in addition to the first item in my willingness to trust measure, I also use two items from the human-computer trust scale that Madsen and Gregor (2000) develop to measure faith, which is trust in the capability of the system to "perform even in situations where it is untried". I selected these two items instead of utilizing the entire human-computer trust scale to keep the instrument at a manageable length for the participants. Additionally, given that the E-Val system is predicting future outcomes and events, I expected these two items to be most applicable to this setting.

greater willingness to trust in the algorithm and that greater willingness to trust increases the degree to which individuals incorporate algorithmic advice into their final estimate.

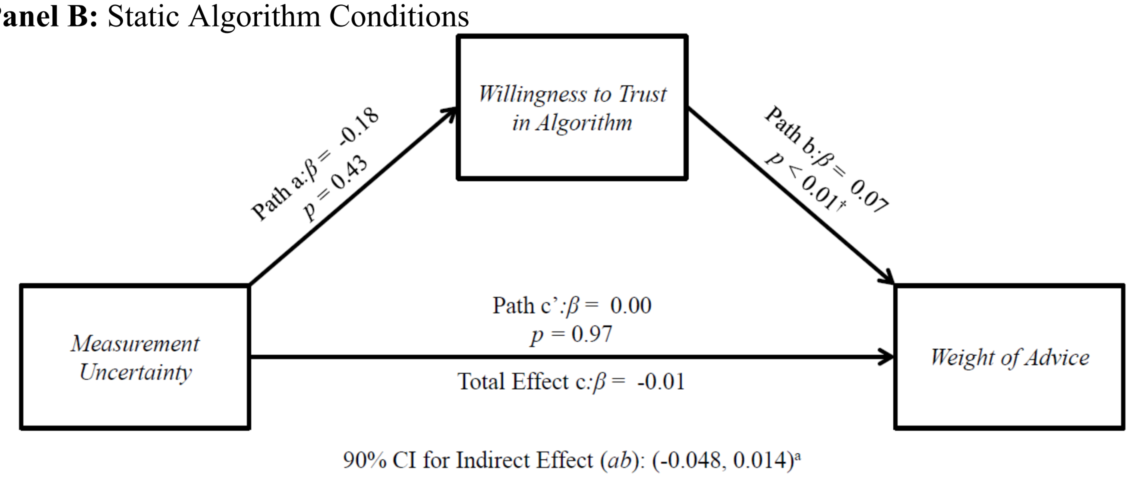
FIGURE 9
Moderated Mediation Analysis

Panel A: Learning Algorithm Conditions

Index of Moderated Mediation
Difference (Static vs. Learning): 0.043**,a
(Bootstrapped CI: 0.002 → 0.098)[a]



Panel B: Static Algorithm Conditions



Note: The above diagram represents a moderated mediation model (Hayes 2018). For visual simplicity, I present results separately for the learning and static algorithm conditions, even though the model is calculated simultaneously for all conditions using Model 8 in the PROCESS macro in SPSS. See notes in Figure 8 for descriptions of dependent variables, independent factors, and mediator. All continuous variables are mean-centered to facilitate interpretation of the coefficients.
[a] To test for indirect effects, I construct 90% confidence intervals for the product of paths *a* and *b*. I use 10,000 bootstrapped resamples of data with replacement (Hayes 2018). Reflecting my directional predictions, I use 90% confidence intervals (i.e., bounded at 0.05 and 0.95) to test whether one-tailed p-values are less than 0.05.
** denotes statistical significance equivalent to $p < 0.05$, one-tailed.

† one-tailed given directional prediction (all other *p*-values are two-tailed).

Figure 9, Panel B presents results for the static algorithm conditions. The indirect effect is not significant (90 percent confidence interval of -0.048 to 0.014). Examining the coefficients reported in the path model reveals that higher measurement uncertainty does not significantly increase an individual's willingness to trust in the algorithm. This is consistent with literature that identifies algorithm capability, in this case the capability of adapting, as an important factor in the development of willingness to trust in the algorithm. Lastly, I find that the index of moderated mediation is significant (90 percent confidence interval of 0.002 to 0.098, indicating a one-tailed *p*-value less than 0.05), which confirms that the indirect effects estimated at the two levels of algorithm capability are significantly different from each other. Collectively, results of the moderated mediation indicate that the joint effect of measurement uncertainty and algorithm adaptability on individuals' advice utilization operates indirectly through willingness to trust the algorithm. Furthermore, the development of an individual's willingness to trust an algorithm is jointly determined by measurement uncertainty and algorithm adaptability.

Additional Analyses

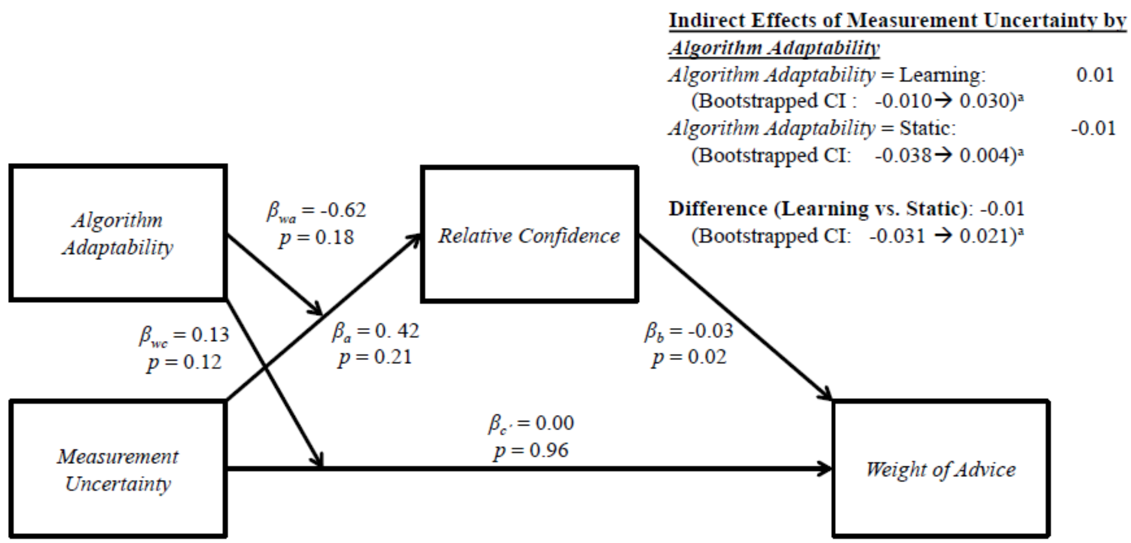
Relative Confidence as an Alternative Mediator

In my paper, I draw upon theory that predicts measurement uncertainty and algorithm adaptability influences individual's degree of advice utilization through an individual's willingness to trust in an algorithm. However, an alternative explanation in the observed results could be that participants' algorithm advice utilization was *solely* driven by their confidence in their own ability relative to their confidence in the algorithm's capability rather than their willingness to trust in the algorithm. Specifically, it is possible that individuals who encounter a task that exhibits greater measurement uncertainty views themselves as less capable of completing the task and as a result, feel less confident in their own ability. Consequently, individuals who feel less self-confident in their own judgments are more likely to incorporate advice from others (See, Morrison, Rothman, and Soll 2011), but only if individuals are less confident in their own abilities relative to their confidence in the algorithm's ability to complete the task.

Confidence is defined as the "belief, based on experience or evidence, that certain future events will occur as expected" (Earle and Siegrist 2006, 386). However, trust is a "reliance upon information received from another person about uncertain environmental states and their accompanying outcomes in a risky situation" (Schlenker, Helm, and Tedeshi 1973, 419). While both trust and confidence in an advisor could both lead to greater weight placed on the advisor's recommendations, confidence is based on past performance or evidence while trust is free of that criterion. In complex accounting estimates settings, individuals may never know the "right answer" or the correct value of an estimate and as a result, may not be able to confirm based on past events that the advisor is capable of providing quality advice. Given the lack of prior evidence or experience necessary to develop an individual's confidence in an advisor's capability of completing a task in complex estimate settings, I predict and find (in Experiment 1) that an individual's willingness to trust in an algorithm is the mechanism that drives individual's decision to utilize the algorithm's advice.

However, to rule out this alternative mechanism, I examine whether participants' algorithm advice utilization was driven by their confidence in their own ability *relative* to their confidence in the algorithm's capability in Experiment 1. I measure participants' relative confidence by asking them to assess the following statement, "How confident are you in your ability relative to the E-Val system's ability to accurately estimate the fair value of the patent" on a 7-point scale with endpoints *More Confident in E-Val System's Ability* (1) to *More Confident in Own Ability* (7). See Figure 10 for the model results.

FIGURE 10



Moderated Mediation Model

Note: The above diagram represents a moderated mediation model (Hayes 2018). I 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 an individual's confidence in their own ability relative to their confidence in the algorithm's ability (i.e., *Relative Confidence*). *Measurement Uncertainty* equals 1 (0) for higher (lower) measurement uncertainty condition. *Algorithm Adaptability* equals 1 (0) for learning (static) algorithm condition. To capture participants' *Relative Confidence*, asking them to assess the following statement, "How confident are you in your ability relative to the E-Val system's ability to accurately estimate the fair value of the patent" on a 7-point scale with endpoints *More Confident in E-Val System's Ability* (1) to *More Confident in My Own Ability* (7).

[a] To test for indirect effects, I construct 90% confidence intervals for the product of paths *a* and *b*. I use 10,000 bootstrapped resamples of data with replacement (Hayes 2018). Reflecting my directional predictions, I use 90% confidence intervals (i.e., bounded at 0.05 and 0.95) to test whether one-tailed p-values are less than 0.05.

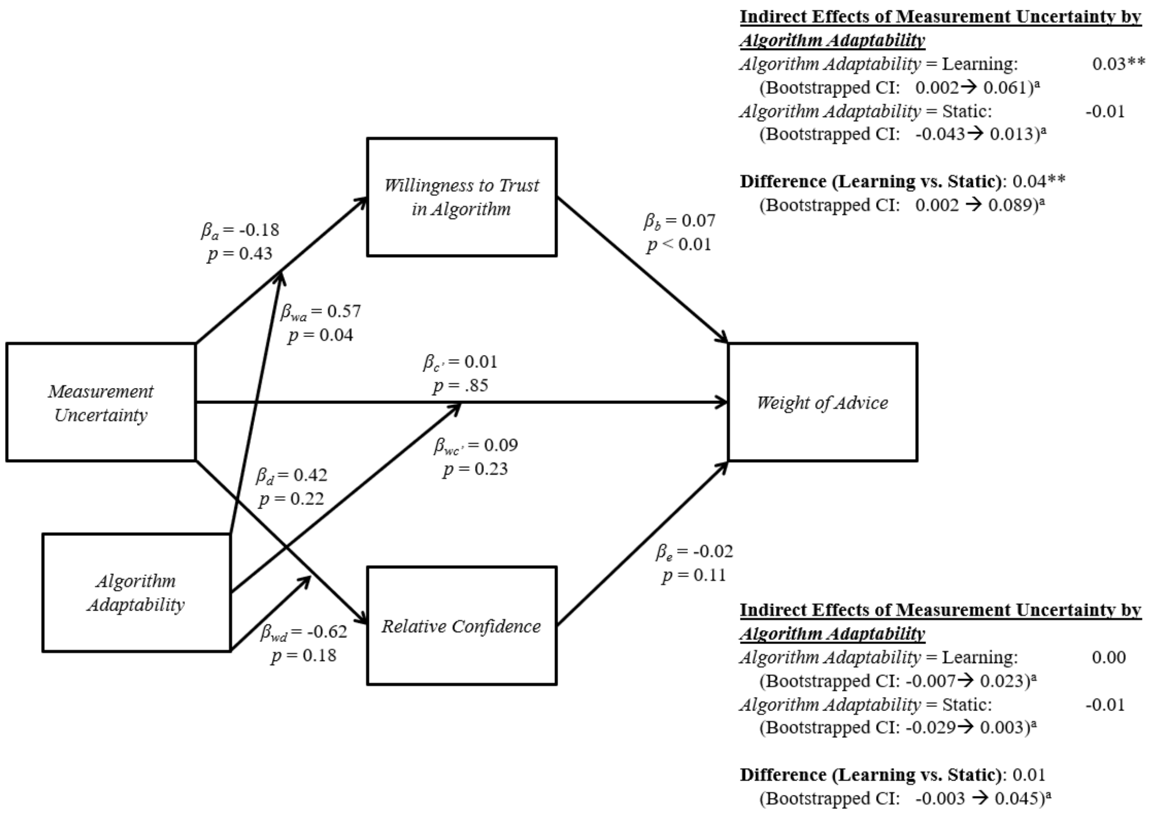
† one-tailed given directional prediction (all other *p*-values are two-tailed).

Following the procedures described by Hayes (2018), I conduct a moderated mediation analysis using the SPSS PROCESS macro (model 8) with participants' relative confidence as the mediator. To test for indirect effects, I construct 90% confidence intervals with 10,000 bootstrapped resamples of data with replacement. Figure 10 results reveal that participants' relative confidence does not mediate the interactive effect of measurement uncertainty and algorithm adaptability on participants' algorithm advice utilization. Specifically, indirect effects are not significant for the learning algorithm conditions (90 percent confidence interval of -0.010 to 0.030) nor static algorithm conditions (90 percent confidence interval of -0.038 to 0.004). Additionally, the index of moderated mediation is not significant (90 percent confidence interval of -0.031 to 0.021).[27] Collectively, these results suggests that individuals' confidence measures do not mediate the interactive effect of measurement uncertainty and algorithm adaptability on individuals' advice utilization.

