EMERGING TECHNOLOGIES AND THE ACCOUNTING PROFESSION: FRIEND OR FOE? IS THE PROFESSION IN DANGER?

by

Helen Buck

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Approved by:

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Dr. Hughlene Burton

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Dr. Jill Yavorsky

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Dr. Jack Cathey

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Dr. David Woehr

ABSTRACT

HELEN BUCK. Emerging Technologies And The Accounting Profession: Friend Or Foe? Is The Profession In Danger? (Under The Direction Of DR. HUGHLENE BURTON)

It is no secret that technological innovations have interrupted businesses in every sector, across all industries and the Accounting profession is no exception. Some of the most disruptive technologies include Artificial Intelligence, Big Data Analytics, Machine Learning, Blockchain and Robotic Process Automation and affect entry-level positions. The Big Four Accounting firms are now responding by investing in these technologies to stay ahead of the competition. Due to these significant investments, entry-level accountants need to acquire new technical skills to become employable. Using signaling theory as a springboard, my study seeks to examine whether job seekers with technology skills will apply to the accounting profession based on the investment signals from these firm. The study also examines the influences of perceived ease of use, perceived usefulness, gender and race.

Keywords: accounting, accounting profession, technology, signal of technology

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DEDICATION

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
BT	Blockchain Technology
BDA	Big Data Analytics
RPA	Robotic Process Automation
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
ST	Signaling Theory
TAM	Technology Acceptance Model

CHAPTER 1: INTRODUCTION

Technology is "the process by which an organization transforms labor, capital, materials, and information into products and services of greater value" (Jodie Moll & Ogan., 2019). Technology was previously associated with back-office and clunky mainframe computers (Dewett & Jones, 2001). However, it has become the most significant investment of a company and a source of innovation (Karhade & Qi Dong, 2021) and competitive advantage (Hannah, 2017; Li & Richard Ye, 1999) of many companies across multiple sectors and multiple industries (X. Zhang, Xu, & Ma, 2023) and has the potential to increase a company's productivity and profitability (Li & Richard Ye, 1999).

Technological innovations have disrupted almost every facet of businesses, and it is imperative that all businesses keep up to survive. The mounting threat of competition and the need to better serve their clients is driving accounting and audit companies to improve their processes to differentiate themselves and obtain a competitive advantage (Manita, Elommal, Baudier, & Hikkerova, 2020). Technology innovations threaten to wreak havoc on the accounting profession, leading accountants to fear whether technology will replace them in the future (Lacurezeanu, Tiron-Tudor, & Bresfelean, 2020; Jodie Moll & Ogan., 2019; Richins, Stapleton, Stratopoulos, & Wong, 2017).

Despite these fears, the accounting/auditing industry has traditional rules and principles that do not usually change (Damerji & Salimi, 2021; Gulin, Hladika, & Valenta, 2019), and auditors traditionally prefer human assistance rather than technology intervention (Baldwin, Brown, & Trinkle, 2006). However, the accounting industry is no exception to the technology invasion (Gulin et al., 2019), and they have to adjust their recruitment processes to position themselves better to be competitive.

A technology and investment leader at an accounting firm cautions, "It is becoming very apparent to us that Artificial Intelligence is going to have a huge impact on our business; therefore, we are building stronger and stronger capability in that space, as investment in these areas is likely to grow at an exponential rate (Hannah, 2017). Also, in their paper, McAfee & Brynjolfsson (2012) said, "We have become convinced that almost no sphere of business activity will remain untouched by this [technology] movement" (McAfee & Brynjolfsson, 2012).

This phenomenon touches a large number of accounting functions however, it will mostly threaten entry-level accountants by automating repetitive tasks, (Al-Htaybat, von Alberti-Alhtaybat, & Alhatabat, 2018; C. Zhang, Dai, & Vasarhelyi, 2018; Y Zhang, Xiong, Xie, Fan, & Gu, 2020) especially in the audit division. "Workflow automation, data analytics and artificial intelligence are fundamentally changing how audit is done," mentions a Deloitte executive (Agnew, 2016). Accounting will transform from using structured data to unstructured data such as videos, e-mails, and social media, allowing firms to perform more predictive and insightful decision-making (Gulin et al., 2019). According to a study performed by the BBC, accountants rank 21st out of 366 occupations that are likely to be eliminated due to the introduction of technology such as AI (Gulin et al., 2019), with an elimination rate of 96% (Y Zhang et al., 2020). However, the Big 4 accounting firms are not sitting on their hands and are investing in technology to address this issue (Agnew, 2016; Gulin et al., 2019; Salijeni, Samsonova-Taddei, & Turley, 2019; Y Zhang et al., 2020). KPMG and PwC, two of the Big Four accounting firms, have both conducted research to discover what areas they will have to digitalize in their companies (Gulin et al., 2019). They have also developed financial robots to generate financial reports, that also necessitates the evaluation of the role of the auditor and accountant (Y Zhang et al., 2020).

To add to the technology complexity, students do not seem to be attracted to the profession as they are concerned about the negative image of the accounting profession (Daniel, 2015). Some think that CPA firms are like sweat shops that demand excessive, inflexible hours and that accountants are dull and boring (Malthus & Fowler, 2009; Tan & Laswad, 2006). Others are negatively influenced by family (Tan & Laswad, 2006). However, for technology to be helpful, assets such as human capital (for example, accountants) are needed to work with these systems (Grover, Chiang, Liang, & Zhang, 2018; Müller, Fay, & vom Brocke, 2018; Ohlhorst, 2013). This human capital refers to those adequately trained to extract valuable information from technology such as big data (Grover et al., 2018; Müller et al., 2018). The acquisition of human capital to facilitate this endeavor is arguably the most critical element in the technology infrastructure, and they must be highly talented (Dagilienė & Klovienė, 2018; Whitelock, 2018). These resources are responsible for executing processes that lead to the production of valuable information which in turn leads to better decision making; but these resources are in short supply (M. C. Cohen, 2018). However, if they are not highly talented, they should train or acquire knowledge quickly (Maroufkhani, Tseng, Iranmanesh, Ismail, & Khalid, 2020).

Emerging technology plays an essential role in the accounting and auditing profession, necessitating that both the academic and the practitioner pay attention and address the effect of these technologies (Tapis & Hines, 2021). In his article "Losing Sleep," Daniel (2015) surveyed accounting business leaders and came up with 'nightmares' of the profession. One of the 'nightmares' was that the industry was deemed to become obsolete because of technology and was losing its relevance in the eyes of the clients. Also, it was concerning because accountants were perceived as reactive, not proactive, and unprepared to adapt to technological changes

(Daniel, 2015; Liew, Boxall, & Setiawan, 2022; Schmidt, Riley, & Swanson Church, 2020). The accounting profession needs to be proactive as, "Technology is moving so fast that all the bean-counting that has been the heart and soul of the industry is disappearing fast," warned 2020 Group USA chairman Chris Frederiksen, describing how basics of accounting like recording purchases, writing checks, invoicing, and others have disappeared in the face of automation. (Daniel, 2015).

