What are the Factors that Influence the Adoption of Data Analytics and Artificial Intelligence in Auditing?

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WHAT ARE THE FACTORS THAT INFLUENCE THE ADOPTION OF DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE IN AUDITING?

by

GRACE TSAO

A thesis submitted in partial fulfillment of the requirements for the Honors in the Major in Accounting in the College of Business Administrations and in The Burnett Honors College at the University of Central Florida Orlando, Florida

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ABSTRACT

Although past research finds that auditors support data analytics and artificial intelligence to enhance audit quality in their daily work, in reality, only a small number of audit firms, who innovated and invested in the two sophisticated technologies, utilize it in their auditing process. This paper analyzes three factors, including three individual theories, that may influence the adoption of data analytics and artificial intelligence in auditing: regulation (Institutional theory: explaining the catch-22 between the auditors and policymakers), knowledge barrier (Technology acceptance model's theory: explore the concept of ease of use), and people (algorithm aversion: a phenomenon that auditors believe in human decision makers more than technology). Among the three barriers, this paper focuses more on the people factor, which firms can start to overcome early. Past research has shown the existence of algorithm aversion in audit, so it is important to identify ways to decrease algorithm aversion. This study conducted a survey with four attributes: transparency-efficiency-trade-off, positive exposure, imperfect algorithm, and company's training. The study results shows that transparency-efficiency-trade-off can be a potential solution for decreasing algorithm aversion. When auditor firms implement transparency-efficiency-trade-off in their company training, auditors may give more trust to the technologies. The trust may lead to the increase of data analytics and artificial intelligence in audit.
DEDICATION

For my mom, who always encourages and supports me in each stage of my life.

   For my dad, who inspires me to overcome every challenge.

   For my brother, who always stand by my side.
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INTRODUCTION

With the rapid rate of digital technology improvement in the accounting field, auditors need to adapt to the continuously evolving information age and increase their ability to transform the auditing firm. Protiviti, a global consulting firm, has redefined the term “next generation” for future auditors. They believe that for future auditors, “next generation” means “[a]n agile, multiskilled technology-enabled function able to recognize emerging risks and changes to the organization’s risk profile quickly enough to reflect them in a timely manner in the audit plan so they can be addressed in the assurance the function delivers.” Protiviti’s definition of the “next generation” emphasizes the relationship between digital technology and how quickly auditors can reflect and embrace the latest auditing technology tool (“the Bulletin Protiviti’s,” 2019).

Data analytics and artificial intelligence are two tools auditors use, and they are going through continuous innovation. The four largest accounting firms - Deloitte, EY, PwC, and KPMG, popularly known as the Big Four, have invested $9 billion into data analytics and artificial intelligence in recent years (Bureau, 2020). The investment provides a way to understand the level of importance that the Big Four places on data analytics and artificial intelligence. They believe that the two digital auditing tools will benefit them by increasing the effectiveness of auditor’s work, lower the fraud risk, decrease their operation cost, and increase audit quality (Earley, 2015; Hussein et al., 2016). Taken together, data analytics and artificial intelligence should lead to the creation of more effective auditors and high-quality audits. Forbes Insights and KPMG has reported in “Audit 2025: The Future Is Now,” on how technology has changed the profession of auditing over the past several years (Forbes Insight, 2018). A survey in the report found out that “four in five respondents—80%—say auditors should use bigger
samples and more sophisticated technologies for gathering data and performing analysis in their daily work (Forbes Insight, 2018).” The sophisticated technologies will be in three key areas - artificial intelligence, data analytics, and the smart digital hubs (Forbes Insight, 2018). We can see that 80% of the auditors support using the professional audit technologies in their work, and data analytics and artificial intelligence are the top two sophisticated technologies. Therefore, the Big Four are investing in data analytics and artificial intelligence and expecting the two valuable auditing tools may reshape the identities of accounting in the current and future years.
LITERATURE REVIEW

- Data Analytics

Data analytics is the combination of information technology, statistics, and business. It contains four primary steps: data mining, data management, statistical analysis, and data presentation. In the first step data mining, auditors will convert all the raw data, such as written text or extensive complex database, into a useful and manageable format by performing ETL (extract, transform, and load data). In the second step data management, auditors will create and manage SQL (Structured Query Language) databases to access the results of data mining more easily. Besides SQL, Non-relational database (also called NoSQL) is becoming more popular with auditors today. (“What is Data”, 2021). A non-relational database is “a database that does not use the tabular schema of rows and columns found in most traditional database systems.” (“Non-relational data”, 2018). In the third step, statistical analysis is the core of data analytics. In this step, auditors use big data to create a statistical model that can analyze and show data patterns. The last step is data presentation, when the auditors present the result of the data analysis to their stakeholders by using a data visualization tool, which can help both the audience and the auditor understand the story of the data. Data visualization can also provide executives and managers with greater insight into the data results (“What is Data”, 2021).

Data analytics is an efficient technique and has been widely used in both large and small auditing firms. The rise of data analytics has made a critical impact on conventional auditing techniques. Traditionally, auditors could only test samples; however, with data analytics, auditors can include the whole population, which may increase the accuracy of the result. Also, compared to the traditional auditing techniques, data analytics can help auditors in risk...
assessment to point out the most profitable and high-cost part that they need to investigate further through the identification of anomalies and patterns (Murphy and Tysiac, 2015). Unlike the past digital auditing tools, data analytics can increase auditors’ insights into the clients’ process and transform the business decision. An example of a traditional digital auditing tool is CAATs, computer-assisted audit tools and techniques, a computer program that increases the speed and accuracy of auditor’s work. CAATs enables auditors to easily check the total balance, find the mismatched entry in the accounting book, and check the potential regulation issues (Lacoma, 2021). Also, compared to manual auditing techniques, CAATs can make better estimates about the data they are auditing, since CAATs can test the population and uncover the data that is undetected (“Knowledge base-what,” 2009). However, data analytics can collect, analyze, and convert the data into a visualization model which is better able to assist the decision-making process, thereby increasing both the efficiency and effectiveness of auditor’s work.

- **Artificial Intelligence**

  Artificial intelligence (also known as “AI”) is not a new technology in the auditing profession but may lead to tremendous future changes. Artificial intelligence is a “computing system that exhibits some form of human intelligence, which covers several interlinked technologies, including data mining, machine learning, speech recognition, image recognition, and sentiment analysis” (Boillet, 2018). For example, KPMG has partnered with IBM’s Watson Artificial Intelligence Technology to develop an AI audit tool called “The KPMG Contract Abstraction Tool,” which can help auditors reviewing contracts (Arrowsmith, 2018). This tool applies “IBM Watson Explorer, a cognitive exploration and content analysis platform, identifies
trends, patterns, anomalies, and relationships within the leasing data. (Arrowsmith, 2018).” The main benefit of this tool is that it can shorten the auditor’s time when reading lease contracts in three steps. First, the Contract abstraction tool will convert the leasing file into a machine-readable format. Second, depending on the type of lease contract, the AI, which has learned the three different contract types (real estate, IT, and vehicles), then detects specific attributes present in different lease contracts. The last step is to structure the extracted attributes’ format and export the attributes into the lease accounting tool (“Automated contract data,” 2017). A 2015 World Economic Forum Survey predicted that AI would perform 30 percent of corporate audits by 2025. Also, some people in the survey believe that “in the future [...] AI may audit 100 percent of a company’s financial transaction” (Meek, 2017). From the survey, we know that AI will decrease the operating cost (less employees needed to do the pre-audit work, such as data mining) while also increase audit quality. Since AI would perform 30 percent of auditors’ job, auditors can spend more time on communicating with clients, estimating the data, and making business decisions. Therefore, many accounting firms have invested in and are heavily involved in developing AI audit tools.

PricewaterhouseCoopers (PwC) has established an innovation lab since 2009 called “Center for Technology and Innovation” (also called CTI) (“37 Corporate Innovation,” 2020). Their goal is to develop and innovate technologies that can improve the quality of employees’ works. In 2006, Halo, a data auditing technology to test information reliability, created by PwC, has “won the 2016 Audit Innovation of the Year” at “International Accounting Bulletin (“Audit Explorer,” 2019).” The unique part of Halo is that it contains artificial intelligence, which can test and analyze an entire population of data and visually present it with an interactive dashboard
in one platform. This tool can help auditor’s insight into the company’s risks and opportunities (“Audit Explorer,” 2019).

Although data analytics and artificial intelligence have been beneficial for auditors by increasing their performance, the two digital auditing tools have not been widely adopted by all auditing firms yet. Most of the firms that utilized data analytics and artificial intelligence in their auditing process are the ones which invested in it or innovated it because they see and expect the benefits that the two auditing tools will bring and the way it will reshape the identities of the accounting industry in the short-term and in future years. For example, PwC is one that sees the benefit of data analytics and artificial intelligence. The firm adopted the two auditing tools by investing money and establishing an innovation lab to facilitate the firm's application and innovation. This paper discusses the reason why all auditing firms have not widely adopted data analytics and artificial intelligence through one leading theory and three sub-theories: innovation diffusion theory (the leading theory), institutional theory (sub-theory), technology acceptance model theory (sub-theory), and the theory of algorithm aversion (sub-theory).