To provide additional evidence that individuals' willingness to trust is the mechanism that drives individuals weight of advice decision, I conduct a conditional parallel mediation analyses using Model 8 in the SPSS Process macro with willingness to trust in the algorithm and relative confidence included as parallel mediators. This model examines whether individuals' willingness to trust in the algorithm continues to mediate the interactive effect of measurement uncertainty and algorithm adaptability's effect on weight of advice while including individual's relative confidence in the model. Figure 11 presents the results of the model.

[27] Indirect effects for learning algorithm conditions (80 percent confidence interval of -0.031 to 0.000) and static algorithm conditions (80 percent confidence interval of -0.006 to 0.024) remain nonsignificant when I construct 80% confidence intervals with 10,000 bootstrapped resamples of data with replacement.

FIGURE 11
Conditional Parallel Mediation Model



Note: The above diagram represents a moderated parallel mediation model (Hayes 2018). I use a Model 8 with two mediators. Specifically, *Algorithm Adaptability* is depicted as having a moderating effect on the mediation paths from *Measurement Uncertainty* to *Weight of Advice* (i.e., weight placed on algorithm's advice) via two parallel mediators: *Willingness to Trust in Algorithm* and *Relative Confidence.* See notes in Figure 8 and Figure 10 for descriptions of dependent variable, independent factors, and mediators.

[a] To test for indirect effects, I construct 90% confidence intervals for the product of paths *a* and *b*. I use 10,000 bootstrapped resamples of data with replacement (Hayes 2018). Reflecting my directional predictions, I use 90% confidence intervals (i.e., bounded at 0.05 and 0.95) to test whether one-tailed p-values are less than 0.05.

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

† one-tailed given directional prediction (all other *p*-values are two-tailed).

Results in Figure 11 reveal a significant indirect effect for the learning algorithm conditions (90 percent confidence interval of 0.003 to 0.061, indicating a one-tailed *p*-value less than 0.05) and nonsignificant indirect effect for the static learning algorithm conditions (90 percent confidence interval of -0.043 to 0.013). Lastly, I find that the index of moderated mediation is significant (90 percent confidence interval of 0.002 to 0.089, indicating a one-tailed *p*-value less than 0.05), which confirms that the indirect effects estimated at the two levels of algorithm capability are significantly different from each other. However, results for individuals' relative confidence measure as a mediator reveal two nonsignificant indirect effects and a nonsignificant index of moderated mediation. Collectively, results of the conditional parallel mediation model indicate that the joint effect of measurement uncertainty and algorithm adaptability on individuals' advice utilization operates indirectly through willingness to trust the algorithm even when including individuals' relative confidence in the model.

Additional Analysis on Ordinal Interaction

Following research documenting that tests of contrasts are generally more appropriate to analyze the ordinal interaction effect (e.g., Buckless and Ravenscroft 1990; Guggenmos, Piercey, and Agoglia 2019), I conduct the three-part approach discussed in Guggenmos et al. (2018) to examine whether my results conform to the specific ordinal interaction pattern suggested by my interaction hypothesis. To test this ordinal interaction, I use contrast weights of +3 for high measurement uncertainty, learning algorithm and -1 for the other three conditions (see Table 3).[28] First, a visual evaluation of fit supports my

[28] These contrast weights reflect my hypothesis by testing whether individuals will weight evidence from an algorithm more heavily when they face higher measurement uncertainty and use a more capable algorithm compared to when participants use a less capable algorithm and/or face lower measurement uncertainty.

expected pattern of means as the condition assigned a weight of +3 is the highest condition in Figure 7 compared to the other three conditions, which are assigned -1. Second, this contrast is significant ($F_{1,141}$ = 6.95; p < 0.01) and the semi-omnibus test of residual variance is not significant ($F_{1,141}$ = 0.16; p = 0.85). A non-significant semi-omnibus F-test provides evidence of no additional systematic effects in the data after controlling for the contrast. Lastly, the proportion of the remaining unexplained between-cells variance to the total explainable variance in the experiment (q^2) is 4.4 percent. Collectively, these results

provide strong support for my theory-based predictions in my interaction hypothesis.

TABLE 3

Contrast and Residual Between Cells Variance Test

Source	Sum of Squares	*df*	*F*	*p*
[-1, +3, -1, -1] for [A, B, C, D]	0.40	1	6.95	< 0.01
Residual between-cells variance	0.02	2	0.16	0.85
Contrast Variance Residual, q^2	4.4%			

Note: The dependent variable is participants' advice utilization, which is measured as weight of advice (WOA). WOA equals (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). I manipulate the capability of the algorithm as static algorithm versus learning algorithm (i.e., less versus more capable), between participants, and the degree of measurement uncertainty as greater future uncertainty versus lower future uncertainty, between participants.

† *p*-values are equivalent to a one-tailed test, consistent with my directional predictions.

Factor Analysis on Willingness to Trust

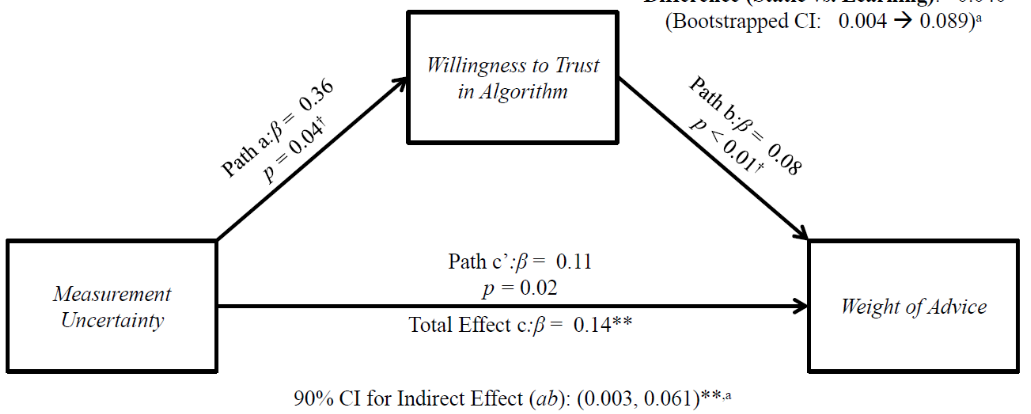
In my moderated mediation analyses for Experiment 1, I develop a composite measure of an individual's willingness to trust in the algorithm by averaging my three-item scale (see Figure 8 note for description of the three items). To further examine whether I capture one underlying factor, I conduct a factor analysis of the three items utilizing an oblique oblimin rotation. Results indicate only one factor with an eigenvalue greater than 1. The underlying factor has an eigenvalue of 1.87 which accounts for 62.35% of the variance. All items meaningfully load onto this underlying factor as all rotated factor loadings were greater than 0.30 (Raykov and Marcoulides 2008, 265). Thus, the three trust items appear to capture a single underlying construct. I utilize this factor as the mediator in my moderated mediation model to validate that my results remain unchanged when using the factor variable. See Figure 12 for results. Results remain unchanged. Specifically, the indirect effect is significant for the learning algorithm conditions (90 percent confidence interval of 0.003 to 0.061, indicating a one-tailed *p*-value less than 0.05) while the indirect effect for the static algorithm conditions is not significant (90 percent confidence interval of -0.043 to 0.014). Additionally, the index of moderated medication indicates that the indirect effects are statistically different (90 percent confidence interval of 0.004 to 0.089, indicating a one-tailed *p*-value less than 0.05).[29]

[29] Although I expected only one factor to emerge during the factor analysis, if there were more than one factor present, theoretically those factors would be related. Thus, I utilize an oblique oblimin rotation, which allows the underlying factors to correlate. Results are inferentially identical if I use an orthogonal (i.e., uncorrelated) varimax rotation.

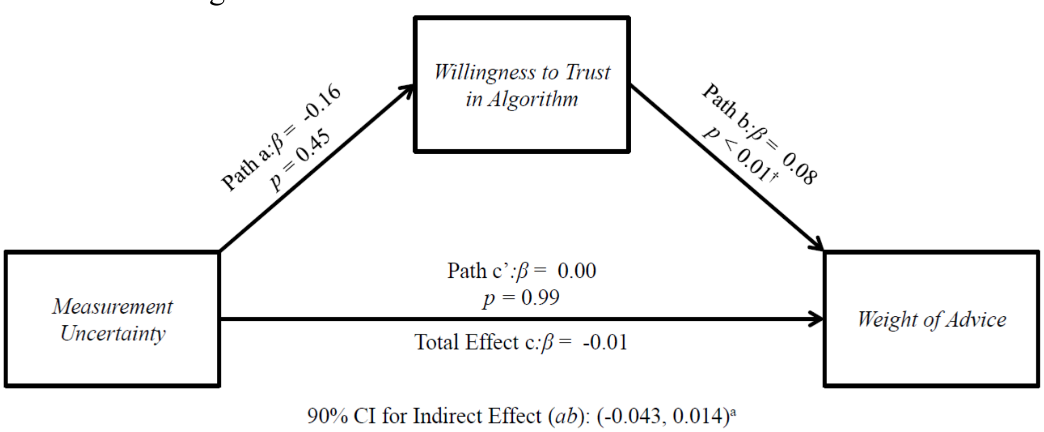
FIGURE 12
Moderated Mediation Analysis

Panel A: Learning Algorithm Conditions

Index of Moderated Mediation
Difference (Static vs. Learning): 0.040**,a
(Bootstrapped CI: 0.004 → 0.089)[a]



Panel B: Static Algorithm Conditions



Note: The above diagram represents a moderated mediation model (Hayes 2018). For visual simplicity, I present results separately for the learning and static algorithm conditions, even though the model is calculated simultaneously for all conditions using Model 8 in the PROCESS macro in SPSS. See notes in Figure 8 for descriptions of dependent variables and independent factors. To construct the mediator, I 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). I then conduct a factor analysis of the three items utilizing an oblique oblimin rotation and extract one factor called *Willingness to Trust in Algorithm.* All continuous variables are mean-centered to facilitate interpretation of the coefficients.

[a] To test for indirect effects, I construct 90% confidence intervals for the product of paths *a* and *b*. I use 10,000 bootstrapped resamples of data with replacement (Hayes 2018). Reflecting my directional predictions, I use 90% confidence intervals (i.e., bounded at 0.05 and 0.95) to test whether one-tailed p-values are less than 0.05.

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

† one-tailed given directional prediction (all other p-values are two-tailed).

EXPERIMENT 2 – DESIGN, METHODS, AND RESULTS

Design and Participants – Experiment 2

Experiment 2 serves two purposes. First, this experiment examines the extent to which the results I find in Experiment 1 generalizes to other financial settings involving uncertainty. Specifically, Experiment 2 examines whether individuals who face high task solution or outcome uncertainty will more heavily weight advice provided by an algorithm capable of adapting relative to an algorithm not capable of adapting. Unlike Experiment 1 where participants forecasted cash flows and developed a patent fair value, in Experiment 2 participants provide a stock price forecast. Secondly, Experiment 2 provides evidence that validates my algorithm adaptability manipulation. In the task, participants are provided with historical stock prices and are asked to forecast the stock's future price. I use a 1 × 2 between-participants design, manipulating the adaptive capability of the algorithm that provides advice to the participant as an algorithm capable of adapting (i.e., learning algorithm) or not capable of adapting (i.e., static algorithm).[30]

Participants are 41 graduate students enrolled in a Masters of Finance program from a large public university. All participating students were enrolled in upper-division finance courses such as "Financial Modeling and Analysis", "Investments", and "Options, Futures, and Derivatives". Participants had a reasonable understanding of accounting and finance as, on average, they completed seven accounting and finance courses. To ensure that participants have a basic amount of experience of forecasting stock prices, participants

[30] Participants were also assigned to one of two conditions (manipulating whether participants received an algorithm's forecast for next week's or next year's closing stock price). As the manipulation had little effect on participants' reliance on advice ($F_{1,37} = 0.22$, $p = 0.65$, untabulated) and did not interact with my algorithm adaptability manipulation ($F_{1,37} = 0.36$, $p = 0.55$, untabulated), I collapse my analyses across the manipulated algorithm adaptability variable.

were asked to indicate their level of experience with forecasting stock prices on a seven-point Likert scale (1 – "No Experience at All" and 7 = "Highly Experienced"). Additionally, I ask participants to evaluate their level of knowledge of stock prices and probability on a seven-point Likert scale (1 = "Very Poor" and 7 = "Very Good"). On average, participants report having a basic level of forecasting experience (mean = 2.5) and knowledge of stock prices (mean = 3.6). See Table 4 for demographic information for the final sample. Overall, participants were 24 years old and reported a mean of approximately 2 years of work experience.

TABLE 4

Demographic Information

Final Sample (n=41)

Variable	N	Mean	Median
FinAcctCourses	41	7.0	7.0
Forecast Experience	41	2.5	2.00
Stock Knowledge	41	3.6	3.0
Work Experience	41	2.3	1.0
Age	41	24.4	24.5

	N	Percent
Gender (female)	41	36.6%

This table provides descriptive statistics on demographic information of participants.