The Big Four firms have three main divisions. Auditing, Tax, Consulting or Advisory. Technology touches all of these areas in some form. For example, the Consulting divisions in Big Four Accounting firms are now using artificial intelligence to provide meaningful data to their clients to assist them (Agnew, 2016) and Big Data Analytics tools can be used to produce impressive analytical reports that could be used to provide clients with information that they perceive to be useful, understandable and of value (Salijeni et al., 2019). However, the implosion of new technology will primarily threaten entry-level accountants across a large number of accounting functions specifically in the audit division (Agnew, 2016; Brown-Liburd & Vasarhelyi, 2015). Some audit techniques usually performed by entry-level staff will most likely become obsolete, such as sampling (Agnew, 2016), while BDA technology opens the possibility of how audits are conducted (Salijeni et al., 2019). For example, entry level auditors are usually responsible for pulling invoices for inspection. Additionally, entry-level individuals usually examine a great number of documents to identify those with inconsistencies or lacking authorization. BDA tools can electronically identify flaws such as unauthorized invoices (Salijeni et al., 2019) and purchase orders are now retained digitally instead of in hard copies (Liew et al., 2022). This change results in a quicker way to identify these source documents, which further demonstrate that the job duties of an entry-level auditor will be threatened with these technologies. As Liew et al (2022) states, “Junior auditors were previously allocated the mundane tasks of “tick and hash” to substantiate the chosen samples by locating the source documents as proof of evidence. Such mundane tasks are now being carried out by data analytic tools and matched automatically across the entire 100% of the data population, thereby requiring fewer labor hours” (Liew et al., 2022).

Some of these disruptive technologies that impact the accounting profession include Artificial Intelligence (AI) (Al-Htaybat et al., 2018; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Y Zhang et al., 2020), Machine Learning (Gramling & Stone, 2001; Jodie Moll & Ogan., 2019) Blockchain Technology (BL), (Abreu, Aparicio, & Costa; Al-Htaybat et al., 2018; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Y Zhang et al., 2020), Robotic Process Automation (Ashaari, Singh, Abbasi, Amran, & Liebana-Cabanillas; Harrast, 2020; Kokina & Blanchette, 2019; Lacurezeanu et al., 2020) and Big Data Analytics (BDA), (Al-Htaybat et al., 2018; Cao, Chychyla, & Stewart, 2015; Dagilienė & Klovienė, 2018; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Whitelock, 2018). There may be other technologies disruptive to the accounting profession as well, but our discussion focuses only on the ones described above.

AI is the ability of machines to think and make decisions like humans (Stancu & Duţescu, 2021; Y Zhang et al., 2020). It is used to put together large amounts of unstructured data to replicate complex tasks previously performed by humans (Commerford, Dennis, Joe, & Ulla, 2022) and could also be defined as where ML is used to drill into big data to learn the data and predict outcomes (Y Zhang et al., 2020). AI is desirable because it makes accounting tasks more efficient and effective (Damerji & Salimi, 2021) and is one of the most prevalent technologies that is poised to disrupt the accounting world (Al-Htaybat et al., 2018; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Y Zhang et al., 2020).

ML is an arm of artificial intelligence, described as "the science of computers running without being explicitly programmed” (J Moll & Yigitbasioglu, 2019; Y Zhang et al., 2020). “It applies a series of statistical techniques, such as mathematical modeling, data visualization, and pattern recognition, to conduct self-learning activities with input data to predict and understand data trends and patterns" (Y Zhang et al., 2020). This information could be used to build predictive models based on historical transactions. AI and ML could be used to provide real-time reporting to businesses (Gulin et al., 2019). They could also be used to assist accountants in classifying expenses and detecting fraudulent tax practices (J Moll & Yigitbasioglu, 2019; Y Zhang et al., 2020). AI adoption is an essential area of study for educators as AI will have a long-lasting impact on the accounting profession due to its ability to automate tasks in less time. However, there is a concern that this technological advancement will attract non-accountants with technical competencies to the accounting profession (Qasim & Kharbat, 2020; Richins et al., 2017).

Another emerging technology, Blockchain (BL), is defined as shared, distributed ledgers that facilitate recording transactions and tracking assets in a business network (Abreu, Aparicio, & Costa, 2018; Fanning & Centers, 2016; Y Zhang et al., 2020). BL is poised to address issues such as transparency, decentralization, immutability, tamper resistance, and strong authentication (Han, Shiwakoti, Jarvis, Mordi, & Botchie, 2023). Businesses usually operate on technological platforms, but traditional accounting and auditing practices are paper-based (Stancu & Duţescu, 2021). BL addresses this shortcoming by offering an electronic way of auditing and performing accounting processes (Dai, Wang, & Vasarhelyi, 2017; Y Zhang et al., 2020). "Blockchain aims to end the traditional methods of billing, documentation, processing, registering, inventory systems, and paying for business. This technology will allow companies to record both sides of a transaction simultaneously in a shared book in real time rather than keep audited records of financial transactions in separate privately created databases or accounting books" (Kwilinski, 2019). "The need for traditional double-entry accounting will disappear as the legality of accounting will be fully automated. Therefore, consideration of issues related to the use of the accounting infrastructure in the block is important and relevant. This process will ensure the quality, transparency, efficiency, safety, control and management processes at the enterprise." (Kwilinski, 2019).

Another disruptive technology, Robotic Process Automation (RPA) is a process where programmable robots are used to automate processes, imitating keyboard strokes that were previously performed by humans (Ashaari et al., 2021; Harrast, 2020; Moffitt, Rozario, & Vasarhelyi, 2018), especially those that are repetitive in nature. This process reduces the need for human intervention with better efficiency and reduced costs. The robot is not limited to eight hours a day, nor does it need a day off. RPA has been identified as most suitable for accounting and finance processes due to its repetitive nature (Harrast, 2020; Moffitt et al., 2018). In fact, approximately 53% of a Deloitte survey indicates that many firms have started implementing RPA (Kokina & Blanchette, 2019). Again, this significantly impacts the need for an entry-level accountant.

Big Data Analytics (BDA) refers to vast and complex data that is difficult to navigate with traditional or conventional tools (Huidong, Mustafa Raza, Muhammad Safdar, Siming, José António, & Jacob, 2020; Lawler & Joseph, 2017).. BDA is also a disruptive technology, and is used to systematically extract information from big data sets that are too large or complex to be dealt with by traditional data-processing application software (Cao et al., 2015; Dagilienė & Klovienė, 2018). BDA is needed in the financial sector as finance usually generates a large amount of data. BDA in accounting is one of the most promising technologies that has necessitated a change in how to do business in the financial sector. (Grover et al., 2018; Huidong et al., 2020; Müller et al., 2018), Moreover, it will enjoy better firm performance from using BDA assets than other less data-intensive industries (Müller et al., 2018).

Due to the arrival of these emerging technologies, the accounting profession is changing, and even though some traditional accounting skills are valuable, such as compliance, ethics, and financial reporting, to keep up with the business environment, other skills, such as data analytics, data manipulation, and data interpretation cannot be ignored (Earley, 2015; Tapis & Hines, 2021). In order for the entry-level accountant to thrive, graduates need to have a wide variety of knowledge and skills (Jeffrey Cohen & Hanno, 1993; Kroon, Alves, & Martins, 2021; Manita et al., 2020; Tysiac & Drew, 2018) but unfortunately, the accounting curriculum is rigid and has not been open to incorporate technological competencies (Qasim & Kharbat, 2020) even though prior research indicates that it must do so (Al-Htaybat et al., 2018). The lack of technological knowledge makes accounting graduates less prepared and makes technology harder to implement. Due to the advent of technologies such as AI, ML, BL, RPA and BDA, there is less need for an entry-level accountant, as these technologies can perform tasks previously performed by an accountant and challenge the status quo (Schmitz & Leoni, 2019).