• Innovation Diffusion Theory (Leading Theory)

Innovation diffusion theory originated from Schumpeter's innovative theory (Rogers, 1995), which studied the behavior of “imitation” in the early 20th century (Li and Sui, 2011). Innovation means “an idea, practice, or object that is perceived as new by an individual or another unit of adoption” (Rogers, 1995, p. 11). Relatively, diffusion means “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1995, p. 5). The theory of innovation diffusion states that “potential users make decisions to adopt or reject an innovation based on beliefs that they form about the
innovation” (Agarwal, 2000, p. 90). Innovation diffusion theory has been widely applied in different industries, such as agriculture, education, and pharmaceutical (Li and Sui, 2011). With the improvement of digital technology, more new products have emerged in the market, and the theory has frequently been used in studies that have examined factors that limit IT adoption in healthcare, a study arguing about the adoption of innovation in agriculture, and a political science study that examined the diffusion of why some states more readily adopt new programs in the United States (Ward, 2013; Geoffrey 2009; Walker, 2014). Through the innovation diffusion theory, decision-makers consider factors that will influence their decision to adopt or reject the innovation. In this paper, we focus on using innovation diffusion theory to analyze the barriers that may impact data analytics and artificial intelligence to improve the adoption of the two auditing technologies - data analytics and AI. There will be three different types of barriers (regulations, knowledge barriers, and people) that may affect the adoption of both data analytics and artificial intelligence.

- Three Sub-Theories and Three Barriers

  First, regulation is a barrier to the diffusion of data analytics and artificial intelligence. From institutional theory, we know that organizations tend to engage in legal activities instead of only pursuing economic growth and the latest technology (Suddaby, 2010). Lincoln (1995, p. 1147) has defined institutional theory as: “the tendency for social structures and processes to acquire meaning and stability in their own right rather than as instrumental tools for the achievement of specialized ends.” Organizations and most business companies take regulations into account while making decisions. Regulations provide the legal framework that sometimes is needed to bring about acceptance and adoption of a product. Therefore, regulations give auditors
more comfort in their work because they have rules to follow (Austin et al., 2020). Without regulation, the adoption and application of data analytics and artificial intelligence may be slow. Auditors won’t be comfortable about whether they are using the technology correctly or not. There is not a complete standard for data analytics and artificial intelligence yet. PCAOB Chief Auditor Megan Zietsman reported in the NASBA Annual Meeting that PCAOB is still studying the use of technology and wanted to do a deep assessment on how auditing firms use data analytics and artificial intelligence before announcing guideline (“PCAOB Still Studying,” 2021). However, the relationship between auditing firms and PCAOB is catch-22. It is “a difficult situation in which the solution to a problem is impossible because it is also the cause of the problem (‘catch-22,’ 2021).” It is a logical problem that cannot be simply solved since both PCAOB and accounting firms are waiting for each other to take the first step. The situation is like a student trying to find a job after graduation; however, companies may only be looking for people who have job experiences. It will be impossible for a student who doesn’t have a job experience to find a job if companies only hire people who have job experience. Therefore, if PCAOB and auditing firms reject taking the first step, then the barrier of regulation will continue to exist and slow the application and adoption of data analytics and artificial intelligence throughout the audit firms. Although many auditors are not comfortable with data analytics and artificial intelligence, the innovators and early adopters in the technology adoption lifecycle who have tried using the two digital tools in the audit can provide some assessment data to educate the PCAOB (D’Cruz, 2003). The education may give PCAOB some idea about the digital auditing techniques.
Second, knowledge barriers affect the decision to adopt data analytic and artificial intelligence. Unlike regulations that focus on whether the auditors are willing to adopt the technology, knowledge barriers emphasize the auditor’s ability to apply the technology (Suddaby, 2010). If the auditors don’t know what data analytics is, then they cannot choose to adopt data analytics in their work. Most auditors today know about the basic concept of data analytics. However, the level of understanding of data analytics will also determine whether there is still a knowledge barrier that exists or not and how great the knowledge barrier might be. An example of how the knowledge barrier impacted the adoption of an audit technology is Deloitte’s STAR, Statistical Techniques for Analytical Review. This tool was underutilized for almost 35 years because auditors did not understand statistics and the power of the device. STAR was developed and used in audits beginning in 1971 (Stewart et al., 1992). “[It] is a software tool that assists the performance of substantive analytical procedures by using regression analysis to model the relationship between an amount being tested and data expected to be predictive of the amount (Stewart et al., 1992).” STAR was supposed to be a popular audit regression tool to help auditors in the substantive analytical procedures; however, “[a]s […] [a] new techniques into a large organization, individual reactions vary between the extremes of enthusiastic acceptance and skepticism or opposition (Stringer, 1975).” Since most auditors don’t learn enough about regression analysis (lack of ability), they have little chance to choose to adopt STAR. Although auditors, who did not understand statistics, realized the advantage of STAR, they will still stop by the knowledge barrier.

Another aspect of this barrier is whether the auditors understand the benefits of technology or not. If the auditors understand the benefit of technology, it will increase their
willingness to adopt the tools. For example, the Big Four have invested $9 billion into data analytics and artificial intelligence in recent years because they saw the benefit that data analytics and artificial intelligence may bring to their firms in current and future years.

Another aspect is that auditors avoid learning data analytics and artificial intelligence because they believe that it will be hard to learn how to operate the two digital tools. Fred Davis developed the theory of technology acceptance model in 1983; it argues that innovation should be both useable and useful for people to accept (Sauro, 2019). One of the biggest factors in the technology acceptance model's theory is perceived ease of use, which is “a term referring to the learners’ impression that a certain system is easy or effortless to handle (AL-Rahmi et al., 2019).” If the auditors think that interaction with the new tools is hard, they will refuse to learn them. They might think that the tools are too difficult for them to operate. Traditional companies with senior age auditors might have this problem with data analytics and artificial intelligence. Since senior-age auditors are used to the manual auditing tools, it might be hard for them to accept learning and adopting the new digital tools. Tableau is easier for auditors to accept and has been widely used in accounting (Charles, 2004). However, Power BI, “a business intelligence platform that provides nontechnical business users with tools for aggregating, analyzing, visualizing and sharing data,” is complicated and difficult to understand (Post, 2018; Rouse, 2018). Therefore, due to the level of difficulties, auditors may prefer to learn Tableau more than Power BI.

The last barrier is that people may trust humans more than they trust technology. According to a study of human health and behavior, research findings indicate, on average, technology is 10% more accurate than a human being when forecasting the future (Grove et al.,
Data analytics and AI can avoid frauds better than people. It is faster for data analytics and artificial intelligence to uncover frauds instead of humans checking manually. However, the theory of algorithm aversion states that, people believe in human forecasters more than statistical forecasters (Dietvorst et al., 2015). The reason is that people may lose confidence in technology quicker than human forecasters when an error occurs (Dietvorst et al., 2015). This is a barrier that humans need to face themselves. Technology keeps growing and will be a trend in auditing. Data analytics and artificial intelligence will do much of the works for auditors. If auditors don’t trust the data and forecast, then it loses the value of applying audits in technology.

Data analytics and artificial intelligence are not the only technologies whose adoption might be explained by reference to innovation diffusion theory, institutional theory, technology acceptance model, and the theory of algorithm aversion. The earlier digital auditing tool-CAATs, computer-assisted audit tools and techniques, also encountered similar issues regarding its adoption by all the auditing firms in the past. An article in 2008, states that internal auditors prefer to use CAATs for specific investigation; however, external auditors do not adopt CAATs in testing the financial statement assertion. CAATs was not utilized widely in the auditing firms (Janvrin, 2008). Today however, most CPA firms use some form of CAATs on traditional accounting and auditing processes (Bourke, 2010). Auditors find it easier to use CAATs to analyze large scale data and obtain data files (Bourke, 2010). With the adoption of CAATs, auditors can perform a better and more accurate risk assessment than using traditional accounting tools. The following discusses the same three barriers (regulations, knowledge barriers, and people) that CAATs underwent from the four theories discussed earlier.
Regulation will affect auditors concern about the precision of their audit work (Ling, 2018). However, since the innovation of CAATs, regulators have issued more and more assessments about how the tool should be applied in auditing firms. In 2008, ISACA, Information System Audit Control Association, focused more on IT technical issues and published an auditing guideline for CAATs (“G3 USE OF,” 2008). Even though ISACA in not a regulatory agency, it is a well-respected and recognized organizations that frequently provides guidance to auditors, and the guidance that it provided related to CAATs gave auditors the comfort they needed to adopt it. “There is not a CPA firm today that does not use some form of CAATS on the traditional accounting and auditing engagement. It may be far-reaching, but the simple use of a computer on such engagement would be considered the use of CAATS (Bourke, 2010).” Due to the high acceptance of CAATs in the article, institutional theory tells us that with the guidelines in place from ISACA, auditors should be more comfortable in utilizing CAATs in auditing work.