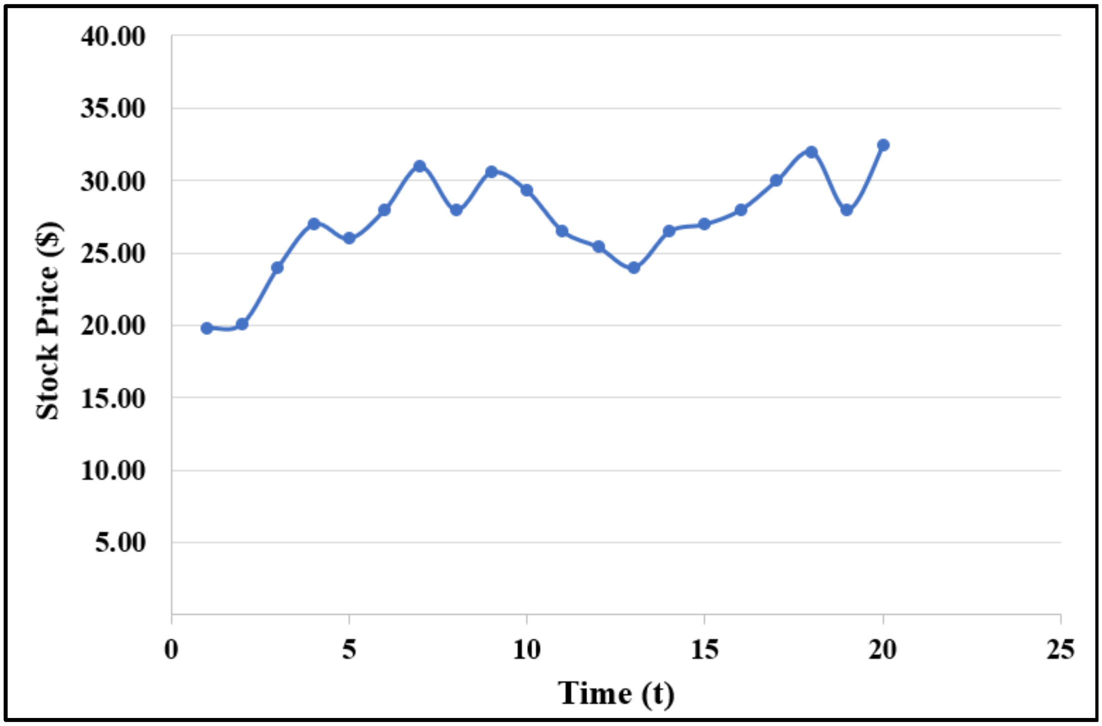
Variable Definitions:
FinAcctCourses = number of finance and accounting courses participant has completed;
Forecast Experience = participants assessed their level of experience with forecasting stock prices on a 7-point scale with endpoints *No Experience at All* (1) to *Highly Experienced* (7); and
Stock Knowledge = participants assessed their level of knowledge on stock prices and probability on a 7-point scale with endpoints *Very Poor* (1) to *Very Good* (7);
Work Experience = participant's work experience in years;
Age = participant's age in years*; and*
Gender = female or male.

Graduate students with a basic knowledge of forecasting stock prices are appropriate participants for my study because I am examining a psychological phenomenon that does not necessarily require specialized knowledge or extensive prior expertise. Although the experimental task involves forecasting a stock price, the task is straightforward, and the setting is simplified by providing participants limited amount of information to base their stock price forecasts. Furthermore, I am mainly interested in the weight placed on the advice provided by the algorithm not necessarily how well the participants performed in the stock price forecast. Thus, given that a *basic* familiarity with forecasting stock prices was required, I believe the knowledge base of my participants matches the requirement of the task and the goals of my research (Libby et al. 2002).

Materials, Manipulations, and Dependent Measure – Experiment 2

Similar to Experiment 1, participants provide their initial estimate and then finalized their estimate after receiving advice from an algorithm. Participants complete a paper-and-pencil task in which they were instructed to assume the role of equity analyst for a large investment management firm. They are told that their job is to develop financial projections and forecasts that will be used by their firm's investment advisors. Participants were then provided with information to assist with their stock forecast, such as a time series plot of the stock's historical price, and then asked to forecast the stock's future price. See Figure 13 which presents the time series plot for a stock that was provided to all participants.

FIGURE 13
Time Series Plot for Stock



Note: The purpose of Figure 13 is to illustrate the information provided to all participants to assist them with forecasting the stock's future price.

Next, participants learn that their firm developed a proprietary algorithm that can assist equity research analysts by providing financial guidance and expert knowledge of stocks and bonds. In all conditions, participants are informed that their firm partnered with a large international technology company with leading experts in the field to develop the algorithm. Similar to Experiment 1, the description of the algorithm contains my algorithm adaptability manipulation. Participants in the learning algorithm condition were informed that the algorithm can adapt and improve by modifying its model's weights and identifying new predictors. Participants in the static algorithm condition read that the algorithm is based on a complex mapping of if-then statements and rules. Following this, participants received the algorithm's estimate that the closing price of the stock is $25. See Figure 14 which presents the experimental manipulation of algorithm adaptability. Similar to Experiment 1, I measure participants' WOA, which captures the extent to which an individual incorporates the algorithm's estimate into their final estimate. WOA values can range from 0 to 1 where 0 represents a complete discounting of the algorithm's estimate and 1 represents full weighting of the algorithm's estimate.

FIGURE 14
Experimental Manipulation for Algorithm Adaptability

Panel A: Description of Learning Algorithm

This algorithm provides advice based on executing a complex mapping of if-then statements and rules. These rules are then used to train the algorithm's model to predict future stock performance. Additionally, the algorithm can **learn independently** from its environment, **understand the pattern** that underlies the data, and **adapt to improve** its future predictions. An example of a model used by the algorithm to predict future stock price is provided below. Y is the future stock price and X's are pieces of information that the model is trained on, such as historical stock prices, financial data, and analysts' forecasts. The β is the weight that is applied to the piece of information in predicting future stock price (Y). Because the algorithm can independently learn, the algorithm can **modify the weights** (β) applied to the pieces of information (X). Additionally, as the algorithm learns, it can **identify new predictors** ($\beta_n X_n$) and add it to the model to improve the accuracy of future forecasts.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}_{\text{New information can be added to model by the algorithm to improve predictions}}$$

Panel B: Description of Static Algorithm

This algorithm provides advice based on executing a **complex mapping of if-then statements and rules**. These rules are then used to train the algorithm's model to predict future stock performance. An example of a model used by the algorithm to predict future stock price is provided below. Y is the future stock price and X's are pieces of information that the model is trained on, such as historical stock prices, financial data, and analysts' forecasts. The β is the weight that is applied to the piece of information in predicting future stock price (Y).

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

Note: The purpose of Figure 14 is to illustrate the information participants were provided in the learning and static algorithm conditions.

Results - Experiment 2

Manipulation Check

To assess whether individuals attend to my manipulation, I ask participants to assess whether their firm's algorithm can independently adapt and learn over time (1 = "Strongly Disagree" and 7 = "Strongly Agree"). Participants in the learning algorithm condition (mean = 4.65, standard deviation = 1.50) more strongly agreed with the statement than participants in the static algorithm condition (mean = 3.55, standard deviation = 1.98, t_{39} = 1.60, p = 0.06, one-tailed), suggesting a successful manipulation of algorithm adaptability. [31]

Results of Experiment 2

Experiment 2 examines whether individuals who face high measurement uncertainty will differentially weight an algorithm's advice depending on whether the algorithm is capable of adapting or not. Forecasting stock prices is a task that exhibits measurement uncertainty given that predicting a stock's future price is ambiguous and requires numerous assumptions about the future (Bratten et al. 2013). Furthermore, measurement uncertainty can "magnify difficulties" individuals experience in estimating items, such as future stock price (Bratten et al. 2013, 11). Although the setting differs from Experiment 1, participants in Experiment 2 assessed their forecasting task to be similarly difficult as Experiment 1 participants' difficulty assessments in the higher measurement uncertainty conditions. Participants in Experiment 2 (1) were asked to assess how difficult it was to accurately forecast the stock price (estimate the fair value of the Patent) on a 7-point Likert scale with endpoints of: 1 = "Not at All Difficult" and 7 = "Very Difficult".

[31] Consistent with my directional prediction, all reported *p*-values are one-tailed equivalents, unless otherwise noted.

On average, participants in the higher measurement uncertainty conditions for Experiment 1 (mean = 5.25, standard deviation = 1.40) assessed a similar degree of difficulty as participants in Experiment 2 (mean = 5.32, standard deviation = 1.51). Additionally, in both experiments, participants' assessment of the difficulty of providing an accurate estimate is significantly greater than the mid-point on the scale (untabulated). Furthermore, in Experiment 2, participants in the algorithm capable of adapting condition (mean = 5.45, standard deviation = 1.47) did not assess the task as more or less difficult to accurately forecast the stock price than participants in the algorithm not capable of adapting condition (mean = 5.19, standard deviation = 1.57, t_{39} = 0.55, two-tailed, untabulated). Collectively, these analyses provide evidence that the stock forecasting task in Experiment 2 exhibited high measurement uncertainty.

I examine whether participants more heavily rely on advice provided by a learning algorithm relative to a static algorithm when facing high measurement uncertainty. Table 5, Panel A reports descriptive statistics for the WOA by condition. Table 5, Panel B reports the results of my one-way Analysis of Variance and Panel C reports the simple effects. This simple effect supports my expectation that when individuals place greater weight on advice from an algorithm when the algorithm exhibits adaptive capabilities relative to an algorithm not capable of adapting (0.63 vs 0.41; p = 0.05). These results corroborate my findings from Experiment 1 in a different financial setting and provide further evidence that individuals place more value on an algorithm's capability to adapt when facing high measurement uncertainty. Additionally, Experiment 2's results validate my algorithm adaptability manipulation and expectation that algorithm adaptability is an important factor that individuals consider when deciding the degree to which they will rely on algorithmic advice.

TABLE 5

Weight of Advice

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

	Algorithm Adaptability	
	Learning Algorithm	*Static Algorithm*
	0.65	0.41
	(0.09)	(0.09)
	[20]	[21]
	B	D

Panel B: ANOVA[a]

Source	Sum of Squares	*df*	*F*	*p*
Algorithm Adaptability	0.48	1	2.72	0.05†
Error	6.83	39		

Panel C: Simple Effects Test[a]

Source	*df*	*t*	*p*
Learning Algorithm vs. Static Algorithm (B vs D)	1,39	1.65	0.05†

Note: The dependent variable is participants' advice utilization, which is measured as weight of advice (WOA). WOA equals (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). I manipulate the adaptive capability of the algorithm as static algorithm versus learning algorithm (i.e., not capable of adapting versus capable adapting), between participants.
† *p*-values are equivalent to a one-tailed test, consistent with my directional predictions.

CHAPTER 4

CONCLUSION

Contribution and Implications

I provide experimental evidence on how the effect of measurement uncertainty and algorithm capability affect the weight accounting practitioners place on advice provided by an algorithm. I propose and find that when individuals face higher measurement uncertainty, they will weight an algorithm's advice more heavily, especially if the algorithm is a learning algorithm rather than a static algorithm. Furthermore, I also find that individuals' willingness to trust an algorithm mediates the joint effect of measurement uncertainty and algorithm capability on advice utilization. However, when measurement uncertainty is lower, algorithm capability has no differential effect on individual's advice utilization. My predictions build on advice-taking literature by examining algorithms as the advisor and whether an algorithm's capability affects individuals' advice utilization.

My results are important for accounting practitioners as companies continue moving towards implementing AI systems to assist accounting practitioners with more subjective and judgment-based tasks, such as complex estimates (Deloitte 2018c; KPMG 2020a). Prior literature finds that as tasks increase in subjectivity, individuals become more concerned that algorithms lack the necessary competencies to complete the task and as a result, are reluctant to rely on algorithmic evidence (Castelo et al. 2019). Accounting firms may take comfort in knowing that in my study, individuals exhibited a greater wiliness to utilize advice from algorithms when facing higher measurement uncertainty. Though it is important to note that this effect is only significant when advice is provided by a learning algorithm. My findings can also inform other disciplines how individuals, such as physicians or investment analysts, facing decisions in uncertain environments will utilize advice from advanced technology.

Although a learning algorithm is inherently more capable than a static algorithm, practitioners have voiced concerns regarding an inability to trust a learning algorithm due to a lack of understanding regarding how the algorithm develops its recommendation (i.e., decision making processes), which is commonly referred to as the “black box” concern (CPA Canada and AICPA 2019). If the inability to understand the advisor’s decision process deters individuals from relying on the advisor’s recommendation, then given that a static algorithm’s process is more clear and transparent than a learning algorithms’ process, individuals could equally or more heavily weight a static algorithm’s recommendation compared to a learning algorithm’s recommendation (Yaniv and Kleinberger 2000; Yaniv 2004). Furthermore, given that documentation and justification for accounting choices are important features of the accounting profession (Koonce, Anderson, and Marchant 1995; Kadous, Leiby, and Peecher 2013; Deloitte 2015), regardless of how capable an algorithm is, accounting practitioners may disregard an algorithm that lacks interpretability and transparency. If individuals are unwilling to trust and rely on advice provided by learning algorithms, then firms may not capitalize on resources spent on developing these advanced technologies. It may be comforting for accounting practitioners to know that my results show that individuals are more than willing to rely on learning algorithms. However, a potential consequence is that accounting practitioners and auditors could face challenges when documenting and justifying their estimate, which could increase litigation risk or management not accepting the auditors’ estimate.