Technology knowledge is fundamental in financial reporting (Haislip, Peters, & Richardson, 2016), but information about technologies and their impact on the accounting and auditing profession is severely limited. Tapis and Hines (2021) encouraged future studies on how keeping up with emerging technology may attract students to accounting. "Put simply, many of the profession's best and brightest see little or no future in the traditional public accounting industry, and firms of all sizes must focus intently on how to attract not only Certified Public

Accountants (CPAs), but also talent in data analysis, computer science, statistics, and other areas of expertise that are already changing the face of the profession and that will continue to do so." (Daniel, 2015).

The accounting profession as we know it, has existed for many decades and has withstood other changes around it. However, there is a need for a vulnerability check to see what may happen if these technological changes in the industry go ignored. What would happen if accounting firms received more applications from non-accountants with strong technological skillset? Would this impact the profession? This research is important because, left unstudied, accountants would not know how vulnerable conventional accountants would be compared to their technologically advanced counterparts. This study is also essential because it contributes to the literature on the impact of technology in accounting, exposing the intent of the non-accountant to apply for a position in the accounting profession. Additionally, practitioners and academia must be aware of the danger of not exposing accountants to technology and how race and gender influence technology use and adoption. They will also be informed about the need to pay attention to the new skillset needed by the auditing/accounting industries because, while some view emerging technologies as a friend that streamlines accounting processes and increases efficiency, others see technology as a foe threatening the profession's very existence.

The accounting/auditing industry, more specifically, the Big Four accounting firms, have taken notice of the potential efficiencies to be gained by incorporating technology into this space. They have invested heavily in technological tools (Damerji & Salimi, 2021; Gulin et al., 2019; Y Zhang et al., 2020), which signals their intention to continue on this path long term. For example, EY incorporated BDA into their work, while Deloitte developed a software called Optix for data analytics (Damerji & Salimi, 2021).

Also, these accounting firms have started incorporating AI into their work by using robots to do repetitive tasks. One example is Alpha Sense, an intelligent financial search engine that collects a massive amount of information, such as regulatory documents (Y Zhang et al., 2020). Big Four Accounting firm KPMG uses IBM Watson, which is AI designed to change unstructured data into structured data to identify the correct treatment of tax deductions (Kokina & Davenport, 2017; Jodie Moll & Ogan., 2019; Y Zhang et al., 2020). Deloitte's use of AI using a Natural Processing Language (NLP) can automate document reviews, and process tax returns (Y Zhang et al., 2020). Deloitte also partnered with Kira Systems to document, review, and extract specific information, such as terms, from its database (Damerji & Salimi, 2021; Kokina & Davenport, 2017; Richins et al., 2017). PwC's own AI technology, called GL.ai, is programmed to detect irregular transactions in the general ledger and is likely to give the company a competitive advantage, and KPMG uses an RPA technology called K-Analyzer that can analyze thousands of tax transactions in minutes and summarize the results (Y Zhang et al., 2020).

Deloitte is creating BL labs to improve its AI capabilities, to improve audits and to help businesses with their initiatives, manage opportunities, and work on improving issues associated with the phenomenon in its infancy and growth (Bonyuet, 2020; Y Zhang et al., 2020). They have over 800 professionals in BL Labs in New York, Dublin, and Hong Kong (Y Zhang et al., 2020). PwC was not going to be left out. They developed a new BL solution to discover patterns that are not obvious to humans (Y Zhang et al., 2020). EY also developed a Blockchain Analyzer, a technology used to review and audit cryptocurrency transactions (Bonyuet, 2020; Han et al., 2023; Y Zhang et al., 2020). KPMG also came up with KPMG Digital Ledger Services, a BL technology used to automate back-office operations for financial institutions (Y

Zhang et al., 2020). These technologies can replace the duties usually performed by traditional accountants. In response to these emerging technologies, accountants will need to develop new skills and competencies to survive in the technological world (Dagilienė & Klovienė, 2018; Earley, 2015; Kroon et al., 2021; Jodie Moll & Ogan., 2019). Previous research indicates that enough attention has not been given to how technology affects accountants (Jodie Moll & Ogan., 2019).

My study investigates this phenomenon by using perceived usefulness (PU) and perceived ease of use (PEOU) measures of the Technology Acceptance Model (TAM) developed by Fred Davis, together with gender and race, to investigate the strength of the relationship between the signal of accounting firms use of technology and a job seeker's intention to apply for a job in the accounting profession. I focus on the Big Four accounting firms, Deloitte, EY, KPMG and PwC as they embrace technology more than their smaller counterparts and are considered to play an essential role in the deployment of technology (Jodie Moll & Ogan., 2019). Using Signaling Theory (ST) as a springboard, I plan to survey potential job seekers, such as students, to explore whether their knowledge or perceptions of technology will influence their intention to apply for a job in the accounting profession.

Based on this knowledge, I expect that job seekers with little or no accounting knowledge will be more likely to apply to the accounting profession because of the expansion of technology use by accounting firms. I expect this to be especially true for those job seekers who perceive that knowledge of technology is useful for the job and those that perceive that technology is easy to use. I also expect to find that the relationship would be influenced by gender and race, and it is highly likely that those gravitating to the accounting profession would be primarily white males. Taken together, I expect that my study will add to the literature by informing academia of the need to incorporate technology into the accounting curricula for the profession to remain viable. This study will also highlight the potential exclusion of valuable resources such as women and minorities.

The rest of the paper is arranged as follows: Chapter 2 is the literature review that discusses the disruptive technologies of AI, ML, BL, RPA, and BDA, and addresses how the accounting firms are responding to this by their significant investments, thereby signaling that they have technologically prowess. Chapter 2 also discusses signaling theory and how perceived ease of use and perceived usefulness can strengthen or weaken the relationship between the signal of technology use and the intention to apply to the profession. I also discuss race, and gender. Chapter 3 describes the theoretical model and offers the hypotheses.

CHAPTER 2: LITERATURE REVIEW

Technology continues to be a significant disruption to businesses across all industries and all sectors. The accounting profession is no exception. Accounting is referred to as the language of business, and its origin is credited to the "Father of Accounting," Luca Pacioli, in 1494 (Richins et al., 2017). Accounting "measures an organization's economic activities and communicates such information to related stakeholders, such as corporate managers, creditors, consumers, and regulators" (Y Zhang et al., 2020).

Technology can refer to a huge phenomenon. For this paper, I restrict our reference to technology to the following areas of technology that are most disruptive to the accounting profession such as AI (Al-Htaybat et al., 2018; Kroon et al., 2021; Manita et al., 2020; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Y Zhang et al., 2020), ML (Audrey & Dan, 2001; Jodie Moll & Ogan., 2019), BL, (Abreu et al., 2018; Al-Htaybat et al., 2018; Kroon et al., 2021; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Y Zhang et al., 2020) RPA (Ashaari et al., 2021; Harrast, 2020; Kokina & Blanchette, 2019; Lacurezeanu et al., 2020) and BDA, (Al-Htaybat et al., 2018; Cao et al., 2015; Dagilienė & Klovienė, 2018; Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020; Whitelock, 2018).