From Bourke’s, we know that after 2008, the usage of CAATs increased. However, before ISACA published the guidance, CAATs were not widely used in the auditing firms. Temesgen (2005) states that “[…] CAATs are only for large and resource rich firms. Consequently, still small and modest sized auditing firms are not fully engaged in the use of such tools”. The situation is similar to artificial intelligence in auditing today. Most of the innovations and use of artificial intelligence in auditing is by the largest firms. However, it is still crucial for all auditing firms to learn and track the newest auditing techniques. Although most of the auditing firms today utilize CAATs in their auditing process. However, there are still a few audit companies’ who do not use the professional auditing tools. A survey about the use of auditing
tools in Portugal found out that older auditors tend to use essential accounting tools, such as Microsoft Access, instead of professional auditing tools (Dias and Marques, 2018). From this, we can analyze and assume some reasons why a few companies today didn’t adopt CAATs.

First, the auditors might not learn and keep track of the latest information about the upcoming auditing tools. When most auditors are familiar with CAATs today, they are behind. Therefore, it is essential for auditors today to learn about data analytics and artificial intelligence in auditing, although the regulation hasn’t come out.

The second reason is related to the technology acceptance model theory. When CAATs was first introduced, auditors could have thought that it was too hard for them to learn and apply it to the auditing work. They refused to accept CAATs and adopt it into practice. Also, auditors prefer to use the accounting tools that they have more knowledge about. Therefore, today it is essential for policymakers and auditing firm’s managers to design more educational programs for their auditors about data analytics and artificial intelligence. From the training program, auditors can quickly obtain the skills they need and apply it to the tools, leading to a reduction in the knowledge barriers. Although the investment and the training fees of the two digital auditing tools will likely cost a vast amount of money for the firms, auditors can gain the skills and work more effectively. Besides the training classes, understanding the benefit of CAATs will increase the company’s willingness to adopt this auditing tool.

The last barrier is that people trust human beings more than technologies. Since CAATs were an early digital auditing innovation, there was a lot of doubt about the accuracy of the results calculated by technology. The theory of algorithm aversion emphasized that humans have less tolerance of technology. If technology makes a mistake, auditors will doubt the result they
get from the tool every time. Therefore, when the tools did not help them achieve their desired outcome, they will start to doubt that technology (Dietvorst et al., 2015). The theory of algorithm aversion may help to explain the lack of adoption by auditors to use digital auditing tools. Although most firms today adopted CAATs, there are still a few companies that did not, which means the theory of algorithm aversion may yet exist among the firms. To successfully facilitate the widespread use of data analytics and artificial intelligence, regulation, knowledge barriers, and people are the three barriers’ auditors need to overcome.
THEORY AND HYPOTHESIS DEVELOPMENT

• Background

Data analytics and artificial intelligence are useful tools; however, auditors have not yet widely adopted them. The literature review concluded that regulation, knowledge barriers, and people (algorithm aversion) are three barriers toward data analytics and artificial intelligence’s adoption. People are one of the barriers, which firms can start to overcome early. Past research has stated that auditors lack the expertise to evaluate complex situations and rely on an expert specialist in their audit firm or specialist systems, such as data analytics and artificial intelligence (Commerford et al., 2020). However, the use of data analytics and artificial intelligence will benefit the quality and result of an audit because it is less subjective and more independent than a human specialist.

Prior research has shown the existence of algorithm aversion in different fields (Commerford et al., 2020; Castelo et al., 2019; Dietvorst et al., 2015). In a previous audit article, researchers used the examination of commercial loan grades to test the existence of algorithm aversion in an audit (Commerford et al., 2020). They believed that algorithm aversion could be problematic in the audit setting because discounting the weight of evidence from a human expert would cause an increased weight of evidence in the algorithm (Commerford et al., 2020). Participants in the research assumed themselves to be an “in-charge auditor on the financial statement audit of Heartland National Bank” (Commerford et al., 2020). There were five steps in the experiment. First, participants received the “background information about the hypothetical audit firm (Clark & Miller, LLP) and Heartland’s allowance [of loan losses]” (Commerford et al., 2020). Second, participants were informed about the methodology (human specialist or
specialist system) used for auditing or estimating the allowance. Third, participants received memos from both audit firms and clients regarding the methodologies they applied. Forth, participants received a comprehensive summary from the “potential audit difference” to the “management’s position and methodology of estimating the allowance” (Commerford et al., 2020). Last, the study subjects were asked to “proposed an audit adjustment, complete the post-experimental questionnaire, including a manipulation check question and demographic questions” (Commerford et al., 2020). The result of this research found that algorithm aversion influences auditors by discounting the weight of evidence more from a human expert than a specialist system (Commerford et al., 2020). The research also found out that the audit adjustment will be lower when it includes objective inputs (Commerford et al., 2020). Objective inputs mean that auditors receive more objective information before implementing the methodology (human specialist or specialist system).

Past scholars believed that algorithm aversion affects humans’ willingness to use algorithm in any task (Castelo et al., 2019). In Castelo et al., two studies examined if humans are less willing to trust and use algorithms in subjective tasks. In study 1, they examined 26 tasks to test the theory in various dimensions. There are two samples in study 1. One sample of 250 participants rates the tasks among the algorithm’s objectivity, result, and familiarity. Another sample of 387 participants rates their trust either in the algorithm or in humans for each task. Study 1 found that faith in the algorithm is higher in objective tasks than subjective tasks, like the finding in the Commerford’s article (Castelo et al., 2019). Objective tasks include more facts than subjective tasks; subjective tasks relate to more feeling than objective tasks. Study 2 focused on the field of marketing. Prior researchers created four advertisements (2 humans
versus algorithmic advisor; 2 objectives versus subjective) for the experimental procedures. Participants were asked to click on an ad they want to learn more about (e.g., humans or algorithms). Study 2 found out that people have lower trust in the algorithm when they are subjective. For example, when evaluating a job candidate, managers can either use a psychometric test (objective) or conduct an interview that relies on one's gut feeling (subjective). Most companies have in-person or virtual interviews (subjective), but not all of the companies use psychometric test (objective) to select candidates. The study found that people have more trust in higher objective tasks (Castelo et al., 2019). For example, when managers looking at a resume, they will priority focus on the education and work experience (objective) than the executive summary (subjective). The first two studies show the existence of algorithm aversion in general tasks and within the field of marketing. Moreover, the study emphasized the correlation between algorithm aversion and objective tasks. The high objective tasks led to lower algorithm aversion.

Another article examined student success in their forecasting's ability to test for the existence of algorithm aversion (Dietvorst et al., 2015). This research was based on five studies, which were all based on real data and real outcome (Dietvorst et al., 2015). Most of the studies asked the participants to act as an MBA officer to forecast the actual success of each MBA applicants (Dietvorst et al., 2015). The researchers defined success as the "equal weighting of 1) GPA, 2) respect of fellow students, 3) the prestige of employment upon graduation, and 4) job success two years after graduation" (Dietvorst et al., 2015). There were two forecast methods: human forecaster and algorithm forecast. In study 1, participants first received some information about human forecasting and algorithm forecasting's performance. Second, subjects received
information about the applicants before proposing a forecast for each applicant. After understanding each applicant's background, the subjects were asked to create a human forecast. Later, they received the result from the algorithm forecast and decided either to choose the prediction made by themselves or the algorithm's estimates. Also, they were asked questions to assess their belief in the human forecaster and algorithm forecaster. The outcome found that participants choose the human forecast that produced 13–97% more error than algorithms, after seeing those algorithms had errors (Dietvorst et al., 2015).

In summary, past research (audit, marketing, and student success forecasting) has experimentally confirmed the existence of algorithm aversion and how algorithm aversion has significantly influenced humans' decisions for making forecasts. Although the three articles' experimental case are different, the primary result that human's trust human forecasters more than system forecasters is the same.

Since data analytics and artificial intelligence have become a trend in the accounting world to enhance audit quality, it is essential to find a solution to ease algorithm aversion. When algorithm aversion is reduced, auditors will give more trust to data analytics and artificial intelligence. The article "Complex estimates and auditor reliance on artificial intelligence" has mentioned that "future researchers could explore theory-grounded interventions that decrease the effects algorithm aversion" (Commerford et al., 2020). Therefore, this study attempts to provide a potential solution for people's barrier by examining attributes, which may decrease algorithm aversion. Four attributes will be examined: transparency-efficiency-trade-off, positive exposure, imperfect algorithm, and company's training.
• Four Attributes to Decrease Algorithm Aversion

The first attribute is transparency-efficiency-trade-off, which leads humans into believing that they are interacting with human agents instead of machines (Schiffer, 2020). It may be easier for auditors to be tolerant and empathetic toward technology when treating the tools as their colleagues. The second attribute is positive exposure. Previous research stated that when a firm introduces a mature technology and provides people with enough time to interact with it, they will utilize it in their work (Luong et al., 2019). Therefore, the study could be expected to show that the more positive exposure auditors have toward data analytics and artificial intelligence, the more trust they will have while utilizing the tools. The third attribute is the imperfect algorithm. Previous research found out that "one can reduce algorithm aversion by giving people some control—even a slight amount—over an imperfect algorithm's forecast" (Simmons, 2016). Findings suggest that generally people prefer an imperfect algorithm's forecast. This study will examine whether minimal controls or great number of controls will better decrease algorithm aversion.
The fourth attribute is the company's training. A comprehensive training program on data analytics and artificial intelligence will allow auditors to understand data analytics and artificial intelligence capabilities. A previous article about artificial intelligence mentioned how it is critical for humans to understand an explanation about algorithms to create a level of trust calibration (Tomsett et al., 2020). The trust calibration is "the process through which the human sets their trust level appropriately to the AI's trustworthiness" (Tomsett et al., 2020). Auditors set their trust levels based on two criteria.