Limitations and Future Research Opportunities

I acknowledge several limitations in this study. First, participants are provided an abbreviated description of the algorithm and how the model works. It is possible that accounting practitioners would receive more information or training on utilizing advanced technology to assist with developing complex estimates. One important aspect of providing more information on an algorithms' processes is understanding how much information is adequate. In other words, there may be a point where providing too much information on an algorithm's processes would reduce an individual's willingness to rely on the algorithm. I leave this for future studies to examine potential interventions that can increase reliance on evidence provided by an algorithm, such as increasing justifiability or transparency. Second, in my experiment, participants first provide their initial estimate, then receive the algorithm's estimate prior to submitting their final estimate. I acknowledge that this two-stage process of submitting an initial and final estimate may not reflect the actual process managers follow when utilizing technology to develop an estimate. However, it is reasonable to assume that managers will gather information to develop a reasonable expectation of the estimate's value and then reconcile their expectation with an additional evidence (i.e., algorithm's estimate). To the extent that the participants' development of their initial estimate reflects the process of managers gathering information to develop an expectation of the estimate's value, I would expect my results to generalize to settings where managers utilize technology to develop an estimate. Finally, my participants do not have any prior experience using the algorithm. It is possible that overtime, the degree of reliance on less capable algorithms would increase to a similar level of more capable algorithms. However, based on advice-taking literature, individuals tend to exhibit lower reliance on individuals that they view as inherently less capable than themselves. This finding is relatively consistent and robust across various decision domains. Future studies could also examine whether reliance on algorithmic evidence increases with repeated exposure in highly uncertain decision domains.

APPENDIX A: RESEARCH INSTRUMENT – EXPERIMENT 1

This appendix presents screenshots of the research instrument for Experiment 1 (beginning on the next page) provided to participants. Participants were provided with a link used to access the case information through Qualtrics. Text boxes (in red font) were added to the screenshots to clarify where necessary.

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You are being invited to take part in a research study about judgment and decisions. Although you will not get personal benefit from taking part in this research study, your responses may help us understand more about the financial environment. There are no known risks to participating in this study.

Do not take this survey on a mobile or tablet device, your submission will not be approved. Please take it on a tablet or desktop only.

We hope to receive completed questionnaires from about 200 people, so your answers are very important to us. We estimate that the survey will take no more than 15 minutes. You will be paid $1.75 USD (allow for variance due to conversion rate) for completing this survey.

Your response to the survey is anonymous, which means no names will appear or be used on research documents or be used in presentations or publications. The research team will not know that any information you provided came from you, nor even whether you participated in the study. Participation is voluntary. By returning your responses, you freely provide consent and acknowledge your rights as a voluntary participant.

If you have any questions about the study, please feel free to ask; my contact information is given below. If you have complaints, suggestions, or questions about your rights as a research volunteer, contact the staff in the University of Kentucky Office of Research Integrity at 859-257-9428 or toll-free at 1-866-400-9428.

Thank you in advance for your assistance with this important project.

Jenny Wang
Gatton College of Business & Economics
University of Kentucky
E-MAIL: jennifer.wang@uky.edu

Please select one of the two options below:

I **consent** with the information above and volunteer to take the survey.

I **do not consent** with the information above and do not want to take the survey.

→

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General Instructions

Your Role: You are a manager at Heartland Resource Corporation (hereafter, "Heartland") - a publicly-traded oil and gas company located in the United States that engages in acquisition, exploration, and production of crude oil and natural gas.

Your Task: Heartland's CFO has asked you to estimate the ***fair value of a patent***. In the following case, you will be provided with background information about the patent. After reading the information provided, you will ***project patent-related sales revenue***, which is a key input for estimating the ***patent's fair value***. You will then receive a series of questions about the case and demographic information.

When completing the case, please keep in mind that there are no correct answers other than your honest judgments about the information provided.

Please also be aware that the case is ***not intended to include all of the information*** that would be typically available in a real-world situation. Therefore, for the purposes of this study, please base your judgments only on the information provided.

→

Heartland's "Deep Imaging" Patent

In 2018, your company (Heartland) acquired a patent for a new drill called "Deep Imaging". The Deep Imaging drill tracks subsurface geological composition and provides live diagnostic data to the engineers drilling for natural gas. The Deep Imaging drill enables companies to maximize production and avoid nonproductive drilling and wasteful exploration spending. The patent obtained by Heartland gives the company the legal right to exclude others from commercial exploitation of the invention.

At the beginning of 2019, about one year after obtaining the patent, Heartland entered into an agreement with a manufacturing firm named KSR, Inc. ("KSR"). The agreement gave KSR exclusive rights to manufacture and sell the Deep Imaging drill for 11 years, which is the remaining useful life of the patent. In exchange, Heartland receives a yearly royalty payment in the amount of 10% of ***revenue from Deep Imaging drill sales***. The drills are quite expensive, selling for about $4 million each. In 2019, KSR had $45 million sales revenue from Deep Imaging drill sales and Heartland received royalty revenue of $4.5 million (i.e., 10% of $45 million) from KSR.

→

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Estimating the Fair Value of the Patent

Recently, changes in the business climate required Heartland's management to re-estimate the value of the Deep Imaging patent (i.e., the patent could be overvalued). Specifically, several competing drill technologies are being developed and will be on the market within the next 5 to 10 years, which would affect the demand for the Deep Imaging drill and thus, the royalty revenue received from KSR. If the patent is overvalued, then Heartland is required to reduce the recorded value of the patent and, as a consequence, earnings (i.e., net income) would be reduced as well.

→

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Heartland's management has asked you to use a discounted cash flow model to ***estimate the fair value of the Deep Imaging drill patent***. The discounted cash flow model estimates the value of the patent by converting projected future cash flows generated from Deep Imaging drill sales revenue into current-dollar amounts (i.e., present value). The patent's future cash flow is primarily driven by estimates of ***annual sales revenue*** related to the Deep Imaging drill.

In addition to projected future cash flows, other key inputs for a discounted cash flow model are the discount rate and the expected life of the asset. These key inputs are unobservable and are largely based on judgment and assumptions. Thus, applying the discounted cash flow approach ***requires a great deal of professional judgment*** to ensure that future expectations and inputs used in the model are reasonable and supportable.

→

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Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

Heartland receives a yearly royalty payment from KSR in the amount of 10% of the revenue from sales of the Deep Imaging drill.

True

False

The patent's projected future cash flow is primarily driven by estimates of the

Deep Imaging drill's annual sales revenue.

discount rate.

expected life of the asset.

←

→

<u>Fair Value of Patent: Estimating the Key Inputs for the Discounted Cash Flow Model</u>

Heartland's management estimated that the discount rate is 5% and that the expected remaining life of the asset is 10 years.

You will estimate the final key input for the discounted cash flow model, which is Deep Imaging drill's projected sales revenue. To assist you with estimating the sales revenue, your valuation team has gathered the following information on the next screen.

→

Low Measurement Uncertainty Conditions

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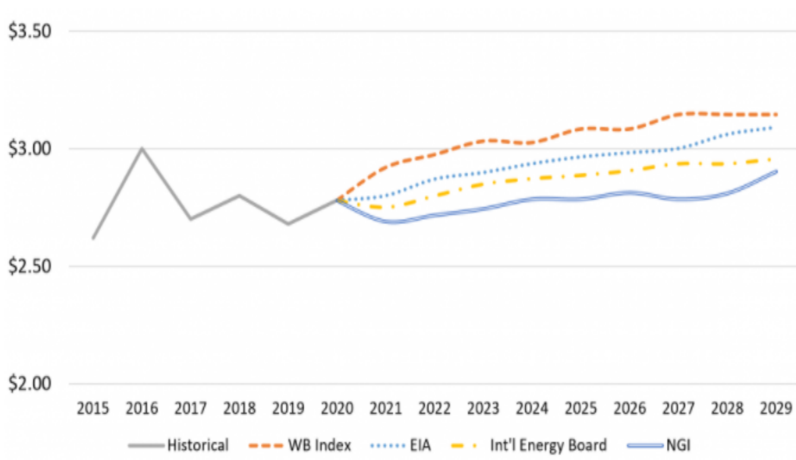
Additional Evidence Gathered

Your team gathered the following additional evidence to assist you in projecting the sales revenue of the Deep Imaging drill.

Forecasted natural gas price is a major macroeconomic input that affects projected revenues, and thus the estimated fair value of the Deep Imaging patent. Generally, increasing natural gas prices is a good macroeconomic indicator of demand for products from companies in the industry, especially from companies with products related to the extraction of natural gas. Thus, projected future natural gas prices are generally used as an indicator of whether ***projected revenues are reasonable***. Below is graph of historical natural gas prices and forecasted natural gas prices based on four nationally recognized price indices.

Natural Gas Forecasts Based on Four Major Price Indices



Analyst Quotes

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

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

→

High Measurement Uncertainty Conditions

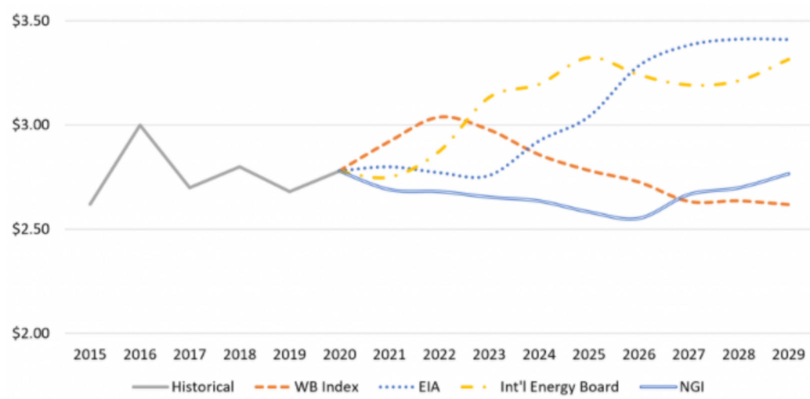
University of Kentucky

Additional Evidence Gathered

Your team gathered the following additional evidence to assist you in projecting the sales revenue of the Deep Imaging drill.

Forecasted natural gas price is a major macroeconomic input that affects projected revenues, and thus the estimated fair value of the Deep Imaging patent. Generally, increasing natural gas prices is a good macroeconomic indicator of demand for products from companies in the industry, especially from companies with products related to the extraction of natural gas. Thus, projected future natural gas prices are generally used as an indicator of whether ***projected revenues are reasonable***. Below is graph of historical natural gas prices and forecasted natural gas prices based on four nationally recognized price indices.

Natural Gas Forecasts Based on Four Major Price Indices



Analyst Quotes

"On average, natural gas prices are expected to increase modestly, but the four national price indices are quite divergent on their projections. The growing uncertainty surrounding the natural gas market makes 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 confident about future natural gas prices."

"On average, natural gas prices are expected to increase modestly, but the four national price indices are quite divergent on their projections. The growing uncertainty surrounding the natural gas market makes 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 confident about future natural gas prices."
[Analyst B]

←

→

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For the question below, please circle the number on the scale that represents your assessment. You may go back and review the information in the previous page.

1. How ***certain or uncertain*** are future natural gas prices?

Very Certain 1	2	3	4	5	6	Very Uncertain 7

← →

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Valuation Team's Expectations

Projected Revenue Growth Rate. You will project the sales revenue of the Deep Imaging drill by ***estimating the revenue growth rates percentage*** for each year. Your valuation team has provided some additional information regarding their expectations on revenue growth rates.

1. Growth Rate Years **2020 – 2025**: Based on prior sales performance of similar drills, your valuation team expects positive annual revenue growth rate as high as 15% from 2020 through 2025.
2. Growth Rate Years **2026 – 2029**: Due to the introduction of newer technology on the market, your valuation team expects negative annual revenue growth rate as low as -30% through the remainder of the patent's life.

→

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Valuation Team's Expectations

Projected Revenue Growth Rate. You will project the sales revenue of the Deep Imaging drill by ***estimating the revenue growth rates percentage*** for each year. Your valuation team has provided some additional information regarding their expectations on revenue growth rates.

1. Growth Rate Years 2020 – 2025: Based on prior sales performance of similar drills, your valuation team expects positive annual revenue growth rate as high as 15% from 2020 through 2025.
2. Growth Rate Years 2026 – 2029: Due to the introduction of newer technology on the market, your valuation team expects negative annual revenue growth rate as low as -30% through the remainder of the patent's life.

Instructions for using the DCF Spreadsheet. The discounted cash flow schedule is provided below to assist you with estimating the fair value of the patent.

1. In each blank yellow box below, enter in your estimate of the percentage of ***annual revenue growth rate*** for each year based on ***your professional judgment*** and all of the information provided to you.
   a. For years that you estimate ***positive*** annual revenue growth, enter in a ***positive number*** in the yellow box.
   b. For years that you estimate a ***negative*** annual revenue growth (i.e., the growth rate in the current year is lower than the prior year), enter in a ***negative number*** in the yellow box.
2. Once you finish entering in the percentages, in the spreadsheet below, the number in the blue box is the estimated fair value of the patent that you have calculated. Please enter that amount in the empty box located at the bottom of this screen.