To address this phenomenon, the Big Four accounting firms have already started planning to incorporate technology into their processes (Moffitt et al., 2018; Y Zhang et al., 2020). For example, Deloitte uses robotic technology within its audit division to perform some tasks, leaving humans to focus on other decision-making tasks (Bullock, 2017). This change will eliminate the need for primary processing, thereby threatening entry-level job applicants and interrupting accounting practices, forcing the accountant to develop new skills in anticipation of these disruptive technologies (Kroon et al., 2021; Tysiac & Drew, 2018). Similarly, PwC uses

RPA to convert balance sheet information to tax information, making it easier to prepare income tax returns. PwC has also incorporated AI into its processes by using robots to make decisions that a seasoned auditor would make (Y Zhang et al., 2020). Similarly, EY, uses drones for inventory counting and observation, transmitting the data directly into their system (Kokina & Davenport, 2017). They also use ML technology to detect fraud. The other Big Four accounting firm, KPMG, uses AI, called the FBT Automator, to complete compliance tasks (Y Zhang et al., 2020) that can run analysis on tax and payroll tax returns.

These are a few technological tools that the accounting giants have implemented to gain efficiencies and productivity in their businesses. The Big Four accounting firms reveal two common trends. First, the accounting profession is increasingly investing in AI and its integration into the core business, signaling their intent to continue to use technology; second, the Big Four claim that AI is a crucial factor for future success in the accounting field" (Bonyuet, 2020; Kokina & Davenport, 2017; Y Zhang et al., 2020). I will discuss these disruptive technologies separately.

2.0:Technology and the Accounting Profession

2.10: Disruptive Technology: Big Data Analytics

BDA is arguably one of the most impactful technologies in recent years, especially in the financial sector. It is used to extract information from huge, complex data that is difficult to navigate with traditional or conventional tools (Huidong et al., 2020; Lawler & Joseph, 2017). The overwhelming phenomenon of big data is associated with the Vs which are, volume, velocity, variety (Andrew & Erik, 2012; Arthur & Owen, 2019; Dagilienė & Klovienė, 2018; Farboodi & Veldkamp, 2020; Grover et al., 2018; Huidong et al., 2020; Maroufkhani et al., 2020; McAfee & Brynjolfsson, 2012; Niebel, Rasel, & Viete, 2019; Saha, 2019; Thuy Duong &

Teuteberg, 2019; Vasarhelyi, Kogan, & Tuttle, 2015; Zhu, 2019) and veracity (Huidong et al., 2020; Ohlhorst, 2013) and value (Grover et al., 2018; Rezaee & Jim, 2017). Other authors include validity and volatility (Whitelock, 2018). Examples of big data include millions of Twitter posts daily or thousands of pictures on Instagram daily. Big data is instrumental in the financial world as it can help auditors to identify and assess risks of material misstatements and perform other assessments (Cao et al., 2015). However, finance professionals such as accountants must possess the necessary skills to utilize the technology to produce meaningful decisions (Huidong et al., 2020; Kroon et al., 2021; Maroufkhani et al., 2020; Müller et al., 2018).

Big data could be accessed and manipulated using BDA tools. For example, it could identify audit risks of audit engagement, material misstatements, environmental risks, and many more (Cao et al., 2015). This process has changed how business is conducted in various sectors and is particularly significant in the financial industry (Huidong et al., 2020). This technology provides an opportunity for finance and accounting professionals to gain insights into big data (Lawson & Hatch, 2020), as the industry is known to collect a massive amount of data. Therefore, those in the accounting profession must be competent to process and analyze this information (Cockcroft & Russell, 2018; Dagilienė & Klovienė, 2018) For many, this will require developing new skills, including enhanced abilities to organize, structure, and understand data sets and the ability to provide more in-depth and strategic analysis (Kroon et al., 2021; Lawson & Hatch, 2020; Tysiac & Drew, 2018).

Analyzing audits has evolved through the integration of big data tools (Huidong et al., 2020) and firms have pledged to put significant resources into such tools (Austin, Carpenter, Christ, & Nielson, 2021; Lawler & Joseph, 2017; Schmidt et al., 2020). Both practitioners and academics agree about the importance of data analytics (Perols, Bowen, Zimmerman, & Samba, 2017; Srinivasan & Swink, 2018; Thuy Duong & Teuteberg, 2019) and that BDA is more powerful than the usual audit tools, which can take the auditing profession to new heights (Cao et al., 2015). Whether by identifying fraud indicators, or using it to process loans or assess patterns in insurance or supporting trade, BDA has become a big part of everyday lives and collecting and evaluating both financial and non-financial data and the advent of BDA can tremendously influence the industry (Arthur & Owen, 2019; Warren, Moffitt, & Byrnes, 2015). The Accounting sector could also leverage its data analytic assets to improve marketing, identify new customers, and personalized services (Arthur & Owen, 2019).

Academia is encouraged to incorporate BDA into the curriculum for both graduate and undergraduate levels to teach students how to better use these tools (Cao et al., 2015; Rezaee & Jim, 2017). The knowledge of these tools would help them to respond to the need for data analysts due to the growing demand and short supply of big data professionals. In a qualitative study of practitioners and academics, both groups agreed that it was essential to incorporate BDA into accounting courses to capture the techniques (Rezaee & Jim, 2017). One of these techniques include using sensors that can assist in tracking, which in turn results in extracting valuable data. It is particularly useful in finance as it can track inventory and produce other information that auditors can use to gain efficiencies.

Accountants and financial analysts can use big data to manage and eliminate some risks (Huidong et al., 2020). For example, BDA allows companies to measure data more precisely, leading to better predictions and more intelligent decisions, signifying to leaders across industries that BDA is a management revolution (McAfee & Brynjolfsson, 2012). According to Kirkos, Spathis & Manolopoulos (2007), fraud costs US businesses more than $400 billion annually (Kirkos, Spathis, & Manolopoulos, 2007), and $3.5 trillion worldwide (Rezaee & Jim, 2017). Forensic accounting, using technology tools can now incorporate data visualization, predictive analytics, behavior, and content analytics to expose fraud patterns and suspicious transactions (Rezaee & Jim, 2017). Financial statement fraud could be a costly problem that leads to significant negative consequences, and BDA techniques could be used to improve fraud prediction models by identifying and partitioning different types of fraud (Perols et al., 2017). Therefore, it would be easier to determine whether fraud was perpetrated in revenues, bankruptcy, or whether there were material weaknesses in internal control (Perols et al., 2017).

In an ethnographic study, Arthur & Owen (2019) found that BDA tools were used to analyze information, which allowed banks to utilize vast amounts of payment card data. This data was transformed into valuable insights for the banks and was used for loyalty programs and helped to keep both old customers and attract new customers (Arthur & Owen, 2019). These tools could be used to mine data to expose customers' behaviors; what they bought and from whom, how much they spent, and the location of the purchase. This information gave them valuable insights into managing their loyalty program (Arthur & Owen, 2019).