First is the relative task experience (Holmstorm, 2020). Auditors who have tremendous background knowledge about data analytics and artificial intelligence will have a different view than auditors who don't know about the two tools. Auditors who are more familiar with the technology will trust the device more. The second criteria are how detailed and clear the company explains the technology in their training. The more accurate and fully the company explains to the auditor about what the data analytics and artificial intelligence do, the more critical it is to trust calibration. An accurate trust calibration will increase auditor's trust in the result data analytics and artificial intelligence make.

Besides auditors' understanding of data analytics and artificial intelligence, the AI system needs to be correctly set up about what it should perform (Tomsett et al., 2020). When the information about data analytics and artificial intelligence's capabilities have been thoroughly explained to auditors and the audit information about what auditors expect the two technology to do has correctly been set up on data analytics and artificial intelligence, auditors will have more tolerance for data analytics and artificial intelligence to make mistakes. The reason is that the
auditors already know what the tools can and cannot do. Therefore, the result of the study could be predicted that company training will decrease the effect of algorithm aversion.

Based on the results of past research, formally I predict:

**Hypothesis 1:** Providing information about one (or all) of the four attributes (transparency-efficiency-trade-off, positive exposure, imperfect algorithm, and company's training) will decrease algorithm aversion related to a forecast decision.

In auditing, evaluating the client's going-concern is a difficult part of the audit (Chow et al., 1987). In a going-concern evaluation, auditors need to gather specific financial information from the audit examination to "diagnose" a firm’s financial health (Lehmann et al., 2006). The process includes a vast amount of audit tasks. Moreover, past studies have found that the order of evidence received may influence the likelihood of auditors' judgments on whether there is a going-concern problem or not (Asare, 1992). The review of the literature shows that algorithms are more accurate and efficient than human beings, thus this study would expect the audit opinion about company's going-concern decision to be more comprehensive if auditors use specialist systems versus human experts.

Because of algorithm aversion, auditors may choose to use human experts rather than data analytics and artificial intelligence to make the going-concern evaluation. The goal of this study is to find attributes that may decrease algorithm aversion. Once the algorithm aversion is decreased, auditors will be more likely to adopt data analytics and artificial intelligence while doing audit examinations. To make the experimental scenario more complex, the study will utilize the Altman Z-score, which is similar to the going-concern evaluation made by human beings.
Altman Z-score

Altman Z-score is a formula used to predict bankruptcy one to two years before financial distress (Chouhan et al., 2014). The formula was developed by Edward I. Altman in 1968 (Altman, 2000). He was the “first researcher [that] apply[ied] the Multiple Discriminant Analysis (MDA) approach to the financial distress prediction domain” (Chouhan et al., 2014). The formula is:

\[ Z\text{-score} = 1.2(X1) + 1.4(X2) + 3.3(X3) + 0.6(X4) + 1.0(X5) \]

- \(X1= \) working capital / total assets
- \(X2= \) retained earnings / total assets
- \(X3= \) earnings before interest and tax / total assets
- \(X4= \) market value of equity / total liabilities
- \(X5= \) sales / total assets

(Chouhan et al., 2014).

The critical range Altman set for the Z-score is 1.81 to 2.99 (Chouhan et al., 2014). If the Z-score is lower than 1.81, then the company is in the distress zone (likely to be bankrupt) (Chouhan et al., 2014). If the Z-score is between 1.81 and 2.99, the company is in the gray zone (stable) (Chouhan et al., 2014). If the Z-score is higher than 2.99, then the company is in the safe zone (will not be bankrupt) (Chouhan et al., 2014). However, the accuracy of the bankruptcy prediction will taper off over time (Chouhan et al., 2014). For example, the result is 95% accurate for the first year, but drops to 75% for the second year (Chouhan et al., 2014).
Technology Model

The technology, which will be introduced in the experiment will utilize a description of a combination of data analytics and artificial intelligence. Past research stated that using both data analytics and artificial intelligence as the bankruptcy prediction model can provide a more accurate result for the going-concern decision (Hafiz et al., 2015). Quantitative data sources, such as DataStreme¹ and FAME² can provide financial information (or financial ratio) about many companies in the U.S. and other countries. Besides financial ratios, qualitative information, such as economic news articles are also crucial inputs for making the going-concern decision (Jo et al., 2016). Most of these two types of data sources can be exported directly to excel allowing for data mining and web indexing (Hafiz et al., 2015). Unstructured data sources, such as online economic news articles, won’t be a problem since data analytics is good for analyzing unstructured data (Hafiz et al., 2015). However, the major problem for data analytics is that it is hard to continuously retrain the volume of new data (Hafiz et al., 2015). Therefore, artificial intelligence can be combined and help to solve this problem. Artificial intelligence can help eliminate the continuous retraining of data and improve learning of new data, so the process bankruptcy model can be smooth and constantly updated (Hafiz et al., 2015).

¹ “Datastream is a global financial and macroeconomic data platform providing data on equities, stock market indices, currencies, company fundamentals, fixed income securities and key economic indicators for 175 countries and 60 markets (“Datastream,” 2021).”

² FAME (Financial Analysis Made Easy) navigates individual companies’ information and do detailed analysis (“Fame,” 2021).
METHOD

- Experimental Design Flow:

```
Control group

Four treatment groups
1. Transparency-efficiency-trade-off
2. Company training
3. Imperfect algorithm
4. Positive exposure

Experimental information
1. Auditors making going-concern decision
2. Information about technology (BPM)
3. Information about Altman Z-score
4. Information about company

1. Make a bankruptcy prediction based on both Altman Z-score and BPM output
2. The decision relied how much percentage on Altman Z-score and N-ratio

Manipulation questions
```

- Experiment Procedures

The experimental scenario (see APPENDIX A) for this study will focus on determining the going-concern of three different companies and how much each decision relied on information provided to the subjects, Altman Z-score and/or N-ratio. There will be five groups of subjects. The subjects will play a role as an auditor in the ABC, CPA, audit firm. Each subject will be randomly assigned to one of the different groups. They will receive information about why auditors make going-concern decisions (understanding the importance and how complicated for auditors it is to make a going-concern decision), the Bankruptcy Prediction Model (BPM) (combines data analytics and artificial intelligence), information about the Altman Z-score (brief information about what it is and how it is used to make a going-concern decision), and background of the client's company (actual company information in the market, Altman Z-score of the company, and the BPM result of the company). After receiving all the information,

\[\text{3 Instead of teaching participants about how to use the technology, they will receive a description about the technology model.}\]
participants will be asked to make a going-concern decision based on Altman Z-score and N-ratio (BPM result) provided for a particular company and will be asked how much their decision relied on either the Altman Z-score and/or the N-ratio. Subjects will be randomly provided information from a range of actual companies, with the result of data analytics and artificial intelligence related to bankruptcy including the high likelihood of going bankrupt (low Z-score/high N-ratio), the low likelihood of going bankrupt (high Z-score/low N-ratio), and somewhere in the middle (gray zone). By giving subjects in each group companies that fall in all three categories, the study can determine whether algorithm aversion will be consistently decrease across all three categories or only affects specific zones. The only difference between control group and four treatment groups is additional information about the data analytics and artificial intelligence attributes' features are provided to four treatment groups. Subjects in the four treatment groups will be randomly assigned to one of the four treatments. Lastly, the participants will be asked to answer two manipulation questions to test the accuracy of the data.

- Four Type of Additional Information Related to the Attributes

The first additional information is about transparency-efficiency-trade-off. This group of subjects will first view the results from the data analytics and artificial intelligence system (BPM) as if it came from a group of experts, called BPM, in their firm. The misguiding process is critical in testing this attribute. From the literature about algorithm aversion, findings have shown that humans trust the result made by human beings more than technology. They may have less tolerance for technology to make mistakes than human beings to make mistakes (Dietvorst et al., 2015). Therefore, this research will test whether human beings may have more tolerance toward technologies when they do not know that they are interacting with technologies. In the
misguiding part, subjects will be asked to make a going-concern decision based on the value calculated by a group of experts in their firm and the given value of Altman Z-score. Later, the experiment will disclose the reality that the experts are machines. In the disclosing part, subjects will be asked to make the going-concern decision again. However, the second decision is to find out whether participants will change the result of their first decision or not and the percentage they trust in the technology and Altman Z-score. If participants rely more on BPM than Altman Z-score after the disclosure, it will indicate that transparency-efficiency-trade-off has a high possibility to decrease Altman Z-score.

The following is the design flow (transparency-efficiency-trade-off):

```
Misguiding -> Information about Altman Z-score and company -> Make going concern decision

Disclosure -> Information about technology (BPM) -> Make going concern decision
```

The second additional information is about positive exposure. This group of subjects will be provided with ads, slogans, and other people’s stories about using data analytics and artificial intelligence in similar scenarios. It is expected that the more positive exposure auditors have toward data analytics and artificial intelligence, the more trust they will have while utilizing the tools. The increased trust that results from the attribute of positive exposure is predicted to decrease algorithm aversion.