Royalty Discounted Cash Flow Analysis

ALL NUMBERS ARE IN MILLIONS

2019 Revenue	$ 45.0									
Discount rate:	5%									
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 Dril	$ 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	$ -									

The number above in the blue box is your estimate of the fair value of the Deep Imaging Patent. Please enter your estimate below (**only enter numbers, no words, and without the $**):

→

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2. **Your Confidence**: How ***confident*** are you in ***your ability*** to accurately estimate the fair value of the Patent?

Not at All Confident 1	2	3	4	5	6	Very Confident 7

→

Static Algorithm Conditions

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Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

Your company (Heartland) has developed a proprietary software system, the E-Val System, that you and your valuation team can use to help with estimating asset and liability valuations, such as the fair value of the Deep Imaging patent. To develop the E-Val system, your company partnered with a large international technology firm with leading experts in developing prediction models. Additionally, your company gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. Your company has invested significant resources developing and testing the E-Val system.

→

Static Algorithm Conditions

Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

Your company (Heartland) has developed a proprietary software system, the E-Val System, that you and your valuation team can use to help with estimating asset and liability valuations, such as the fair value of the Deep Imaging patent. To develop the E-Val system, your company partnered with a large international technology firm with leading experts in developing prediction models. Additionally, your company gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. Your company has invested significant resources developing and testing the E-Val system.

The E-Val system utilizes ***static algorithm*** to detect patterns in the data and provide assistance with estimates. Static algorithms are detailed mapping 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 methods are ***fixed and do 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_n) and predictor weights (β_n) are ***fixed and stay constant***.

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

← →

Static Algorithm Conditions

Heartland's E-Val System

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

All changes and updates to the model are reviewed and approved by your company. Your company's management has indicated that the overall predictions from the E-Val system are reasonably accurate and are ***considered an approved source of information***. However, while the system aims to make well-calibrated predictions, it will not be perfect. Additionally, the resulting estimates will reflect significant measurement uncertainty, meaning that the actual fair value of the asset or liability could be materially different from the E-Val's estimate.

Firm guidance indicates that you and your team can use evidence from the E-Val system to help develop conclusions about fair value estimates. However, you and your valuation team are still free to use your own judgment.

← →

Static Algorithm Conditions

University of Kentucky

Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

1. The E-Val system relies on ***static and fixed*** algorithms that do ***not adapt over time*** to improve the accuracy of its estimation.

True.

False.

This information was not provided.

2. Your company, Heartland, views the E-Val system as an approved source of information.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

← →

Learning Algorithm Conditions

University of Kentucky

Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

Your company (Heartland) has developed a proprietary software system, the E-Val System, that you and your valuation team can use to help with estimating asset and liability valuations, such as the fair value of the Deep Imaging patent. To develop the E-Val system, your company partnered with a large international technology firm with leading experts in developing prediction models. Additionally, your company gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. Your company has invested significant resources developing and testing the E-Val system.

→

Learning Algorithm Conditions

Heartland's E-Val System

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The E-Val system utilizes ***learning algorithms*** (i.e., machine learning technology) that can detect patterns in the data and provide assistance with estimates. Learning algorithms are detailed mapping 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 methods ***adapt and improve 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.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}_{\boxed{\text{New predictors can be identified by the E-Val system}}}$$

→

Learning Algorithm Conditions

University of Kentucky

Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

Your company (Heartland) has developed a proprietary software system, the E-Val System, that you and your valuation team can use to help with estimating asset and liability valuations, such as the fair value of the Deep Imaging patent. To develop the E-Val system, your company partnered with a large international technology firm with leading experts in developing prediction models. Additionally, your company gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. Your company has invested significant resources developing and testing the E-Val system.

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$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}_{\text{New predictors can be identified by the E-Val system}}$$

All changes and updates to the model are reviewed and approved by your company. Your company's management has indicated that the overall predictions from the E-Val system are reasonably accurate and are ***considered an approved source of information***. However, while the system aims to make well-calibrated predictions, it will not be perfect. Additionally, the resulting estimates will reflect significant measurement uncertainty, meaning that the actual fair value of the asset or liability could be materially different from the E-Val's estimate.

Firm guidance indicates that you and your team can use evidence from the E-Val system to help develop conclusions about fair value estimates. However, you and your valuation team are still free to use your own judgment.

→

Learning Algorithm Conditions

University of Kentucky

Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

1. The E-Val system relies on ***machine learning*** algorithms and ***can learn and adapt over time*** to improve the accuracy of its estimation.

True.

False.

This information was not provided.

2. Your company, Heartland, views the E-Val system as an approved source of information.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

←

→

University of Kentucky

E-Val System's Estimate of the Patent's Fair Value

Your firm's E-Val system developed a fair value estimate of the Deep Imaging Patent using a discounted cash flow model. Both your estimate and the E-Val System's estimate suggest that the patent is overvalued and that its value needs to be reduced. However, the E-Val system's fair value estimate ***differed*** from your fair value estimate.

→

Note: Participants enter in their initial estimate on page 84. As an example, I entered in 100, which populates below under "Your initial estimate". The E-Val System's estimate is calculated as 20% less than the participant's initial estimate. In the example below, the E-Val System's estimate is $80 million.

University of Kentucky

E-Val System's Estimate of the Patent's Fair Value

Your firm's E-Val system developed a fair value estimate of the Deep Imaging Patent using a discounted cash flow model. Both your estimate and the E-Val System's estimate suggest that the patent is overvalued and that its value needs to be reduced. However, the E-Val system's fair value estimate ***differed*** from your fair value estimate.

Upon further investigation, the differences in the fair value estimate are primarily attributed to differences in the projected revenues, which then affects estimated future cash flows. Although the E-Val System agrees that due to emerging technology from competitors the growth rate will being to decline, the E-Val System estimated the decline to start earlier than what you projected. Additionally, projected revenues are generally lower than yours. Ultimately, the E-Val System estimate of the patent's fair value is lower than your patent fair value estimate.

Your initial estimate the patent's fair value was $100 million, but the E-Val System's estimate is **$80 million**.

	Your initial estimate	E-Val System's estimate
Estimated Fair Value of Patent	$100 million	$80 million
Fair Value Difference:	**$-20 million**	

Earnings Impact of Patent Valuation

As indicated in the table above, the E-Val's fair value estimate is $20 lower your estimate. Recall that a lower fair value estimate will result a greater reduction of the recorded value of the patent, which will reduce reported earnings.

→

University of Kentucky

E-Val System's Estimate of the Patent's Fair Value

Your firm's E-Val system developed a fair value estimate of the Deep Imaging Patent using a discounted cash flow model. Both your estimate and the E-Val System's estimate suggest that the patent is overvalued and that its value needs to be reduced. However, the E-Val system's fair value estimate ***differed*** from your fair value estimate.

Upon further investigation, the differences in the fair value estimate are primarily attributed to differences in the projected revenues, which then affects estimated future cash flows. Although the E-Val System agrees that due to emerging technology from competitors the growth rate will being to decline, the E-Val System estimated the decline to start earlier than what you projected. Additionally, projected revenues are generally lower than yours. Ultimately, the E-Val System estimate of the patent's fair value is lower than your patent fair value estimate.

Your initial estimate the patent's fair value was $100 million, but the E-Val System's estimate is **$80 million**.

	Your initial estimate	E-Val System's estimate
Estimated Fair Value of Patent	$100 million	$80 million
Fair Value Difference:	**$-20 million**	

Earnings Impact of Patent Valuation

As indicated in the table above, the E-Val's fair value estimate is $20 lower your estimate. Recall that a lower fair value estimate will result a greater reduction of the recorded value of the patent, which will reduce reported earnings.

Your Final Estimate of the Patent's Fair Value

As the manager of Heartland, you will ultimately decide the fair value estimate that you will report to management.

Decide on the final fair value estimate of the patent that you will report to management. Values can reflect your original estimate ($100 million), the E-Val System's estimate ($80 million), or anywhere in between.

Please enter your ***final fair value estimate*** for the patent below (without the $):

→

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For questions below, please select the number on the scale that represents your assessment.

1. **Your Confidence**: How ***confident*** are you in ***your ability*** to accurately estimate the fair value of the Patent?

Not at All Confident 1	2	3	4	5	6	Very Confident 7

→

University of Kentucky

For questions below, please select the number on the scale that represents your assessment.

2. **Difficulty of Estimate**: How ***difficult*** was it to accurately estimate the fair value of the patent?

Not at All Difficult 1	2	3	4	5	6	Very Difficult 7

3. **Relative Confidence**: How ***confident*** are you in ***your ability*** relative to the ***E-Val system's ability*** to accurately estimate the fair value of the Patent?

More Confident in E-Val System's Ability 1	2	3	4	5	6	More Confident in My Own Ability 7

→

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4. **Decision-Making Process**: How *similar* is the E-Val system's ***decision-making process*** compared to your decision-making process?

Not at All Similar 1	2	3	4	5	6	Very Similar 7

5. **Comfort**: How ***comfortable*** do you feel relying on advice provided by the E-Val system?

Not at All Comfortable 1	2	3	4	5	6	Very Comfortable 7

6. **Quality of Estimate – E-Val System**: What is the ***quality*** of the E-Val system's estimate of the Patent's fair value?

Very Low Quality 1	2	3	4	5	6	Very High Quality 7

→

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<u>For questions on this page, please rate on a scale of Strongly Disagree to Strongly Agree.</u>

7. When I am uncertain about a decision, I believe the E-Val system rather than myself.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

8. The E-Val system ***responds the same*** way under the same conditions over time.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

9. I ***understand*** the process that the E-Val system uses to assist me with decisions.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

10. I believe advice from the E-Val system even when I don't know for certain that it is correct.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

11. The E-Val system is trustworthy.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

→

University of Kentucky

Questions About the Case

1. Assess the degree of uncertainty associated with estimating the patent's fair value.

High **Certainty** 1	2	3	4	5	6	High **Uncertainty** 7

2. Among the following two descriptions, which is more similar to the algorithm that best describes your company's E-Val system.

Utilized static algorithms and prediction methods that are fixed and do not adapt over time.

Utilized machine learning algorithms and prediction methods that adapt and improve over time.

Similar to this 1	2	3	4	5	6	Similar to this 7

3. How hard did you work on this Patent Fair Value valuation case? (Your response to this question **will not affect** your compensation for this survey)

Not Hard at All 1	2	3	4	5	6	Extremely Hard 7

→

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The following questions concern you and your experiences. This information will not be used, in any way, to identify you.

1. How many finance classes have you taken? (If zero, enter in 0).

2. How many accounting classes have you taken? (If zero, enter in 0).

3. How many years of work experience do you have? (If zero, enter in 0).

4. Rate your level of experience with making projections and forecasts.

No Experience at All 1	2	3	4	5	6	Highly Experienced 7

5. How comfortable are you relying on technology?

Not at All Comfortable 1	2	3	4	5	6	Very Comfortable 7

6. What is your gender?

Male

Female

Prefer not to answer

7. Enter your age.

8. What is your job description? (if unemployed, type in N/A)

9. What industry is your job in? (if unemployed, type in N/A)

→

University of Kentucky

You have now completed the case. Thank you very much for your help!

When you click the arrow below, your survey will be submitted and you will be redirected back to Prolific.

→

APPENDIX B: IRB CERTIFICATION – EXPERIMENT 1

University of Kentucky | Office of Research Integrity
IRB, RDRC

EXEMPTION CERTIFICATION

IRB Number: 55878

TO: Jennifer Wang, BS and MS
RCTF Graduate Scholarships
PI phone #: 5042147538

PI email: jennifer.wang@uky.edu

FROM: Chairperson/Vice Chairperson
Nonmedical Institutional Review Board (IRB)

SUBJECT: Approval for Exemption Certification

DATE: 1/8/2020

On 1/8/2020, it was determined that your project entitled "*Dissertation -* [redacted]eets federal criteria to qualify as an exempt study.

Because the study has been certified as exempt, you will not be required to complete continuation or final review reports. However, it is your responsibility to notify the IRB prior to making any changes to the study. Please note that changes made to an exempt protocol may disqualify it from exempt status and may require an expedited or full review.

The Office of Research Integrity will hold your exemption application for six years. Before the end of the sixth year, you will be notified that your file will be closed and the application destroyed. If your project is still ongoing, you will need to contact the Office of Research Integrity upon receipt of that letter and follow the instructions for completing a new exemption application. It is, therefore, important that you keep your address current with the Office of Research Integrity.

For information describing investigator responsibilities after obtaining IRB approval, download and read the document "PI Guidance to Responsibilities, Qualifications, Records and Documentation of Human Subjects Research" available in the online Office of Research Integrity's IRB Survival Handbook. Additional information regarding IRB review, federal regulations, and institutional policies may be found through ORI's web site. If you have questions, need additional information, or would like a paper copy of the above mentioned document, contact the Office of Research Integrity at 859-257-9428.

APPENDIX C: RESEARCH INSTRUMENT – EXPERIMENT 2

This appendix presents screenshots of the research instrument for Experiment 1 (beginning on the next page) provided to participants. Participants were provided with a paper copy of the case information. Text boxes (in red font) were added to the screenshots to clarify where necessary.

To: Prospective Research Study Participant:

You are being invited to take part in a research study about judgment and decisions. You are being invited to take part in this research because of **your financial knowledge and qualifications**.

Although you will not get personal benefit from taking part in this research study, your responses may help us understand more about the financial environment. There are no known risks to participating in this study.

We hope to receive completed questionnaires from about 100 people, so your answers are very important to us. Of course, you have a choice about whether or not to complete the survey/questionnaire, but if you do participate, you are free to discontinue at any time.