In another study, Warren et al. (2015) used algorithms for various tasks and videos to monitor whether workers were actively involved in production or doing other nonessential activities, thereby monitoring inventory and property (Warren et al., 2015). The same method could assist auditors in performing their jobs. Audio data could be used for interviewing, and analytical tools could be used to detect speech patterns in the event of fraudulent situations. As auditors use BDA to analyze all these unstructured data, they can combine their findings with financial data to produce more comprehensive audit results. (Perols et al., 2017). Similarly, they could use a Balanced Scorecard which is a system that aligns financial and non-financial measures with the goals of a company and the use of BDA and ML can identify behaviors and predict performance (Goldstein, Spatt, & Ye, 2021). Some analytical tools can discover relationships between management and performance, such as tones of e-mail, which may indicate morale, or computer activity by a manager can demonstrate productivity (Warren et al., 2015). These tools are also helpful to auditors in predicting fraud.

Improved technology has resulted in the advancement in the processing of financial transactions from sales pitches to working papers (Moffitt et al., 2018), and the technology paradigm has shifted from the evolution of accounting records from hand-written entries to electronic entries to present-day Enterprise Resource Planning (ERP) systems (Warren et al., 2015). Mined data is also helpful in predicting bankruptcy or assessing the financial state of a company or, better still, identifying an auditor's engagement risk (Cao et al., 2015) or improving the efficiency and effectiveness of financial statement audits (Dagilienė & Klovienė, 2018). Auditors can use BDA to ensure accuracy, reduce waste, and identify misappropriations (Moffitt & Vasarhelyi, 2013). The Securities Exchange Commission (SEC) also uses analytics to watch market events and identify audit failures and financial statement fraud (Cao et al., 2015).

Accounting firms are poised to reap significant benefits from the application of BDA tools as they can process and review most of their information, rather than a sample as is usual in the accounting industry (Cao et al., 2015; Lawler & Joseph, 2017). They can use correlation in events or transactions to identify items of interest in audits. Management accountants can also use BDA to increase efficiencies by using analysis results to facilitate better decision-making (Qasim & Kharbat, 2020). The financial sector's dependence on BDA is increasing over time, and analytical tools continue to be more sophisticated, which contributes to the finance field moving towards the digitization of big data to help strengthen the performance of companies (Huidong et al., 2020).

Companies now require the use of unstructured data that was previously deemed useless. So, for example, security videos could be used not only to confirm whether clients received shipped goods, but also to observe and deter fraudulent activities. Radio Frequency Identification (RFID) devices could be used to tag inventory by auditors (Moffitt & Vasarhelyi, 2013) for inventory counts, reducing the time it traditionally took to physically count inventories. Additionally, auditors could use web hits to predict purchases and revenues of clients (Vasarhelyi et al., 2015), and BDA could help in tax system reforms, investigation of perceived crimes, increase the rate of automation, transparency, and improved risk analysis (Huidong et al., 2020). In an interview with a chief audit executive, Austin et al. (2021) describes auditors as not looking for unusual transactions but a combination of unusual transactions, indicating a pattern. The interview also revealed that the auditor-interviewees agreed that data analytics improved audit quality and strengthened the relationship between auditor and client (Austin et al., 2021).

Auditors can benefit from data analytic tools which could be used for customer default rates, automatic confirmations (Moffitt & Vasarhelyi, 2013), personal and institutional credit ratings, and online payment services (Huidong et al., 2020) as well as process mining of event logs. Again, the process mining applies to the whole population of items under audit, not just a sample as traditional auditing practice. This process can uncover audit issues such as violation of segregation of duties and unauthorized payment not identifiable using traditional methods (Jans, Alles, & Vasarhelyi, 2014). Such techniques are helpful for the audit process to identify fraudulent transactions or other illegitimate transactions and facilitates tasks that used to take a long time to complete to be done in a relatively short time.

Still, despite all the benefits of BDA tools, it is important to remember that potential success in deploying BDA comes with challenges. In addition to the costs of purchasing BDA assets, which may be prohibitive, training for users of these tools is essential, and there is a need for employees to become proficient in making sense of the data (Thuy Duong & Teuteberg, 2019). The need for training means that companies may have to hire experts to interpret the results. Therefore, more education is necessary (Stancu & Duţescu, 2021) to understand these technological tools. In their paper, McAfee & Brynjolfsson (2012) identified specific challenges associated with big data and one of them was the need for human capital (McAfee & Brynjolfsson, 2012), which may lead to a greater demand for accounting engineers (Gulin et al., 2019) and data scientists (Lawler & Joseph, 2017) or those who are familiar with manipulating the data to extract information (Thuy Duong & Teuteberg, 2019).

2.11. Big Data Analytics and the Signal of Accounting Firms

The field of BDA is essential both in academia and business (Perols et al., 2017; Srinivasan & Swink, 2018; Whitelock, 2018) and was identified as one of the most popular (Dagilienė & Klovienė, 2018), most adopted (Nam, Lee, & Lee, 2019) and most significant technology trends (Chen, Chiang, & Storey, 2012) that has transformed the way companies compete (Maroufkhani et al., 2020). Innovations include fund generation through crowdfunding, online trading, the creation of cryptocurrencies, and mobile banking platforms (Huidong et al., 2020).

In the past, audit firms have used Computer Assisted Audit Techniques (CAAT) (Earley, 2015), Audit Command Language (ACL), and Interactive Data Extraction and Analysis (IDEA) for audit activities and they are considered to be the prelude to BDA (Salijeni et al., 2019). Now audit firms are making significant investments into BDA such as the investments by KPMG of

$100 million, and EY of $400 million for innovation and exploration, as well as PwC's investment and development of Halo, and Deloitte's development of a software called Optix for data analytics (Damerji & Salimi, 2021; Han et al., 2023; Kokina & Davenport, 2017; Salijeni et al., 2019) and other audit firms have invested in BDA software such as Spotlight, Lavastorm, and Alteryx. In addition, the following comments were made by Big Four leaders:

"By combining the leading-edge predictive analytics capability with our data and analytics expertise, we are set to transform our approach to audit to deliver greater quality, value, and actionable insights." (KPMG leader) (Salijeni et al., 2019) and "We are excited about data-enabled auditing, and also about new ways of reporting that reflect society's changing expectations of performance and value." (PwC leader) (Salijeni et al., 2019).

2.12. Disruptive Technology: Artificial Intelligence/ Machine Learning

AI is an umbrella term that captures multiple types of automated technologies, from simple to more complicated technologies, used to mimic human tasks (Bakarich & O'Brien, 2021; Stancu & Duţescu, 2021). AI is important for automating processes, extracting information, and engaging with stakeholders (Bakarich & O'Brien, 2021). AI uses multiple technologies, such as data mining, machine learning, speech, and image recognition (Bakarich & O'Brien, 2021). It is widely available and popular due to its affordability and ability to rapidly process information (Stancu & Duţescu, 2021). It is especially desirable as it can be deployed in the cloud, does not need hardware space, and can utilize structured and unstructured data (Stancu & Duţescu, 2021).