The third additional information is about the imperfect algorithm. This group of subjects will be informed that they have control over the technology (BPM). For example, BPM will allow the user to determine various aspects of the data that a user prefers to use. Also, users can
read economic articles and edit the company information before the computing process. Users can always remove unnecessary details and add additional information to BPM as they prefer. The imperfect algorithm attribute's primary focus is to tell the subjects that they have control over the technology (BPM). In order to let the participants, understand more about what they can control, subjects will be provided with a way to adjust the percentage of quantitative data (financial database) and qualitative data (economics news articles) they want the BPM system to rely on. It is expected that giving subjects information about their ability to control the BPM will lead to a reduction in their algorithm aversion.

The fourth additional information is about a company's training. This assessment will assume that data analytics and artificial intelligence have been correctly configured to what subjects expect. To carry out the experimental assessment, the study will need to know the level of subject’s familiarity with data analytics and artificial intelligence; thus, subjects will be asked to take a survey to assess their familiarity with data analytics and artificial intelligence. Then the subjects will be provided detailed explanations of the two technology's features and will be asked to watch two videos about data analytics and artificial intelligence to make sure all subjects understand the two tools very well.

In this experiment, information concerning the analytics and artificial intelligence will be of a hypothetical system rather than an actual existing system. This scenario will allow us to infer whether a comprehensive company's training may decrease algorithm aversion and whether a successful company's training can offset the lack of relative task experience or the relative task experience still affects algorithm aversion after a comprehensive company’s training.
ANALYSIS

- Participants

The participants for this study were students at a large metropolitan university in Florida enrolled in Accounting for Decision Makers in the Spring 2021 semester. Every student who completed the survey received extra credit in their class. 149 participants were female, 164 participants were male, and 1 participant was non-binary. 218 participants were white, 27 were Asian, 30 were black or African American, 37 participants were other ethnicity, and 2 participants were American Indian or Alaska Native. The participants average age was 22.76 years old. Two manipulation questions were evaluated to estimate participants' understanding of the Altman-Z score and the BPM system. All participants were asked to answer the Altman-Z score's purpose and the technologies that the BPM system leveraged. 511 students participated in the survey; however, after removing participants who did not answer both manipulation questions correctly, the final sample included in the hypothesis test was 314 participants.

- Hypothesis Test Results

After removing the participants who did not answer both manipulation questions correctly and finalizing the final sample, we calculated the average of the BPM reliance score for each of the four attributes (transparency-efficiency-trade-off, positive exposure, imperfect algorithm, and company's training) and the control group, based on the three companies JCPenney (high likelihood of going bankrupt), Tyson (low likelihood of going bankrupt), and GAP (somewhere in the middle). The result of the calculation was coded DA_Reliance – the % that a subject relied on the BPM system in making their going concern decision. To test the hypothesis, a two-way ANOVA utilizing RStudio and the "rstatix" package was conducted. The
hypothesis predicts that providing information about one (or all) of the four attributes will decrease algorithm aversion related to the going-concern decision. The result of the experiment supports the hypothesis that attributes can decrease algorithm aversion. The summary statistics (see APPENDIX B) shows the number, the mean, and the standard deviation of each of the main effects. The average mean (see Table 1) for the control group was 38.09%, for before disclosure was 27%, after disclosure was 48.72%, for positive exposure was 32%, for imperfect algorithm was 41.09%, and for company training was 37.71%. In the two-way ANOVA table (see APPENDIX C), there was no statistically significant interaction between treatments and company (P=0.06), F (5, 1137) = 0.622\(^4\), p = 0.06\(^5\). From the two-way ANOVA computation table (see APPENDIX C), there was a statistically significant difference in treatments (P=0.00), F (5, 1137) = 17.193, p = 0.00. Since there wasn’t a significant interaction between treatments and company, a simple pairwise test was done to determine if any attributes were different from the control.

- Pairwise Comparisons

To test the hypothesis that the attributes would decrease the algorithm aversion simple pairwise comparisons was conducted ("COMPARING MULTIPLE," 2021). The results of the

\(^4\) This is a F-test. \(^5\) indicates the degrees of freedom in the numerator (DFn) and 1137 indicates the degrees of freedom in the denominator (DFd); 0.622 indicates the obtained F-statistic value. When F<1, there are no significance difference between the mean and the sample being compared ("COMPARING MULTIPLE," 2021).

\(^5\) P is p-value. If p-value is >0.05, it is not significant ("COMPARING MULTIPLE," 2021).
simple pairwise comparisons table (see APPENDIX D and Table 2) shows a significant difference between transparency-efficiency-trade-off’s DA_Reliance and the control group’s DA_Reliance, p =0.00. The mean for After Disclosure (AD) was greater than the control group’s mean, which indicates that transparency-efficiency-trade-off may successfully decrease algorithm aversion. The Before Disclosure’s (BD) DA_Reliance mean was 27%, indicating the initial reliance on Altman Z-score; however, after the disclosure occurred, the DA_Reliance mean increased to 48.72%, providing further support of the hypothesis that transparency-efficiency-trade-off had a large effect in decreasing algorithm aversion.

- Additional Analysis

A comparison of the DA_Reliance means between the treatments (see APPENDIX D) showed that there was a significant difference between After Disclosure (AD) and all other attributes (P <0.05).

<table>
<thead>
<tr>
<th>Treatments</th>
<th>AD vs. 3 different treatments’ mean &amp; p value</th>
<th>Significant (p &lt;0.05)/ Insignificant (p &gt;0.05)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company Training (CT)</td>
<td>48.72% vs. 37.71%, p =0.00</td>
<td>Significant</td>
</tr>
<tr>
<td>Imperfect Algorithm (IA)</td>
<td>48.72% vs. 41.09%, p =0.04</td>
<td>Significant</td>
</tr>
<tr>
<td>Positive Exposure (PE)</td>
<td>48.72% vs. 32.00%, p =0.00</td>
<td>Significant</td>
</tr>
</tbody>
</table>
DISCUSSION AND CONCLUSION

Leveraging data analytics and artificial intelligence will optimize auditor's time, enhance audit quality, and enable auditors to focus more on business insights ("DATA ANALYTICS," 2016; Boillet, 2018). With the combination of the two technologies, data results will become more accurate and transparent (Boillet, 2018). The more precise and transparent the audit result is, the greater the stakeholder’s confidence will be about the financial report that the audit the firm provides (Sidhu, 2019). From the literature review, data analytics and artificial intelligence are not widely adopted yet in audits. Most of the audit firms which adopted data analytics and artificial intelligence are the ones that realized the importance of the digital transformation of the audit and invested human specialists and money into the development of data analytics and artificial intelligence.

This research analyzed three barriers, regulation, knowledge barrier, and people that may influence the adoption of data analytics and artificial intelligence in auditing. In the literature review, most accounting firms today have applied some form of the traditional digital auditing tool, CAAT, in their auditing process. However, before ISACA published a guideline, CAATs were mostly employed in large accounting firms. Therefore, it is expected that data analytics and artificial intelligence will be more comprehensive and more widely adopted after regulations have been released. If data analytics and artificial intelligence follows a similar path as CAATs, then our suggestion for the auditing firm is that they can train their employees about the skill of data analytics and artificial intelligence. They can encourage their auditors to trust the technology more. From the experience of CAATs, the regulation barrier can be solved by regulators. However, the knowledge barriers and people are the two factors that firms can have
some control over. People factor should be given more priority than knowledge barriers. Although auditors have the knowledge of data analytics and artificial intelligence, they would not widely utilize the two technologies due to algorithm aversion. Therefore, this paper focused on the people barrier, algorithm aversion.

Since prior research has experimentally demonstrated an algorithm aversion in an audit, marketing, and student success in forecasting contexts, the hypothesis of what attributes will decrease algorithm aversion related to the forecast decision had been developed. The result of the experiment shows that only transparency-efficiency-trade-off had a significant effect in decreasing algorithm aversion among all three companies. Before Disclosure (BD) and After Disclosure (AD), the two parts, may be the reason why transparency-efficiency-trade-off had the largest effect in decreasing algorithm aversion. Compared to other attributes, participants in transparency-efficiency-trade-off experienced a disclosure process, which gave them more time to realize the algorithm was more accurate than human beings. Additionally, since there is no interaction between treatments and companies, transparency-efficiency-trade-off can decrease any type (high/medium/low likelihood of going bankrupt) of the company.

This research provides an important contribution to the study and practice in two aspects. First, the analysis of the three barriers may help audit firms understand better the reasons why data analytics and artificial intelligence are not widely adopted in the audit. This research focuses empirically on how to improve the people factor. However, it provides future researchers opportunities to discuss solutions for regulation barriers and knowledge barriers to help the adoption of digital technologies in the audit profession. Second, this research provided a practical solution to decrease algorithm aversion. Audit firms can implement transparency-
efficiency-trade-off when introducing technologies to their auditors. When transparency-efficiency-trade-off is utilize, algorithm aversion will be reduced and auditors will give more trust to the technologies. The trust may lead to the widely adopt of data analytics and artificial intelligence in audit.
Start of Block: Demographics

Q40 Please answer the following demographic questions. The responses to these and the other data collected as part of this survey will remain anonymous.

Q41 Please choose your gender.