Your response to the survey is anonymous, which means no names will appear or be used on research documents or be used in presentations or publications. The research team will not know that any information you provided came from you, nor even whether you participated in the study. Participation is voluntary. By returning your responses, you freely provide consent and acknowledge your rights as a voluntary participant.

If you have any questions about the study, please feel free to ask; my contact information is given below. If you have complaints, suggestions, or questions about your rights as a research volunteer, contact the staff in the University of Kentucky Office of Research Integrity at 859-257-9428 or toll-free at 1-866-400-9428.

Thank you in advance for your assistance with this important project.

Jenny Wang
Gatton College of Business & Economics, University of Kentucky
E-MAIL: jennifer.wang@uky.edu

University of Kentucky

General Instructions

Your Role: You are a manager at Heartland Resource Corporation (hereafter, "Heartland") - a publicly-traded oil and gas company located in the United States that engages in acquisition, exploration, and production of crude oil and natural gas.

Your Task: Heartland's CFO has asked you to estimate the ***fair value of a patent***. In the following case, you will be provided with background information about the patent. After reading the information provided, you will ***project patent-related sales revenue***, which is a key input for estimating the ***patent's fair value***. You will then receive a series of questions about the case and demographic information.

When completing the case, please keep in mind that there are no correct answers other than your honest judgments about the information provided.

Please also be aware that the case is ***not intended to include all of the information*** that would be typically available in a real-world situation. Therefore, for the purposes of this study, please base your judgments only on the information provided.

→

University of Kentucky

Heartland's "Deep Imaging" Patent

In 2018, your company (Heartland) acquired a patent for a new drill called "Deep Imaging". The Deep Imaging drill tracks subsurface geological composition and provides live diagnostic data to the engineers drilling for natural gas. The Deep Imaging drill enables companies to maximize production and avoid nonproductive drilling and wasteful exploration spending. The patent obtained by Heartland gives the company the legal right to exclude others from commercial exploitation of the invention.

At the beginning of 2019, about one year after obtaining the patent, Heartland entered into an agreement with a manufacturing firm named KSR, Inc. ("KSR"). The agreement gave KSR exclusive rights to manufacture and sell the Deep Imaging drill for 11 years, which is the remaining useful life of the patent. In exchange, Heartland receives a yearly royalty payment in the amount of 10% of ***revenue from Deep Imaging drill sales***. The drills are quite expensive, selling for about $4 million each. In 2019, KSR had $45 million sales revenue from Deep Imaging drill sales and Heartland received royalty revenue of $4.5 million (i.e., 10% of $45 million) from KSR.

→

University of Kentucky

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In 2018, your company (Heartland) acquired a patent for a new drill called "Deep Imaging". The Deep Imaging drill tracks subsurface geological composition and provides live diagnostic data to the engineers drilling for natural gas. The Deep Imaging drill enables companies to maximize production and avoid nonproductive drilling and wasteful exploration spending. The patent obtained by Heartland gives the company the legal right to exclude others from commercial exploitation of the invention.

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<u>**Estimating the Fair Value of the Patent**</u>

Recently, changes in the business climate required Heartland's management to re-estimate the value of the Deep Imaging patent (i.e., the patent could be overvalued). Specifically, several competing drill technologies are being developed and will be on the market within the next 5 to 10 years, which would affect the demand for the Deep Imaging drill and thus, the royalty revenue received from KSR. If the patent is overvalued, then Heartland is required to reduce the recorded value of the patent and, as a consequence, earnings (i.e., net income) would be reduced as well.

→

University of Kentucky

Heartland's "Deep Imaging" Patent

In 2018, your company (Heartland) acquired a patent for a new drill called "Deep Imaging". The Deep Imaging drill tracks subsurface geological composition and provides live diagnostic data to the engineers drilling for natural gas. The Deep Imaging drill enables companies to maximize production and avoid nonproductive drilling and wasteful exploration spending. The patent obtained by Heartland gives the company the legal right to exclude others from commercial exploitation of the invention.

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Estimating the Fair Value of the Patent

Recently, changes in the business climate required Heartland's management to re-estimate the value of the Deep Imaging patent (i.e., the patent could be overvalued). Specifically, several competing drill technologies are being developed and will be on the market within the next 5 to 10 years, which would affect the demand for the Deep Imaging drill and thus, the royalty revenue received from KSR. If the patent is overvalued, then Heartland is required to reduce the recorded value of the patent and, as a consequence, earnings (i.e., net income) would be reduced as well.

Heartland's management has asked you to use a discounted cash flow model to ***estimate the fair value of the Deep Imaging drill patent***. The discounted cash flow model estimates the value of the patent by converting projected future cash flows generated from Deep Imaging drill sales revenue into current-dollar amounts (i.e., present value). The patent's future cash flow is primarily driven by estimates of ***annual sales revenue*** related to the Deep Imaging drill.

In addition to projected future cash flows, other key inputs for a discounted cash flow model are the discount rate and the expected life of the asset. These key inputs are unobservable and are largely based on judgment and assumptions. Thus, applying the discounted cash flow approach ***requires a great deal of professional judgment*** to ensure that future expectations and inputs used in the model are reasonable and supportable.

→

University of Kentucky

Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

Heartland receives a yearly royalty payment from KSR in the amount of 10% of the revenue from sales of the Deep Imaging drill.

True

False

The patent's projected future cash flow is primarily driven by estimates of the

Deep Imaging drill's annual sales revenue.

discount rate.

expected life of the asset.

← →

University of Kentucky

Fair Value of Patent: Estimating the Key Inputs for the Discounted Cash Flow Model

Heartland's management estimated that the discount rate is 5% and that the expected remaining life of the asset is 10 years.

You will estimate the final key input for the discounted cash flow model, which is Deep Imaging drill's projected sales revenue. To assist you with estimating the sales revenue, your valuation team has gathered the following information on the next screen.

→

Low Measurement Uncertainty Conditions

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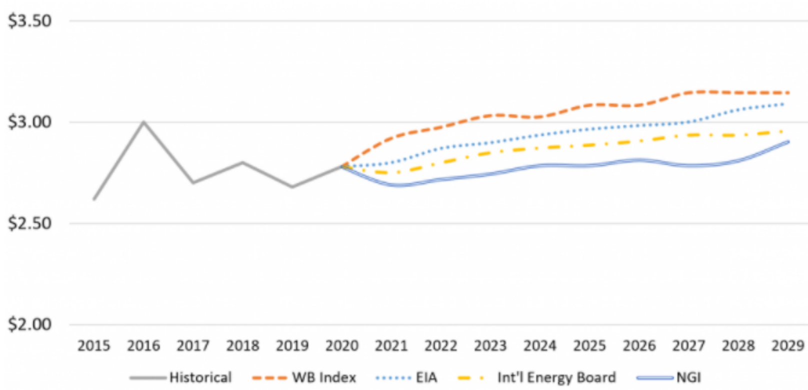
Additional Evidence Gathered

Your team gathered the following additional evidence to assist you in projecting the sales revenue of the Deep Imaging drill.

Forecasted natural gas price is a major macroeconomic input that affects projected revenues, and thus the estimated fair value of the Deep Imaging patent. Generally, increasing natural gas prices is a good macroeconomic indicator of demand for products from companies in the industry, especially from companies with products related to the extraction of natural gas. Thus, projected future natural gas prices are generally used as an indicator of whether ***projected revenues are reasonable***. Below is graph of historical natural gas prices and forecasted natural gas prices based on four nationally recognized price indices.

Natural Gas Forecasts Based on Four Major Price Indices



Analyst Quotes

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

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

→

High Measurement Uncertainty Conditions

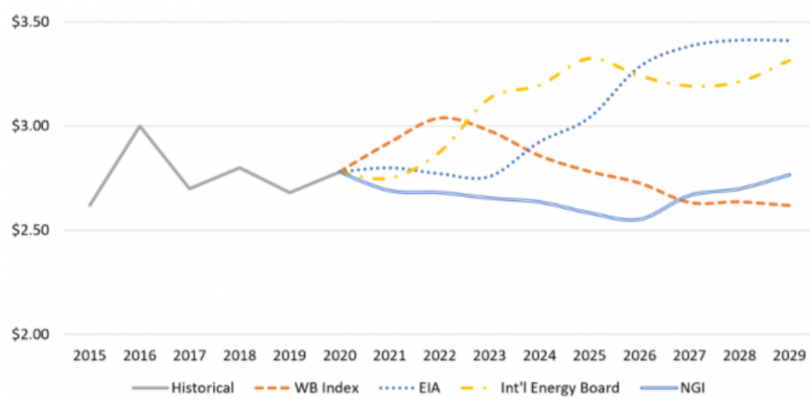
University of Kentucky

Additional Evidence Gathered

Your team gathered the following additional evidence to assist you in projecting the sales revenue of the Deep Imaging drill.

Forecasted natural gas price is a major macroeconomic input that affects projected revenues, and thus the estimated fair value of the Deep Imaging patent. Generally, increasing natural gas prices is a good macroeconomic indicator of demand for products from companies in the industry, especially from companies with products related to the extraction of natural gas. Thus, projected future natural gas prices are generally used as an indicator of whether ***projected revenues are reasonable***. Below is graph of historical natural gas prices and forecasted natural gas prices based on four nationally recognized price indices.

Natural Gas Forecasts Based on Four Major Price Indices



Analyst Quotes

"On average, natural gas prices are expected to increase modestly, but the four national price indices are quite divergent on their projections. The growing uncertainty surrounding the natural gas market makes 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 confident about future natural gas prices."

"On average, natural gas prices are expected to increase modestly, but the four national price indices are quite divergent on their projections. The growing uncertainty surrounding the natural gas market makes 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 confident about future natural gas prices."
[Analyst B]

← →

University of Kentucky

For the question below, please circle the number on the scale that represents your assessment. You may go back and review the information in the previous page.

1. How ***certain or uncertain*** are future natural gas prices?

Very Certain 1	2	3	4	5	6	Very Uncertain 7

← →

University of Kentucky

<u>**Valuation Team's Expectations**</u>

Projected Revenue Growth Rate. You will project the sales revenue of the Deep Imaging drill by ***estimating the revenue growth rates percentage*** for each year. Your valuation team has provided some additional information regarding their expectations on revenue growth rates.

1. Growth Rate Years **2020 – 2025**: Based on prior sales performance of similar drills, your valuation team expects positive annual revenue growth rate as high as 15% from 2020 through 2025.
2. Growth Rate Years **2026 – 2029**: Due to the introduction of newer technology on the market, your valuation team expects negative annual revenue growth rate as low as -30% through the remainder of the patent's life.

→

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Valuation Team's Expectations

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2. Growth Rate Years 2026 – 2029: Due to the introduction of newer technology on the market, your valuation team expects negative annual revenue growth rate as low as -30% through the remainder of the patent's life.

Instructions for using the DCF Spreadsheet. The discounted cash flow schedule is provided below to assist you with estimating the fair value of the patent.

1. In each blank yellow box below, enter in your estimate of the percentage of ***annual revenue growth rate*** for each year based on ***your professional judgment*** and all of the information provided to you.
   a. For years that you estimate ***positive*** annual revenue growth, enter in a ***positive number*** in the yellow box.
   b. For years that you estimate a ***negative*** annual revenue growth (i.e., the growth rate in the current year is lower than the prior year), enter in a ***negative number*** in the yellow box.
2. Once you finish entering in the percentages, in the spreadsheet below, the number in the blue box is the estimated fair value of the patent that you have calculated. Please enter that amount in the empty box located at the bottom of this screen.

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 Dril	$ 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	$ -									

The number above in the blue box is your estimate of the fair value of the Deep Imaging Patent. Please enter your estimate below (**only enter numbers, no words, and without the $**):

→

University of Kentucky

2. **Your Confidence**: How ***confident*** are you in ***your ability*** to accurately estimate the fair value of the Patent?

Not at All Confident 1	2	3	4	5	6	Very Confident 7

→

Static Algorithm Conditions

University of Kentucky

Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

Your company (Heartland) has developed a proprietary software system, the E-Val System, that you and your valuation team can use to help with estimating asset and liability valuations, such as the fair value of the Deep Imaging patent. To develop the E-Val system, your company partnered with a large international technology firm with leading experts in developing prediction models. Additionally, your company gathered input from valuation specialists with expertise in determining fair value of assets and liabilities. Your company has invested significant resources developing and testing the E-Val system.

→

Static Algorithm Conditions

University of Kentucky

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The E-Val system utilizes ***static algorithm*** to detect patterns in the data and provide assistance with estimates. Static algorithms are detailed mapping 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 methods are ***fixed and do 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_n) and predictor weights (β_n) are ***fixed and stay constant***.

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

←

→

Static Algorithm Conditions

University of Kentucky

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

All changes and updates to the model are reviewed and approved by your company. Your company's management has indicated that the overall predictions from the E-Val system are reasonably accurate and are ***considered an approved source of information***. However, while the system aims to make well-calibrated predictions, it will not be perfect. Additionally, the resulting estimates will reflect significant measurement uncertainty, meaning that the actual fair value of the asset or liability could be materially different from the E-Val's estimate.

Firm guidance indicates that you and your team can use evidence from the E-Val system to help develop conclusions about fair value estimates. However, you and your valuation team are still free to use your own judgment.

← →

Static Algorithm Conditions

University of Kentucky

Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

1. The E-Val system relies on ***static and fixed*** algorithms that do ***not adapt over time*** to improve the accuracy of its estimation.