AI applications are widely used. However, firm size plays a role, as only the larger firms can make the significant investment needed for this application (Bakarich & O'Brien, 2021). The Big Four accounting firms are more exposed to the technology and utilize it more widely than their smaller counterparts (Bakarich & O'Brien, 2021). Some of these technologies include Nuance, used to identify voice characteristics that can identify potential fraudulent calls, and Alexa, mainly used by Amazon to perform functions as a personal assistant through voice activation. Banks also use the technology as a means for customers to use their voice to access their bank accounts (Y Zhang et al., 2020).

ML is an arm of Artificial Intelligence and is the ability of computers to self-program (Bakarich & O'Brien, 2021; Stancu & Duţescu, 2021). AI and ML can be used for pattern recognition (Stancu & Duţescu, 2021). Therefore, they can be useful in processes such as reconciliations, eliminating the need for humans to perform the task and giving accountants more time to perform other tasks that need critical thinking. ML is helpful in the accounting/auditing profession as it could be used to classify transactions based on history using algorithms (Jodie Moll & Ogan., 2019; Y Zhang et al., 2020). It could also be deployed to identify fraudulent activities.

2.13. Artificial Intelligence/Machine Learning and the Signal of Accounting Firms

The Big Four accounting firms have also started incorporating AI into their work (Bakarich & O'Brien, 2021; Baldwin et al., 2006; Y Zhang et al., 2020). This introduction may replace the duties usually performed by accountants (Richins et al., 2017). There are various types of AI in the accounting space, such as Alpha Sense, an intelligent financial search engine that collects considerable information, such as regulatory documents. There is also IBM Watson, an AI technology (through a partnership with accounting firm KPMG) designed to change unstructured data into structured data to identify the correct treatment of tax deductions (Kokina & Davenport, 2017; Jodie Moll & Ogan., 2019; Y Zhang et al., 2020) and KPMG’s KRisk, a decision aid tool used to help audit professionals make informed decisions regarding risk assessments for their clients (Baldwin et al., 2006; Bell, Bedard, Johnstone, & Smith, 2002). Clarifai is an AI software used to calculate stock/items to determine how quickly the object moves from the shelf (Y Zhang et al., 2020) and PwC has Planet (Baldwin et al., 2006) and Halo (Kokina & Davenport, 2017) used for analyzing accounting journals and augmenting human support-based business intelligence. Similarly, Deloitte uses AI such as the Kira system which is also called Argus, an ML learning tool used to scan documents to identify and extract specific accounting information (Agnew, 2016; Chiang, Agnew, & Korol, 2021; Damerji & Salimi, 2021; Kokina & Davenport, 2017; Richins et al., 2017) and ADAPT, an audit planning tool (Baldwin et al., 2006).

AI is getting so popular that 75% of corporate executives reported that at least 30% of audits will be performed by AI in the year 2025 (Damerji & Salimi, 2021) because there would be a push to get acceptance of AI into the auditing world. The IBM Watson, KPMG's AI tool, was operationalized using over 10,000 documents and Deloitte's use of AI using a natural processing language (NLP) can automate document reviews, freeing the auditor to move to other tasks allowing Deloitte to process over 50,000 specialized tax returns (Y Zhang et al., 2020).

PwC's AI technology, called GL.ai, is programmed to detect irregular transactions in the general ledger, giving the company a competitive edge (Y Zhang et al., 2020). PwC also uses a natural language generation (NLG) called Quill to produce automated narratives for anti-bribery and anti-corruption reporting, considerably reducing the time to create a report (Y Zhang et al., 2020). They also leverage NLP technology to build AI that could examine lease contracts more efficiently than humans, and their ML technology can detect fraudulent transactions with a 97% accuracy (Y Zhang et al., 2020). They can also use drones to count inventory (Kokina & Davenport, 2017). As Zhang et al. (2020) describe it, "first, the accounting profession is increasingly investing in AI and its integration into core business; second, the Big Four claim that AI is a key factor for future success in the accounting industry” (Y Zhang et al., 2020). As AI starts to 'catch fire,' it will negatively impact the previously successful careers of accountants and accounting students if they are not well equipped to handle these technological advances.

2.14. Disruptive Technology: Robotic Process Automation

RPA is an automated process that could interact with other systems and be used for time-consuming, repetitive, or routine tasks (Rozario & Vasarhelyi, 2018), leading to operational efficiency and effectiveness (Cooper, Holderness, Sorensen, & Wood, 2022). RPA mimics tasks that humans usually perform and was rated as the leading technology priority and strategy for business leaders in upcoming years (Cooper, Holderness, Sorensen, & Wood, 2019). RPA could be used to complete tasks such as spreadsheets, sending e-mails, and other human-related tasks (Y Zhang et al., 2020), reducing processing time and improving accuracy (Cooper et al., 2019). It has been also widely used to automate repetitive tax processes (Cooper et al., 2022; Y Zhang et al., 2020), which can eliminate the need for entry-level tax accountants, resulting in increased available time for tax preparers to focus on other strategic tasks. Both lower-level and higher-level employees in a study believe that there are benefits to using RPA (Cooper et al., 2022). Lower-level employees and managers believe that jobs will be transformed from repetitive tasks to more value-added tasks, leading to better job satisfaction. They also believe that the use of RPA will open career opportunities and lead to the attractiveness of the accounting profession (Cooper et al., 2022).

2.15. Robotic Process Automation and the Signal of Accounting Firms

RPA is desirable to accounting firms because it mimics human tasks (Moffitt et al., 2018). Consequently, EY defined them as "software robots that offer improved business efficiency, data security and effectiveness by mimicking human actions and automating repetitive tasks across multiple business applications." (Bakarich & O'Brien, 2021) Accounting firms have discovered potential benefits in investing in RPA and have made significant investments in the software (Cooper et al., 2022) to help them become more efficient in what they do. For example, auditors usually establish a three-way match of purchase order, receiving document, and invoice when they check to confirm revenue. RPA can be programmed to identify such matches, improving efficiencies (Bakarich & O'Brien, 2021). Also, some accounting companies use software called AI Extractor, which can be used to do the same task (Y Zhang et al., 2020). Audit firms must constantly evolve their processes and models "by acquiring innovative technology to propose digital solutions" (Manita et al., 2020). For example, the Big Four accounting firm KPMG uses an RPA technology called K-Analyzer to analyze thousands of tax transactions and summarize the results in minutes (Y Zhang et al., 2020).

The leading areas of RPA adoption are Tax, Advisory, and Assurance Services (Cooper et al., 2019). RPA software can be programmed to read and send e-mails, open PDF documents, and enter information into ERP systems (Moffitt et al., 2018) and PwC uses the technology to collect tax information (Y Zhang et al., 2020). Additionally, there have been significant gains in RPA by accounting firms. For example, a company reported that they saved over one million human work hours, while another revealed that a 16-hour job performed by humans was turned into a 17-second job when executed by RPA and increased quality approaching 99.9 percent, up 9.9 percent over the human counterpart (Cooper et al., 2019). The takeover by technology of these functions will significantly impact the need entry-level accountants (Liew et al., 2022).