- Male (1)
- Female (2)
- Other (3) ____________________________
Q42 Please indicate your ethnicity.

- White (1)
- Black or African American (2)
- American Indian or Alaska Native (3)
- Asian (4)
- Native Hawaiian or Pacific Islander (5)
- Other (6)

Q43 What is your year of birth?

| Year (3) | ▼ 1900 (1) ... 2049 (150) |

End of Block: Demographics

Start of Block: Auditors making going-concern decision, BPM, Altman Z-score

Q2
In this experiment, imagine you are an auditor in the ABC, CPA, audit firm. Your manager has asked you to make a going-concern opinion for various companies that are audited by ABC. To help you with making the decision, you will be presented with three main information: information about the Bankruptcy Prediction Model (BPM), information about the Altman Z-score, and background of the client's company (actual company information in the market, Altman Z-score of the company, and the BPM result of the company). After receiving all of the information, you will be asked to make a going-concern decision based on Altman Z-score and N-ratio (BPM result) provided for a particular company and be asked how much the decision relied on Altman Z-score and N-ratio.
What is a going-concern decision? Why auditors make a going-concern decision?

A going-concern decision means the judgement that a firm will (or will not) go bankrupt in the next 12 months. In auditing, evaluating the client's going concern status is a difficult part of the audit. In a going-concern evaluation, auditors need to gather specific financial information from the audit examination to "diagnose" a firm's financial health. The process includes a vast amount of audit tasks. Making a reliable going concern decision can help investors better understand the company's financial situation.

Q3
The following is a detailed description of The Bankruptcy Prediction Model (BPM). Please read through it carefully.

The Bankruptcy Prediction Model (BPM) is a technology that combines both data analytics and artificial intelligence. This tool has gathered data on 729,345 US companies’ over the past twenty years to develop a prediction system which allows continuous appended data from new and existing firms. The model includes Lifelong Machine Learning (LML). It also utilizes data from 15 million financial statements that have been involved in bankruptcy.

The following figure indicates the processes used by the Bankruptcy Prediction Model (BPM). There are two data sources that are input into the system, quantitative information and qualitative information. For the quantitative information, the model extracts a large volume of financial data from a financial database and converts it into a Key-Value Pair structure. For the qualitative information, the model includes keyword-based sentiment analysis in determining the percentage of negative sentiment among all economic news articles the model extracts. The result of the sentiment analysis is called pre-N-ratio. From the table below you can see that algorithm calculated pre-N-ratio by finding negative words in news articles, determining the word's part of speech, and assigning negative scores to each of the words.

Both quantitative and qualitative information are imported into a Big Data Analytic database. The BPM system relies on Apache Mahout with Lifelong Machine Learning (LML) to perform a classification analysis about the bankruptcy prediction and evaluation by considering both types of data sources in the BPM. The final result for the bankruptcy prediction and evaluation is the computation of an N-ratio, which combines negative sentiment in the qualitative information and bankruptcy assessment in the quantitative information to show the best estimation toward bankruptcy prediction. The BPM system determines a N-ratio that combines financial analysis and sentiment analysis. The higher/lower the N-ratio is, the more/less likely a company is to go bankrupt within one year.
Q4

The following is the Bankruptcy Prediction Model (BPM) diagram.
Q5

The following table is a brief example of how the pre-N-ratio is calculated. (Note: POS = Part of Speech)

<table>
<thead>
<tr>
<th>Term</th>
<th>POS</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Warning</td>
<td>Noun</td>
<td>-0.846</td>
</tr>
<tr>
<td>Bankruptcy</td>
<td>Noun</td>
<td>-0.750</td>
</tr>
<tr>
<td>Criticism</td>
<td>Noun</td>
<td>-0.500</td>
</tr>
<tr>
<td>Slowdown</td>
<td>Noun</td>
<td>-0.448</td>
</tr>
<tr>
<td>Descent</td>
<td>Noun</td>
<td>-0.444</td>
</tr>
<tr>
<td>Falter</td>
<td>Verb</td>
<td>-0.444</td>
</tr>
<tr>
<td>Limitation</td>
<td>Noun</td>
<td>-0.400</td>
</tr>
<tr>
<td>Sigh</td>
<td>Noun</td>
<td>-0.385</td>
</tr>
<tr>
<td>Dull</td>
<td>Adj</td>
<td>-0.368</td>
</tr>
<tr>
<td>Credit crunch</td>
<td>Noun</td>
<td>-0.360</td>
</tr>
<tr>
<td>Inflation</td>
<td>Noun</td>
<td>-0.360</td>
</tr>
<tr>
<td>Worry</td>
<td>Noun</td>
<td>-0.333</td>
</tr>
<tr>
<td>Urgent</td>
<td>Adj</td>
<td>-0.333</td>
</tr>
<tr>
<td>Anxious</td>
<td>Adj</td>
<td>-0.333</td>
</tr>
<tr>
<td>Pressure</td>
<td>Verb</td>
<td>-0.333</td>
</tr>
</tbody>
</table>
The following is an introduction of the Altman Z-score.

The Altman Z-score is a formula that is used to predict the possibility of a company's bankruptcy within one to two years before financial distress. When first developed the Altman Z-score was found to be 72% accurate; however, over the past 31 years, the Altman Z-score was found to be 80-90% accurate. The Z-score can be correctly calculated by any individual by following a formula, it doesn't require any sophisticated tools to compute the calculation. The formula is:

\[
\text{Z-score} = 1.2(X1) + 1.4(X2) + 3.3(X3) + 0.6(X4) + 1.0(X5)
\]

- X1 = working capital / total assets
- X2 = retained earnings / total assets
- X3 = earnings before interest and tax / total assets
- X4 = market value of equity / total liabilities
- X5 = sales / total assets

The critical range Altman set for the Z-score is 1.81 to 2.99. If the Z-score is lower than 1.81, then the company is in the distress zone (likely to go bankrupt within one year). If the Z-score is between 1.81 and 2.99, the company is in the gray zone (uncertain). If the Z-score is higher than 2.99, then the company is in the safe zone (will not go bankrupt within one year).

During this experiment, instead of using technology (BPM) or calculating the equation (Altman Z-score), you will directly receive an N-ratio (BPM result) and a Z-score (Altman Z-score result) about the company to help you make the going-concern decision.

---

Q44 In the next page, you will receive information about various companies. Each company's information will include the Z-score and the N-ratio. Please read through it carefully, you will soon be asked two questions based on the information provided.

---

End of Block: Description- company information
Start of Block: company information-Tyson Foods, Inc
The following information is about a company in which you will be asked to make a going concern decision.

Tyson Foods, Inc. is an American multinational corporation based in Springdale, Arkansas, that operates in the food industry. The company is the world's second largest processor and marketer of chicken, beef, and pork after JBS S.A. and annually exports the largest percentage of beef out of the United States.

Your audit firm has provided you with the following information about Apple to use in making a going-concern decision:

- Altman Z-score: 3.0214
- N-ratio: 0.1

Q24 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- I believe the company will be bankrupt within the next 12 months. (1)
- I do not believe the company will be bankrupt within the next 12 months. (2)

Q25 Please indicated below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score : ________ (1)

The BPM : ________ (2)

Total : ________

End of Block: company information-Tyson Foods, Inc

Start of Block: Company information- GAP
Q11 The following information is about a company in which you will be asked to make a going concern decision.

Gap was founded in 1969 by Donald Fisher and Doris F. Fisher and is headquartered in San Francisco, California. The company operates six primary divisions: Gap (the namesake banner), Banana Republic, Old Navy, Intermix, Hill City, and Athleta. Gap Inc. is the largest specialty retailer in the United States, and is 3rd in total international locations, behind Inditex Group and H&M.

Your audit firm has provided you with the following information about Gap to use in making a going-concern decision:

- Altman Z-score: 2.230616
- N-ratio: 0.5

Q12 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- I believe the company will be bankrupt within the next 12 months. (1)
- I do not believe the company will be bankrupt within the next 12 months. (2)

Q13 Please indicated below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score : _______ (1)
The BPM : _______ (2)
Total : _______
J. C. Penney Company, Inc. is an American department store chain with 840 locations in 49 U.S. states and Puerto Rico. In addition to selling conventional merchandise, JCPenney offers large Fine Jewelry departments, The Salon by InStyle, and Sephora inside JCPenney.

Your audit firm has provided you with the following information about J.C. Penny Company, Inc. to use in making a going-concern decision:

- Altman Z-score: 0.87517
- N-ratio: 0.99

Q15 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- [ ] I believe the company will be bankrupt within the next 12 months. (1)
- [ ] I do not believe the company will be bankrupt within the next 12 months. (2)

Q16 Please indicated below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score: _______ (1)
The BPM: _______ (2)
Total: _______
Q38 The Altman Z-score is useful for?

- Predicting product's demand. (1)
- Used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. (2)
- Testing how well a company's CEO is doing. (3)

Q39 The BPM system is designed to leverage what technologies?

- Data analytics and artificial intelligence (DA/AI) (1)
- Microsoft Powerpoint (2)
- Microsoft Excel (3)

End of Block: Control Group Manipulation Check

Start of Block: Description- Positive exposure

Q45 In this experiment, imagine you are an auditor in the ABC, CPA, audit firm. Your manager has asked you to make a going-concern opinion for various companies that are audited by ABC. Before making the decision, your manager wants you to carefully review the slogans and information related to data analytics and artificial intelligence.