True.

False.

This information was not provided.

2. Your company, Heartland, views the E-Val system as an approved source of information.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

← →

Learning Algorithm Conditions

University of Kentucky

<u>Heartland's E-Val System</u>

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

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→

Learning Algorithm Conditions

University of Kentucky

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The E-Val system utilizes ***learning algorithms*** (i.e., machine learning technology) that can detect patterns in the data and provide assistance with estimates. Learning algorithms are detailed mapping 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 methods ***adapt and improve 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.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}_{\text{New predictors can be identified by the E-Val system}}$$

→

Learning Algorithm Conditions

University of Kentucky

Heartland's E-Val System

Before submitting your final estimate to Heartland management, you ***receive a fair value estimate*** of the patent developed by your company's software system named the ***E-Val System***.

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$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \underbrace{\boldsymbol{\beta_n X_n}}_{\boxed{\text{New predictors can be identified by the E-Val system}}}$$

All changes and updates to the model are reviewed and approved by your company. Your company's management has indicated that the overall predictions from the E-Val system are reasonably accurate and are ***considered an approved source of information***. However, while the system aims to make well-calibrated predictions, it will not be perfect. Additionally, the resulting estimates will reflect significant measurement uncertainty, meaning that the actual fair value of the asset or liability could be materially different from the E-Val's estimate.

Firm guidance indicates that you and your team can use evidence from the E-Val system to help develop conclusions about fair value estimates. However, you and your valuation team are still free to use your own judgment.

→

Learning Algorithm Conditions

University of Kentucky

Please answer the following questions. You may go back and review the information in the previous page. You must answer all of the following questions correctly before moving on.

1. The E-Val system relies on ***machine learning*** algorithms and ***can learn and adapt over time*** to improve the accuracy of its estimation.

True.

False.

This information was not provided.

2. Your company, Heartland, views the E-Val system as an approved source of information.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

← →

University of Kentucky

E-Val System's Estimate of the Patent's Fair Value

Your firm's E-Val system developed a fair value estimate of the Deep Imaging Patent using a discounted cash flow model. Both your estimate and the E-Val System's estimate suggest that the patent is overvalued and that its value needs to be reduced. However, the E-Val system's fair value estimate ***differed*** from your fair value estimate.

→

Note: Participants enter in their initial estimate on page 116. As an example, I entered in 100, which populates below under "Your initial estimate". The E-Val System's estimate is calculated as 20% less than the participant's initial estimate. In the example below, the E-Val System's estimate is $80 million.

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E-Val System's Estimate of the Patent's Fair Value

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Upon further investigation, the differences in the fair value estimate are primarily attributed to differences in the projected revenues, which then affects estimated future cash flows. Although the E-Val System agrees that due to emerging technology from competitors the growth rate will being to decline, the E-Val System estimated the decline to start earlier than what you projected. Additionally, projected revenues are generally lower than yours. Ultimately, the E-Val System estimate of the patent's fair value is lower than your patent fair value estimate.

Your initial estimate the patent's fair value was $100 million, but the E-Val System's estimate is **$80 million**.

	Your initial estimate	E-Val System's estimate
Estimated Fair Value of Patent	$100 million	$80 million
Fair Value Difference:	**$-20 million**	

Earnings Impact of Patent Valuation

As indicated in the table above, the E-Val's fair value estimate is $20 lower your estimate. Recall that a lower fair value estimate will result a greater reduction of the recorded value of the patent, which will reduce reported earnings.

→

E-Val System's Estimate of the Patent's Fair Value

Your firm's E-Val system developed a fair value estimate of the Deep Imaging Patent using a discounted cash flow model. Both your estimate and the E-Val System's estimate suggest that the patent is overvalued and that its value needs to be reduced. However, the E-Val system's fair value estimate ***differed*** from your fair value estimate.

Upon further investigation, the differences in the fair value estimate are primarily attributed to differences in the projected revenues, which then affects estimated future cash flows. Although the E-Val System agrees that due to emerging technology from competitors the growth rate will being to decline, the E-Val System estimated the decline to start earlier than what you projected. Additionally, projected revenues are generally lower than yours. Ultimately, the E-Val System estimate of the patent's fair value is lower than your patent fair value estimate.

Your initial estimate the patent's fair value was $100 million, but the E-Val System's estimate is **$80 million**.

	Your initial estimate	E-Val System's estimate
Estimated Fair Value of Patent	$100 million	$80 million
Fair Value Difference:	**$-20 million**	

Earnings Impact of Patent Valuation

As indicated in the table above, the E-Val's fair value estimate is $20 lower your estimate. Recall that a lower fair value estimate will result a greater reduction of the recorded value of the patent, which will reduce reported earnings.

Your Final Estimate of the Patent's Fair Value

As the manager of Heartland, you will ultimately decide the fair value estimate that you will report to management.

Decide on the final fair value estimate of the patent that you will report to management. Values can reflect your original estimate ($100 million), the E-Val System's estimate ($80 million), or anywhere in between.

Please enter your ***final fair value estimate*** for the patent below (without the $):

→

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<u>**For questions below, please select the number on the scale that represents your assessment.**</u>

1. **Your Confidence**: How ***confident*** are you in ***your ability*** to accurately estimate the fair value of the Patent?

Not at All Confident 1	2	3	4	5	6	Very Confident 7

→

University of Kentucky

<u>For questions below, please select the number on the scale that represents your assessment.</u>

2. **Difficulty of Estimate**: How ***difficult*** was it to accurately estimate the fair value of the patent?

Not at All Difficult 1	2	3	4	5	6	Very Difficult 7

3. **Relative Confidence**: How ***confident*** are you in ***your ability*** relative to the ***E-Val system's ability*** to accurately estimate the fair value of the Patent?

More Confident in E-Val System's Ability 1	2	3	4	5	6	More Confident in My Own Ability 7

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4. **Decision-Making Process**: How ***similar*** is the E-Val system's ***decision-making process*** compared to your decision-making process?

Not at All Similar 1	2	3	4	5	6	Very Similar 7

5. **Comfort**: How ***comfortable*** do you feel relying on advice provided by the E-Val system?

Not at All Comfortable 1	2	3	4	5	6	Very Comfortable 7

6. **Quality of Estimate – E-Val System**: What is the ***quality*** of the E-Val system's estimate of the Patent's fair value?

Very Low Quality 1	2	3	4	5	6	Very High Quality 7

→

For questions on this page, please rate on a scale of Strongly Disagree to Strongly Agree.

7. When I am uncertain about a decision, I believe the E-Val system rather than myself.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

8. The E-Val system ***responds the same*** way under the same conditions over time.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

9. I ***understand*** the process that the E-Val system uses to assist me with decisions.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

10. I believe advice from the E-Val system even when I don't know for certain that it is correct.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

11. The E-Val system is trustworthy.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7

→

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Questions About the Case

1. Assess the degree of uncertainty associated with estimating the patent's fair value.

High **Certainty** 1	2	3	4	5	6	High **Uncertainty** 7

2. Among the following two descriptions, which is more similar to the algorithm that best describes your company's E-Val system.

Utilized static algorithms and prediction methods that are fixed and do not adapt over time.

Utilized machine learning algorithms and prediction methods that adapt and improve over time.

Similar to this 1	2	3	4	5	6	Similar to this 7

3. How hard did you work on this Patent Fair Value valuation case? (Your response to this question **will not affect** your compensation for this survey)

Not Hard at All 1	2	3	4	5	6	Extremely Hard 7

→

University of Kentucky

The following questions concern you and your experiences. This information will not be used, in any way, to identify you.

1. How many finance classes have you taken? (If zero, enter in 0).

2. How many accounting classes have you taken? (If zero, enter in 0).

3. How many years of work experience do you have? (If zero, enter in 0).

4. Rate your level of experience with making projections and forecasts.

No Experience at All 1	2	3	4	5	6	Highly Experienced 7

5. How comfortable are you relying on technology?

Not at All Comfortable 1	2	3	4	5	6	Very Comfortable 7

6. What is your gender?

Male

Female

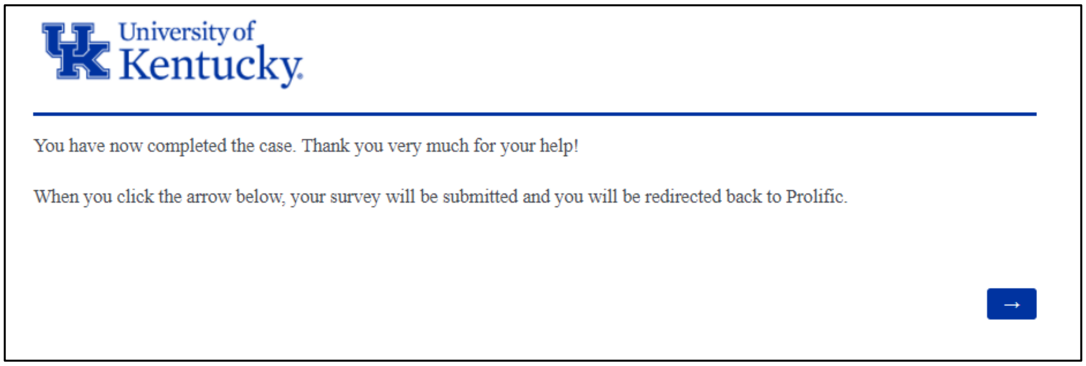
Prefer not to answer

7. Enter your age.

8. What is your job description? (if unemployed, type in N/A)

9. What industry is your job in? (if unemployed, type in N/A)

→


University of Kentucky

You have now completed the case. Thank you very much for your help!

When you click the arrow below, your survey will be submitted and you will be redirected back to Prolific.

General Instructions

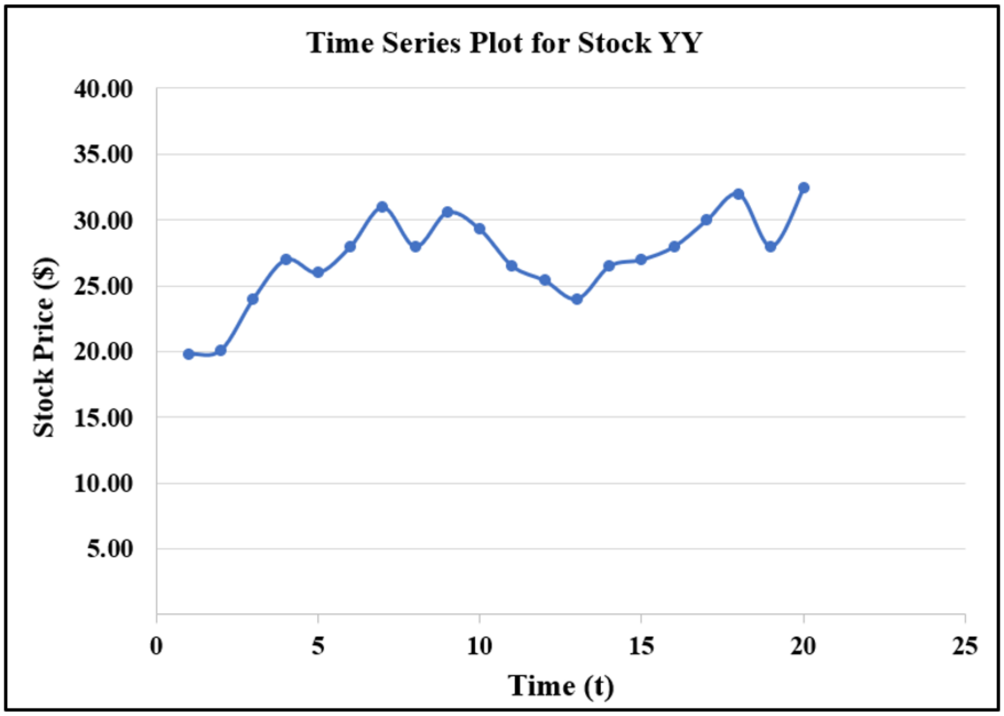
You are an equity analyst for a large investment management firm. Your job is to develop financial projections and **forecasts** that are used by investment advisors and brokers. In this role, equity analysts use many data-modeling programs and methodologies combined with performance and financial data to develop their forecasts.

In the following case, you will be provided with information to forecast a closing price of a stock. You will then receive a series of questions about the case and demographic factors.

When completing the case, please keep in mind that there are no correct answers other than your honest judgments about the information provided.

Please also be aware that the case is **not intended to include all of the information** that would be typically available in a real-world situation. Therefore, for the purposes of this study, please base your judgments on your **prior knowledge and expertise**, as well as on the information provided.