2.16. Disruptive Technology: Blockchain

BL technology is another emerging technology introduced by (Nakamoto, 2008) that is poised to change the accounting landscape and has been described as a game-changer (Jodie Moll & Ogan., 2019; Qasim & Kharbat, 2020). BL can be described as a series of blocks used to establish ownership (Fanning & Centers, 2016; Y Zhang et al., 2020). It could also be defined as a decentralized database, or shared, distributed ledger that facilitates the process of recording transactions and tracking assets in a business network (Abreu et al., 2018; Y Zhang et al., 2020) and has been hailed as the future recordkeeping solution of accounting (Coyne & McMickle, 2017; Dai et al., 2017) because of the potential difficulty in manipulating transactions in its ledgers (Coyne & McMickle, 2017; Dai et al., 2017; Ferri, Spanò, Ginesti, & Theodosopoulos, 2021). Distributed ledgers are more difficult to tamper with or hack, which makes them more desirable to the accountant or auditor, hence improving the authenticity of the audit information (Jodie Moll & Ogan., 2019; Y Zhang et al., 2020).

BL uses encrypted data to identify, authenticate, and authorize access to information (Abreu et al., 2018; J Moll & Yigitbasioglu, 2019) which could be public or private. Its information is stored in blocks on an encrypted peer-to-peer network to validate transactions and is the underlying software for the popular cryptocurrency, Bitcoin (Dai et al., 2017; Jodie Moll & Ogan., 2019). BL technology is projected to be worth $20 billion by 2024 and is estimated to save financial institutions $20 billion annually in various costs (Fanning & Centers, 2016). However, moving BL from concept to adoption has been very slow as there is little technical expertise to manage this phenomenon (Abreu et al., 2018).

BL technologies can be used in auditing (Dai et al., 2017; Fanning & Centers, 2016) to verify or compare financial data while upholding data privacy. BL technology could also be used to evaluate compliance criteria so auditors can check BL ledgers instead of sending out third-party confirmations (Y Zhang et al., 2020), which reduces costs. Third party confirmations are verification documents that auditors send to other organizations to confirm their clients' information. BL technology is desirable because its information is digital and cannot be modified, erased, or changed without the consent of all parties in the block which helps data integrity (Fanning & Centers, 2016; Gulin et al., 2019), and is of extreme importance in audits (Kwilinski, 2019; Y Zhang et al., 2020) and can significantly assist the auditor's work as the system could be trusted(Abreu et al., 2018; Cong, Du, & Vasarhelyi, 2018).

Blockchain is one of the most disruptive technologies (Dai et al., 2017; Fanning & Centers, 2016; Ferri et al., 2021; Jodie Moll & Ogan., 2019) with the capability of radically changing the accounting and auditing profession (Dai et al., 2017; Ferri et al., 2021) and has the potential to create an accounting ecosystem (Dai et al., 2017). It is expected that sometime down the road, BL will become a transformative technology (Fanning & Centers, 2016) with auditing solutions to better address auditing challenges such as lost documents and audit time (Abreu et al., 2018; Fanning & Centers, 2016). A company developing a Blockchain solution explains its goal: "to help auditors expand their ability to offer assurance services to any BL platform and change the timing of their service from post-transaction to real-time. To create software that extracts, normalizes, monitors, notifies, analyses, and reports on data against pre-set rules, notifications, and control frameworks that are specific to specific auditors' approaches and methodologies" (Abreu et al., 2018).

Blockchain technology will revolutionize traditional practices such as invoicing, documentation, processing, registration, inventory management, and payment methods in business (Kwilinski, 2019). This innovative technology enables companies to record both aspects of a transaction simultaneously in a publicly accessible ledger in real-time, eliminating the need for maintaining separate, private databases or accounting books for audited financial record (Kwilinski, 2019). As a result, the conventional practice of double-entry accounting is expected to become obsolete, with the entire accounting process transitioning to full automation (Ferri et al., 2021; Kwilinski, 2019).

Therefore, consideration of issues related to the use of the accounting infrastructure in BL is important and relevant. This will ensure the quality, transparency, efficiency, and safety of accounting and control and management processes at the enterprise. (Ferri et al., 2021; Kwilinski, 2019). Using BL as an accounting/auditing platform will reduce or eliminate the time it takes to perform some accounting processes, such as reconciliations, leading to more efficient and effective processes and also a reduction of fraud as all parties to a block will need to verify the transaction before it is authenticated (Ferri et al., 2021), which is very desirable in the accounting profession. Also, the perception of control has a positive effect on auditors' intention to use BL technology, and it could be considered as a type of database similar to ERPs (Ferri et al., 2021) although ERPs are more centralized in nature as compared to a BL database which is decentralized (Dai & Vasarhelyi, 2017).

Also, BL databases have low tampering risk and are non-labor intensive, requiring minimal human intervention compared to their ERP counterpart (Dai et al., 2017). BL was initially designed to be a public database accessible to the general public. However, for obvious reasons, such as privacy and confidentiality, the needs of auditors would not be served using a public database. Therefore, auditors can utilize a private BL technology that limits access to authenticated participants (Dai et al., 2017; Ferri et al., 2021) and provides a secure database for its clients due to its need for confidentiality and to prevent unauthorized access

(Dai & Vasarhelyi, 2017). BL technology can support an accounting ecosystem by processing automated accounting processes using smart contracts (Dai et al., 2017). The technology can allow business rules and agreements to be embedded into these smart contracts to facilitate automation and storing documents in the ledgers.

2.17. Blockchain and the Signal of Accounting Firms

The Big Four Accounting firms have been researching the BL phenomenon in collaboration with the American Institute for Certified Public Accountants (AICPA) to determine the potential impact of this technology (Bonyuet, 2020). They have partnered with various software companies to formulate a solution to this issue (Bonyuet, 2020) as BL technology has the potential to disrupt the auditing world from the traditional ways of auditing, (Dai et al., 2017; Jodie Moll & Ogan., 2019). Deloitte is getting in the game by creating BL labs to help businesses with their initiatives, manage opportunities and work on improving issues associated with the phenomenon in its infancy and growth (Bonyuet, 2020; Y Zhang et al., 2020) which is evidenced by their over 800 professionals in BL Labs in New York, Dublin and Hong Kong. The Deloitte Blockchain Lab was conceived to help "inspire collaboration, real-world insights, broader perspectives, faster decision making, accelerated implementation and proof of concept development" (Pawczuk, 2020). PwC was not going to be left out. They developed a new BL solution to discover patterns that are not obvious to humans (Y Zhang et al., 2020). Additionally, EY wants to play in the sandbox as well. They developed a Blockchain Analyzer, a technology used to review and audit cryptocurrency transactions (Y Zhang et al., 2020) and it is also used to gather and reconcile data from multiple blockchain ledgers (Zemankova, 2019) which helps in decision-making (Cazazian, 2022).

KPMG also came up with KPMG Digital Ledger Services, a BL technology used to automate back-office operations (Bonyuet, 2020; Y Zhang et al., 2020) to help with some goals such as proof of ownership, enhanced transparency (Ferri et al., 2021), clear order of transactions, verification of transaction legality, and setting up of algorithms for accounting rules (Y Zhang et al., 2020). BL is desirable for some of its valuable properties. For example, transactions on BL technology are difficult to change without permission, therefore, transactions conducted on this technology are reliable and authentic (Abreu et al., 2018). Utilizing a blockchain platform simplifies the process of obtaining auditable information since it seamlessly traces the transaction path, thereby ensuring verifiability (Y Zhang et al., 2020) which is desirable for auditors who can easily verify their clients' transactions.