End of Block: Description- Positive exposure

Start of Block: Positive Exposure Attribute-1

Q52

End of Block: Positive Exposure Attribute-1
Start of Block: Positive Exposure Attribute-2

Q54

End of Block: Positive Exposure Attribute-2

Start of Block: Positive Exposure Attribute-3

Q55

End of Block: Positive Exposure Attribute-3

Start of Block: Positive Exposure Attribute-4

Q56

End of Block: Positive Exposure Attribute-4

Start of Block: Positive Exposure Attribute-5

Q57

End of Block: Positive Exposure Attribute-5

Start of Block: Positive Exposure Attribute-6

Q58

End of Block: Positive Exposure Attribute-6

Start of Block: Positive Exposure Attribute-7
Q59

End of Block: Positive Exposure Attribute-7

Start of Block: Positive Exposure Attribute-8

Q60

End of Block: Positive Exposure Attribute-8

Start of Block: Positive Exposure Attribute-9

Q61

End of Block: Positive Exposure Attribute-9

Start of Block: Positive exposure Manipulation Check

Q69 The Altman Z-score is useful for?

- Predicting product's demand. (1)

- Used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. (2)

- Testing how well a company's CEO is doing. (3)
Q70
The BPM system is designed to leverage what technologies?

- Data analytics and artificial intelligence (DA/AI) (1)
- Microsoft Powerpoint (2)
- Microsoft Excel (3)

End of Block: Positive exposure Manipulation Check

Start of Block: Company Training Attribute-1

Q29 Please select how familiar you are with the use of data analytics in accounting.

- Extremely familiar (1)
- Very familiar (2)
- Moderately familiar (3)
- Slightly familiar (4)
- Not familiar at all (5)
Q30 Please select how familiar you are with the use of artificial intelligence in accounting.

- Extremely familiar (1)
- Very familiar (2)
- Moderately familiar (3)
- Slightly familiar (4)
- Not familiar at all (5)

End of Block: Company Training Attribute-1

Start of Block: Company Training Attribute-2

Q31 The following is the detailed explanation of data analytics and artificial intelligence.

Data analytics and artificial intelligence are two primary digital tools that big accounting firms have continuously invested in and may be widely used in the current and future accounting world. Data analytics is a combination of information technology, statistics, and business. It contains four main steps: data mining, data management, statistical analysis, and data presentation. Among all, data presentation is a unique part of data analytics. It provides auditors with the ability to present results of their analysis to their stakeholders by using a data visualization tool. With the data visualization tool, executives and managers will have greater insight into the data results which can help them to transform their business decisions. Also, compared to traditional auditing techniques, data analytics can help auditors in making their risk assessment and to help determine the most vs. least profitable part of the audit and therefore what they would need to investigate further by identifying anomalies and patterns. Therefore, with data analytics, auditors' work can be efficient and high quality.

Artificial intelligence is a computing system that includes some human intelligence, which can learn from experience. By training and designing, the tool can replace some of the auditor's tasks and provide a more accurate result. BPM is a technology that combines data analytics and artificial intelligence. According to a study of human health and behavior, research findings indicate, on average, technology is 10% more accurate than a human being when forecasting the future. BPM can gather more information, calculate
and analyze more comprehensively, and more independently than humans. Therefore, BPM can be a well-trusted tool for auditors used to make the going-concern decision.

Note: After you finish watching the two videos, please click the yellow arrow to continue with the survey.

Q32 This is a video about data analytics. Please watch carefully.

Q33 This is a video about artificial intelligence. Please watch carefully.

Q34 Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Company Training Attribute-2

Start of Block: Company Training Manipulation Check

Q71 The Altman Z-score is useful for?

- Predicting product's demand. (1)
- Used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. (2)
- Testing how well a company's CEO is doing. (3)
Q72
The BPM system is designed to leverage what technologies?

- Data analytics and artificial intelligence (DA/AI) (1)
- Microsoft PowerPoint (2)
- Microsoft Excel (3)

End of Block: Company Training Manipulation Check

Start of Block: Imperfect Algorithm Attribute

Q46 There are elements of the BPM that a user can control while utilizing the technology.

In the Bankruptcy Prediction Model (BPM), you can control many aspects of the data analytics and artificial intelligence components of the system. For example, you have control over the information that you prefer to use as input in the model. After the BPM gathers a company's financial information and information from economic news articles, you can determine the extent that the BPM will use this quantitative or qualitative information in its bankruptcy algorithm. The result you get from the tool will therefore, to a certain extent, depend on the changes you make during this setup process.

Q47 Based on the description of the control you have on the BPM algorithm, using the sliders below, please choose the percentage of quantitative or qualitative data that you would like the BPM to rely on.

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Sliders</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td><img src="image1" alt="Slider for quantitative data" /></td>
</tr>
<tr>
<td>10</td>
<td><img src="image2" alt="Slider for qualitative data" /></td>
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<tr>
<td>20</td>
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</tr>
<tr>
<td>30</td>
<td><img src="image2" alt="Slider for qualitative data" /></td>
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<tr>
<td>40</td>
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<tr>
<td>50</td>
<td><img src="image2" alt="Slider for qualitative data" /></td>
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<tr>
<td>70</td>
<td><img src="image2" alt="Slider for qualitative data" /></td>
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<tr>
<td>80</td>
<td><img src="image1" alt="Slider for quantitative data" /></td>
</tr>
<tr>
<td>90</td>
<td><img src="image2" alt="Slider for qualitative data" /></td>
</tr>
<tr>
<td>100</td>
<td><img src="image1" alt="Slider for quantitative data" /></td>
</tr>
</tbody>
</table>

reliance on quantitative data (financial database) ()

reliance on qualitative data (economic news articles) ()
Q73 The Altman Z-score is useful for?

- Predicting product's demand. (1)
- Used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. (2)
- Testing how well a company's CEO is doing. (3)

Q74 The BPM system is designed to leverage what technologies?

- Data analytics and artificial intelligence (DA/AI) (1)
- Microsoft Powerpoint (2)
- Microsoft Excel (3)
A going-concern decision means the judgement that a firm will (or will not) go bankrupt in the next 12 months. In auditing, evaluating the client's going concern is a difficult part of the audit. In a going-concern evaluation, auditors need to gather specific financial information from the audit examination to "diagnose" a firm's financial health. The process includes a vast amount of audit tasks. Making a reliable going concern decision can help investors better understanding the company's finance.
Q7 The following is an introduction of the Altman Z-score.

The following is an introduction of the Altman Z-score.

The Altman Z-score is a formula that is used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. When first developed the Altman Z-score was found to be 72% accurate; however, over the past 31 years, the Altman Z-score was found to be 80-90% accurate. The Z-score can be correctly calculated by any individual by following a formula, it doesn’t require any sophisticated tools to compute the calculation. The formula is:

\[
Z\text{-score} = 1.2(X1) + 1.4(X2) + 3.3(X3) + 0.6(X4) + 1.0(X5)
\]

\[X1= \text{working capital / total assets}\]
\[X2= \text{retained earnings / total assets}\]
\[X3= \text{earnings before interest and tax / total assets}\]
\[X4= \text{market value of equity / total liabilities}\]
\[X5= \text{sales / total assets}\]

The critical range Altman set for the Z-score is 1.81 to 2.99. If the Z-score is lower than 1.81, then the company is in the distress zone (likely to go bankrupt within one year). If the Z-score is between 1.81 and 2.99, the company is in the gray zone (uncertain). If the Z-score is higher than 2.99, then the company is in the safe zone (will not go bankrupt within one year).

During this experiment, instead of calculating equation (Altman Z-score), you will directly receive a Z-score (Altman Z-score result) about the company to help you make the going-concern decision.

End of Block: Altman Z-score

Start of Block: Transparency-Efficiency Trade-off Attribute- Disclose

Q66 In reality, the specific going-concern information (N-ratio) is not calculated by a group of experts (there is no team called BPM), but by a data analytics and artificial intelligence system called Bankruptcy Prediction Model (BPM). It was designed to help auditors to make decisions about the client’s going concern. Its accuracy rate is higher than human beings, but is not a hundred percent accurate.

End of Block: Transparency-Efficiency Trade-off Attribute- Disclose
Q8 In this experiment, instead of using technology (BPM), you will directly receive an N-ratio (BPM result) about the company to help you make the going-concern decision. Before receiving the output, you will be given detailed description of the BPM. From the description, you will become acquainted with how BPM determine the likelihood of whether the company will be a going concern in the next 12 months.

The following is a detailed description of The Bankruptcy Prediction Model (BPM). Please read through it carefully.

The Bankruptcy Prediction Model (BPM) is a technology that combines both data analytics and artificial intelligence. This tool has gathered data on 729,345 US companies over the past twenty years to develop a prediction system which allows continuous appended data from new and existing firms. The model includes Lifelong Machine Learning (LML). It also utilizes data from 15 million financial statements that have been involved in bankruptcy.