One Week Ahead Conditions



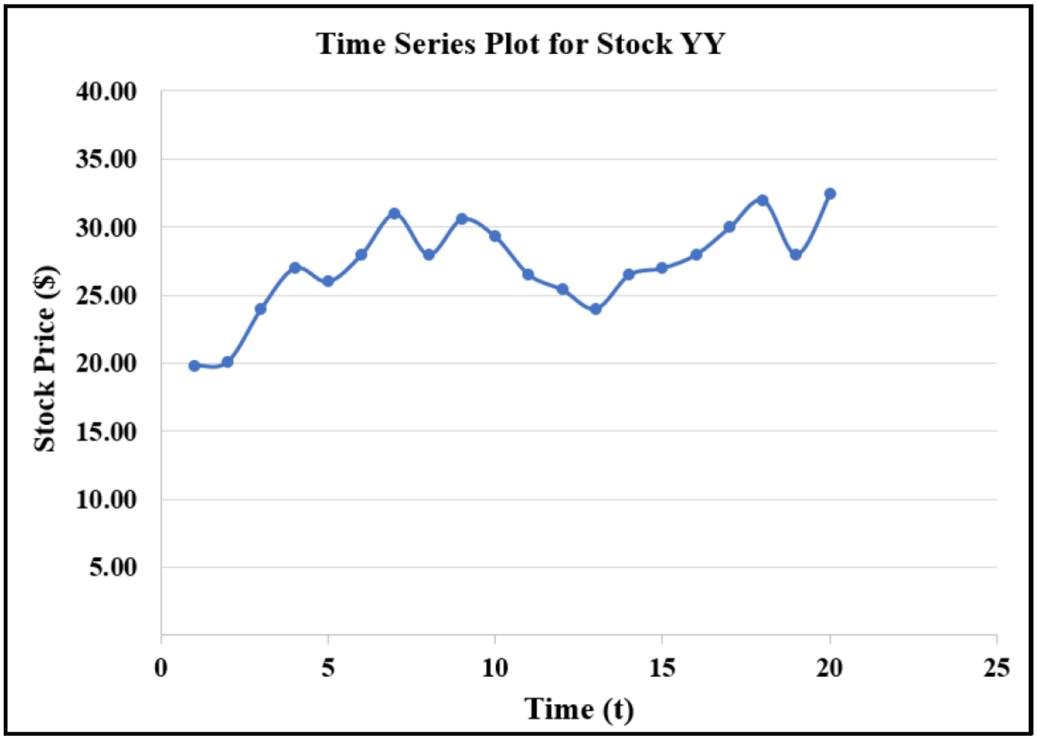
Observed values for the **last four quarters'** closing prices:

TIME PERIOD		CLOSING PRICE
t=17		30.00
t=18		32.00
t=19		28.00
t=20		32.50

Using your **expertise and prior knowledge**, please provide a forecast **based on the information provided**:

My forecast for next **week's** closing price: ______________

One Year Ahead Conditions



Observed values for the **last four quarters'** closing prices:

TIME PERIOD		CLOSING PRICE
t=17		30.00
t=18		32.00
t=19		28.00
t=20		32.50

Using your **expertise and prior knowledge**, please provide a forecast **based on the information provided**:

My forecast for next **year's** closing price: ______________

One Week Ahead - Static Algorithm

Your investment management firm has developed a proprietary algorithm that can assist equity research analysts by providing financial guidance and expert knowledge of stocks and bonds. To develop the algorithm, your firm partnered with a large international technology company with leading experts in the field. Additionally, the firm gathered inputs from professional equity analysts and wealth advisors to develop the algorithm. The algorithm is considered state-of-the-art technology that can synthesize structured and unstructured data.

This algorithm provides advice based on executing a **complex mapping of if-then statements and rules**. These rules are then used to train the algorithm's model to predict future stock performance. An example of a model used by the algorithm to predict future stock price is provided below. Y is the future stock price and X's are pieces of information that the model is trained on, such as historical stock prices, financial data, and analysts' forecasts. The β is the weight that is applied to the piece of information in predicting future stock price (Y).

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

Here is the **forecast provided by the algorithm** regarding this stock's closing value for next week's closing price:

The algorithm's forecast for next **week's** closing price: **25.00**

Please think about your prediction for this stock's closing value and examine the algorithm's forecast given above. Then, if you think you need to, adjust your prediction considering the algorithm's forecast given above.

My adjusted forecast in light of the algorithm's forecast presented above:

My **adjusted** forecast for next **week's** closing price: _____

One Year Ahead – Static Algorithm Conditions

Your investment management firm has developed a proprietary algorithm that can assist equity research analysts by providing financial guidance and expert knowledge of stocks and bonds. To develop the algorithm, your firm partnered with a large international technology company with leading experts in the field. Additionally, the firm gathered inputs from professional equity analysts and wealth advisors to develop the algorithm. The algorithm is considered state-of-the-art technology that can synthesize structured and unstructured data.

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

Here is the **forecast provided by the algorithm** regarding this stock's closing value for next **year's** closing price:

The algorithm's forecast for next **year's** closing price: **25.00**

Please think about your prediction for this stock's closing value and examine the algorithm's forecast given above. Then, if you think you need to, adjust your prediction considering the algorithm's forecast given above.

My adjusted forecast in light of the algorithm's forecast presented above:

My **adjusted** forecast for next **year's** closing price: _____

One Week Ahead – Learning Algorithm Conditions

Your investment management firm has developed a proprietary algorithm that can assist equity research analysts by providing financial guidance and expert knowledge of stocks and bonds. To develop the algorithm, your firm partnered with a large international technology company with leading experts in the field. Additionally, the firm gathered inputs from professional equity analysts and wealth advisors to develop the algorithm. The algorithm is considered state-of-the-art technology that can synthesize structured and unstructured data.

This algorithm provides advice based on executing a complex mapping of if-then statements and rules. These rules are then used to train the algorithm's model to predict future stock performance. Additionally, the algorithm can **learn independently** from its environment, **understand the pattern** that underlies the data, and **adapt to improve** its future predictions. An example of a model used by the algorithm to predict future stock price is provided below. Y is the future stock price and X's are pieces of information that the model is trained on, such as historical stock prices, financial data, and analysts' forecasts. The β is the weight that is applied to the piece of information in predicting future stock price (Y). Because the algorithm can independently learn, the algorithm can **modify the weights** (β) applied to the pieces of information (X). Additionally, as the algorithm learns, it can **identify new predictors** ($\beta_n X_n$) and add it to the model to improve the accuracy of future forecasts.

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

New information can be added to model by the algorithm to improve predictions

Here is the **forecast provided by the algorithm** regarding this stock's closing value for next week's closing price:

The algorithm's forecast for next **week's** closing price: **25.00**

Please think about your prediction for this stock's closing value and examine the algorithm's forecast given above. Then, if you think you need to, adjust your prediction considering the algorithm's forecast given above.

My adjusted forecast in light of the algorithm's forecast presented above:

My **adjusted** forecast for next **week's** closing price: _____

One Year Ahead – Learning Algorithm Conditions

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

New information can be added to model by the algorithm to improve predictions

Here is the **forecast provided by the algorithm** regarding this stock's closing value for next **year's** closing price:

The algorithm's forecast for next **year's** closing price: **25.00**

Please think about your prediction for this stock's closing value and examine the algorithm's forecast given above. Then, if you think you need to, adjust your prediction considering the algorithm's forecast given above.

My adjusted forecast in light of the algorithm's forecast presented above:

My **adjusted** forecast for next **year's** closing price: _____

In a few sentences, please justify why you did (or did not) adjust your stock price forecast.

For the question below, please circle the number on the scale that represents your assessment.

How **difficult** was it to accurately forecast the stock price one week from today?

Not at All Difficult						Very Difficult
1	2	3	4	5	6	7

How **confident** are you in **your ability** to accurately predict the future stock price?

Not at All Confident						Very Confident
1	2	3	4	5	6	7

How **capable** was the algorithm in developing stock price forecast?

Not at All Capable						Very Capable
1	2	3	4	5	6	7

How **accurate** is your stock price forecast compared to the algorithm's stock price forecast?

Less Accurate						More Accurate
1	2	3	4	5	6	7

To what extent did you think about **how** the algorithm could generate an accurate forecast?

Not at All						A Great Deal
1	2	3	4	5	6	7

To what extent did you think about **why** the algorithm could generate an accurate forecast?

Not at All						A Great Deal
1	2	3	4	5	6	7

How **relevant** was the algorithm's forecast in forming your prediction?

Not at All Relevant						Very Relevant
1	2	3	4	5	6	7

Rate how **easy or difficult** it was to **process** the advice provided by the algorithm.

Easy to Process						Difficult to Process
1	2	3	4	5	6	7

How **accurate** do you think **your** stock price forecast is?

Not at All Accurate						Very Accurate
1	2	3	4	5	6	7

How **accurate** do you think **the algorithm's** stock price forecast is?

Not at All Accurate						Very Accurate
1	2	3	4	5	6	7

How **comfortable** do you feel relying on advice provided by the algorithm?

Not at All Comfortable						Very Comfortable
1	2	3	4	5	6	7

I **understand** how the algorithm works.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

Your firm's algorithm can **independently adapt and learn** over time.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

The algorithm is capable of **planned** actions.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

The algorithm has **goals**.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

The algorithm is highly **conscious**.

Strongly Disagree						Strongly Agree
1	2	3	4	5	6	7

<u>Questions About the Case</u>

Please <u>do not go back</u> and examine the case information when answering the remaining questions.

1. Your firm's algorithm **has** the ability to independently learn, adapt, and improve its own predictions overtime.
    a. True.
    b. False.

2. You provided a forecast prediction of the stock's closing value:
    a. One week from today.
    b. One year from today.

The following questions concern you and your experiences. This information will not be used, in any way, to identify you.

1. **How many finance classes have you taken?** ___________

2. **How many accounting classes have you taken?** ___________

3. **Have you invested or plan to invest in common stock or mutual funds?**
   a. Yes – if you have invested in the past, how many times: ___________
   b. No

4. **How many years of work experience do you have?** ___________

5. **Rate your level of experience with forecasting stock prices?**

No Experience At All						Highly Experienced
1	2	3	4	5	6	7

6. **Evaluate your level of knowledge of stock prices and probability.**

Very Poor						Very Good
1	2	3	4	5	6	7

7. **What is your gender?**
   a. Female
   b. Male
   c. Prefer not to answer

8. **Age:** ___________

<u>You have now completed the audit case. Thank you very much for your help!</u>

APPENDIX D: IRB CERTIFICATION – EXPERIMENT 2

University of Kentucky | Office of Research Integrity
IRB, RDRC

Modification Review

Approval Ends: 4/13/2025

IRB Number: 50778

TO: Jennifer Wang, Masters
RCTF Graduate Scholarships
PI phone #: 5042147538

PI email: jennifer.wang@uky.edu

FROM: Chairperson/Vice Chairperson
Non Medical Institutional Review Board (IRB)

SUBJECT: Approval of Modification Request

DATE: 8/13/2019

On 8/12/2019, the Non Medical Institutional Review Board approved your request for modifications in your protocol entitled:

[redacted]

If your modification request necessitated a change in your approved informed consent/assent form(s), the new IRB approved consent/assent form(s) to be used when enrolling subjects can be found in the "All Attachments" menu item of your E-IRB application. [Note, subjects can only be enrolled using consent/assent forms which have a valid "IRB Approval" stamp unless special waiver has been obtained from the IRB.]

Note that at Continuation Review, you will be asked to submit a brief summary of any modifications approved by the IRB since initial review or the last continuation review, which may impact subject safety or welfare. Please take this approved modification into consideration when preparing your summary.

For information describing investigator responsibilities after obtaining IRB approval, download and read the document "PI Guidance to Responsibilities, Qualifications, Records and Documentation of Human Subjects Research" available in the online Office of Research Integrity's IRB Survival Handbook. Additional information regarding IRB review, federal regulations, and institutional policies may be found through ORI's web site. If you have questions, need additional information, or would like a paper copy of the above mentioned document, contact the Office of Research Integrity at 859-257-9428.

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VITA

JENNY (WANG) ULLA

ACADEMIC APPOINTMENTS

University of Nevada – Las Vegas, Las Vegas, NV
Assistant Professor, Expected Fall 2021

EDUCATION

Trinity University, San Antonio, TX
Masters of Science in Accountancy, Spring 2009
Bachelor of Science – Business Administration-Accounting, Spring 2008

TEACHING EXPERIENCE

Teaching Experience:
University of Kentucky
Introduction to Financial Accounting (1 section – Fall 2016) Avg. Rating: 4.5/5.0
Introduction to Financial Accounting (2 section – Fall 2017) Avg. Rating: 4.7/5.0

Courses served as a Teaching Assistant
Non-Profit and Governmental Accounting (1 section – Fall 2018)
Non-Profit and Governmental Accounting (1 section – Fall 2019)

Courses taught prior to University of Kentucky
Introduction to Financial Accounting (Austin Community College– Austin, TX)
Intermediate Accounting I (Austin Community College– Austin, TX)
Non-Profit and Governmental Accounting (St. Edwards – Austin, TX)

GRANTS, HONORS, AND AWARDS:

The Center for Audit Quality (CAQ) Access to Audit Personnel Grant	2020
AAA Deloitte J. Michael Cook Doctoral Consortium Fellow	2019
Gatton Competitive Research and Creative Activities Grant	2019
Max Steckler Fellowship	2018, 2020
Gatton Doctoral Fellowship	2018, 2019
Gatton College Teaching Excellence Award for Graduate Students	2017
Von Allmen School of Accounting Fellowship	2016, 2017, 2020

PROFESSIONAL EXPERIENCE:

Austin Community College, Summer 2015 – Summer 2016, Austin, TX
Assistant Professor

St. Edwards University, Fall 2015, Austin, TX
Adjunct Professor

San Antonio Area Foundation, Spring 2010 – Summer 2015, San Antonio, TX
Controller, Spring 2012-Summer 2015
Senior Accountant, Spring 2010-Spring 2012

Ernst and Young L.L.P., Summer 2009 – Spring 2010, San Antonio, TX
Staff Auditor