The following figure indicates the processes used by the Bankruptcy Prediction Model (BPM). There are two data sources that are input into the system, quantitative information and qualitative information. For the quantitative information, the model extracts a large volume of financial data from a financial database and converts it into a KeyValue Pair structure. For the qualitative information, the model includes keyword-based sentiment analysis in determining the percentage of negative sentiment among all economic news articles the model extracts. The result of the sentiment analysis is called pre-N-ratio. From the table below you can see that algorithm calculated pre-N-ratio by finding negative words in news articles, determining the word's part of speech, and assigning negative scores to each of the words.

Both quantitative and qualitative information are imported into a Big Data Analytic database. The BPM system relies on Apache Mahout with Lifelong Machine Learning (LML) to perform a classification analysis about the bankruptcy prediction and evaluation by considering both types of data sources in the BPM. The final result for the bankruptcy prediction and evaluation is the computation of an N-ratio, which combines negative sentiment in the qualitative information and bankruptcy assessment in the quantitative information to show the best estimation toward bankruptcy prediction. The BPM system determines a N-ratio that combines financial analysis and sentiment analysis. The higher/lower the N-ratio is, the more/less likely a company is to go bankrupt within one year.
Q9
The following is the Bankruptcy Prediction Model (BPM) diagram.

Q10 The following table is a brief example of how the pre-N-ratio is calculated. (Note: POS= Part of Speech)

<table>
<thead>
<tr>
<th>Term</th>
<th>POS</th>
<th>Score</th>
</tr>
</thead>
<tbody>
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<td>Warning</td>
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<tr>
<td>Bankruptcy</td>
<td>Noun</td>
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</tr>
<tr>
<td>Criticism</td>
<td>Noun</td>
<td>-0.500</td>
</tr>
<tr>
<td>Slowdown</td>
<td>Noun</td>
<td>-0.448</td>
</tr>
<tr>
<td>Descent</td>
<td>Noun</td>
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</tr>
<tr>
<td>Failur</td>
<td>Verb</td>
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<tr>
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<td>Noun</td>
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<tr>
<td>Sigh</td>
<td>Noun</td>
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<tr>
<td>Dull</td>
<td>Adj</td>
<td>-0.368</td>
</tr>
<tr>
<td>Credit crunch</td>
<td>Noun</td>
<td>-0.360</td>
</tr>
<tr>
<td>Inflation</td>
<td>Noun</td>
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</tr>
<tr>
<td>Worry</td>
<td>Noun</td>
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</tr>
<tr>
<td>Urgent</td>
<td>Adj</td>
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</tr>
<tr>
<td>Anxious</td>
<td>Adj</td>
<td>-0.333</td>
</tr>
<tr>
<td>Pressure</td>
<td>Verb</td>
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</table>

End of Block: BPM

Start of Block: Transparency-Efficiency Trade-off Attribute- Disclosure Company description
Q67 Knowing that in reality that BPM is a data analytics and artificial intelligence system instead of a team of experts, you will be asked to consider making the going-concern decision for the same three companies.

End of Block: Transparency-Efficiency Trade-off Attribute- Disclosure

Start of Block: Company information-Tyson Foods, Inc.- Transparency-Efficiency Trade-off

Q26 The following information is about a company in which you will be asked to make a going concern decision.

Tyson Foods, Inc. is an American multinational corporation based in Springdale, Arkansas, that operates in the food industry. The company is the world's second largest processor and marketer of chicken, beef, and pork after JBS S.A. and annually exports the largest percentage of beef out of the United States.

Your audit firm has provided you with the following information about Apple to use in making a going-concern decision:

- Altman Z-score: 3.0214
- N-ratio: 0.1

Q27 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- I believe the company will be bankrupt within the next 12 months. (1)
- I do not believe the company will be bankrupt within the next 12 months. (2)
Q28 Please indicate below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score: _______ (1)
The BPM: _______ (2)

Total: _______

---

End of Block: Company information-Tyson Foods, Inc.- Transparency-Efficiency Trade-off

Start of Block: Company information-GAP-Transparency-Efficiency Trade-off

Q17 The following information is about a company in which you will be asked to make a going concern decision.

Gap was founded in 1969 by Donald Fisher and Doris F. Fisher and is headquartered in San Francisco, California. The company operates six primary divisions: Gap (the namesake banner), Banana Republic, Old Navy, Intermix, Hill City, and Athleta. Gap Inc. is the largest specialty retailer in the United States, and is 3rd in total international locations, behind Inditex Group and H&M.

Your audit firm has provided you with the following information about Gap to use in making a going-concern decision:

- Altman Z-score: 2.230616
- N-ratio: 0.5

Q18 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- I believe the company will be bankrupt within the next 12 months. (1)
- I do not believe the company will be bankrupt within the next 12 months. (2)
Q19 Please indicate below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score: _______ (1)
The BPM: _______ (2)
Total: _______

---

Q20 The following information is about a company in which you will be asked to make a going-concern decision.

J. C. Penney Company, Inc. is an American department store chain with 840 locations in 49 U.S. states and Puerto Rico. In addition to selling conventional merchandise, JCPenney offers large Fine Jewelry departments, The Salon by InStyle, and Sephora inside JCPenney.

Your audit firm has provided you with the following information about J.C. Penny Company, Inc. to use in making a going-concern decision:

- Altman Z-score: 0.87517
- N-ratio: 0.99

---

Q21 Based on the information you received about “the company”, please make a going-concern decision by choosing one of the choices below.

- I believe the company will be bankrupt within the next 12 months. (1)
- I do not believe the company will be bankrupt within the next 12 months. (2)
Q22 Please indicated below how much either of the information sources (the Altman-Z score and/or the BPM n-ratio) was relied upon in making your going-concern decision. (The total needs to add up to 100%).

Altman Z-score : _______ (1)
The BPM : _______ (2)

Total : ________

End of Block: Company information-J. C. Penney-Transparency-Efficiency Trade-off

Start of Block: Transparency Efficiency Trade Off Manipulation Check

Q75 The Altman Z-score is useful for?

- Predicting product's demand. (1)

- Used to predict the possibility of a company’s bankruptcy within one to two years before financial distress. (2)

- Testing how well a company's CEO is doing. (3)

Q76 The BPM system is designed to leverage what technologies?

- Data analytics and artificial intelligence (DA/AI) (1)

- Microsoft Powerpoint (2)

- Microsoft Excel (3)

End of Block: Transparency Efficiency Trade Off Manipulation Check
APPENDIX B - SUMMARY STATISTICS

<table>
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<th>sd</th>
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## APPENDIX C - TYPE TWO ANOVA COMPUTATION

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<td>2.00e-16</td>
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APPENDIX D - COMPUTE PAIRWISE COMPARISONS

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<td>PE</td>
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APPENDIX E - IRB APPROVAL LETTER

December 10, 2020

Dear Steven Hornik:

On 12/10/2020, the IRB determined the following submission to be human subjects research that is exempt from regulation:

| Type of Review | Initial Study
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Title</td>
<td>What are the factors that influence the adoption of data analytics and artificial intelligence in auditing?</td>
</tr>
<tr>
<td>Investigator</td>
<td>Steven Hornik</td>
</tr>
<tr>
<td>IRB ID</td>
<td>STUDY00002334</td>
</tr>
<tr>
<td>Funding</td>
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</tr>
<tr>
<td>Grant ID</td>
<td>None</td>
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</table>

Documents Reviewed:
- Algorithm Aversion Survey.docx, Category: Survey / Questionnaire;
- HRP-254-FORM Explanation of Research -Grace Tsao.pcf, Category: Consent Form;
- HRP-255-FORM - Request for Exemption-Grace Tsao.docx, Category: IRB Protocol;
- HRP-255-FORM - Request for Exemption-Grace Tsao.docx, Category: IRB Protocol;
- Recruitment Material.docx, Category: Recruitment Materials

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made, and there are questions about whether these changes affect the exempt status of the human research, please submit a modification request to the IRB. Guidance on submitting Modifications and Administrative Check-in is detailed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Katie Kilgore
Designated Reviewer
# TABLE 1

<table>
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<th>Treatment</th>
<th>reliance on the BPM</th>
<th>Standard Deviation</th>
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<td>Control Group</td>
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<td>Transparency Efficiency</td>
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<td>Effect (Before Disclosure)</td>
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<td>Company Training</td>
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<td>Positive Exposure</td>
<td>32%</td>
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<td>Difference between Control Group and …</td>
<td>P value</td>
<td>Significant (p &lt;0.05)/ Insignificant (p &gt;0.05)</td>
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<td>---------</td>
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<tr>
<td>Imperfect Algorithm (IA)</td>
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<tr>
<td>Positive Exposure (PE)</td>
<td>P = 0.36</td>
<td>Insignificant</td>
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</tbody>
</table>
REFERENCES


Jo, Nam-Ok and Shin, Kyung-Shik. (June, 2016). Bankruptcy Prediction Modeling Using Qualitative Information Based on Big Data Analytics Retrieved from http://jiisonline.evehost.co.kr/files/DLA/20160704142343_03-%EC%A1%B0%EC%98%A5%C2%B7EC%8B%A0%EA%B2%BD%EC%8B%9D.pdf


Simmons, Joseph P. and Massey, Cade. (2016). Overcoming Algorithm Aversion: People will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them Retrieved from https://pdfs.semanticscholar.org/e170/6933e9e1d15515c3a444454c15890e6d134f.pdf