Accounting firms are signaling their intent to invest significantly in these emerging technologies to remain competitive (Schmidt et al., 2020). This necessitates that accounting professionals acquire programming skills to be proficient in these technologies. They must be capable of understanding emergent tools, interfacing with reporting techniques, and interpreting reports to answer questions from authorities. Also, introducing advanced technology into the accounting profession will likely reduce the employment opportunities for traditional or entry-level accountants without programming and analytic skills, because even though most of these technologies impact a wide variety of areas, especially audit, and some tax areas, the focus is mostly on entry or lower-level tasks. It is crucial for accountants to continuously improve their professional knowledge and skills to complete more challenging tasks. At the same time, it is also necessary for education systems to respond accordingly by incorporating a higher level of technological proficiency.

Changes in information technology have severe implications for the Accounting industry. These technological advancements necessitate that auditor acquire another skillset (Earley, 2015; Gulin et al., 2019; Manita et al., 2020), especially those aligned with information technology (IT) (Abreu et al., 2018; Gulin et al., 2019). Potential employees should receive deep training in data processing and analysis, especially in using new technologies. Plus, they may have to be double degreed, majoring in Accounting and Engineering (Liew et al., 2022; Manita et al., 2020; Schmidt et al., 2020). The use of some of these technologies will lead to the potential expansion of hiring in other career fields, especially computer programmers and software engineers (Cooper et al., 2019) and other non-accounting professionals (Schmidt et al., 2020).

To sum it up, "there is evidence that the accounting profession has signaled its commitment to these emerging technologies given that large accounting firms have dramatically increased their purchases of technologies. Also, because accounting firms of all sizes are hiring non-accountant employees at an annual growth rate of nearly 20%" (Tysiac & Drew). As Coyne et al (2017) mentioned, “the current status quo is to hire information systems students to perform even the most menial IT audit and data analysis tasks because accountants lack the relevant knowledge. Yet if accountants continue to not learn IT skills, IT specialists might learn theirs and replace them” (Coyne, Coyne, & Walker, 2017).

2.2. Signaling Theory

In assessing the significant investment of technology by accounting firms and the intention to apply to the profession, we draw on our main theory, Signaling Theory (ST), first introduced by Spence (1973) to help explain the dynamics. ST broadly refers to the "deliberate communication of positive information in an effort to convey positive organizational attributes" (Connelly, Certo, Ireland, & Reutzel, 2011). In his seminal work, Spence (1973) demonstrated how potential employees in labor markets distinguish themselves to employers by investing in education (Spence, 1973). ST describes how two parties communicate when they both have limited information (Connelly et al., 2011). It also shows how insiders (or signalers) deliberately communicate information about their positive attributes to outsiders (Connelly et al., 2011). For example, firms would increase their reputation management activities towards visible stakeholders to signal a higher reputation, charge premium prices, or attract and retain employees (Carter, 2006). It could also be the introduction of a new CEO after a restatement to signal credibility to investors after the CEO certifies the company's financial statement (Yan Zhang & Wiersema, 2009), especially after corporate scandals to restore investor confidence. Or a college football coach who arrives on campus with a luxury limousine complete with the school's logo as a signal of opulence to the young impressionable minds of potential high school recruits (Connelly et al., 2011). ST also posits that job seekers are influenced by company recruiters' impressions (or signals) (Bondarouk, Ruël, & Parry, 2017; Rynes & Miller, 1983). Interestingly, EY, a Big Four accounting firm, has visited university Engineering campuses to recruit their top Engineering graduates (Hannah, 2017) and PwC plan to open a four-year technology apprenticeship where students will undertake both business and computer science degrees (Hannah, 2017). Additionally, the KPMG, Deloitte and PwC have publications on their websites flaunting how BDA can greatly help with efficiency and effectiveness (Cao et al., 2015). These are clear signals that these firms are communicating to the general public, including potential job seekers about their investments in technology.

Signalers are usually insiders, and in our study, they are accounting firms, and the signals are investments in technology. The receiver (job seeker) observes and interprets the signal (investments in technology) and provides feedback to the signaler by applying for a job in the profession. Signaling Theory is useful for explaining behavior when two parties have access to different information. Thus, ST explains how accounting firms' vast investments and implementation of technology processes and artifacts explain the firm's direction to use technology, thereby beckoning those comfortable with technology to come onboard. Signaling Theory can also be explained as how high-quality firms send out signals or communication to their audiences that they have information that their audience does not have and by distinguishing themselves that they are heavily invested in technology, indicating that they are industry leaders (Connelly et al., 2011).

Signaling theory also posits that the signaler must benefit from the signal due to the receiver's action, which they may not have done without the signal. ST suggests a model where (a) recruiter impressions influence perceptions of the organization, and (b) these organizational perceptions subsequently impact applicants' tendencies to seek employment (Rynes & Miller, 1983; Thompson, Braddy, & Wuensch, 2008). We, therefore, infer that the signaling of accounting firms about their investments and use of technology will encourage non-accounting personnel who are comfortable with technology to apply to these accounting firms, and these applicants would not have applied if they had not received the signal.

Intention to apply to the Accounting profession

Understanding human behavior is an intricate endeavor, but studies have focused more on activities from a hiring company's view rather than from the job-seeker's perspective (Bondarouk et al., 2017; Rynes & Miller, 1983). Hiring is a two-way process and both applicants and hiring companies play a role in determining whether they want to form a match. In today's context, researchers and practitioners increasingly acknowledge the importance of comprehending how prospective applicants are drawn to both organizations and specific job roles (Thompson et al., 2008). While non-accounting majors have typically shown little interest in the profession, the integration of technology has sparked a notable shift in perception, rendering it more appealing. Furthermore, the prospect of lucrative salaries is likely to entice these individuals toward pursuing careers in accounting. My study seeks to evaluate how the perception of the use of technology by accounting firms will influence job seeker's intention to apply for a job in the accounting profession. The Technology Acceptance Model (TAM) helps to assess this phenomenon and was introduced by Fred Davis (1989). TAM has two constructs, Perceived ease of Use (PEOU) and Perceived Usefulness (PU). These constructs have been used in a wide variety of studies (Horton, Buck, Waterson, & Clegg, 2001; King & He, 2006; Ma, Andersson, & Streith, 2005; Mishra, Akman, & Mishra, 2014) and have been proven to be reliable across multiple studies (King & He, 2006; Venkatesh & Davis, 2000). The TAM model is a good fit for measuring how people would accept or reject technology. PU refers to the extent to which an individual perceives that utilizing a specific system would improve their job performance and facilitate task execution. It reflects an individual's perception of how technology may enhance efficiency or effectiveness (Davis, 1989).

On the other hand, PEOU pertains to the extent to which an individual believes that using a particular system would require minimal effort (Fred D. Davis, 1989). In essence, the easier and more useful a technology is perceived to be, the greater the likelihood of its adoption. This theory is useful as a moderator as TAM has consistently explained about 40% of the variance in people's behavior (Venkatesh & Davis, 2000). TAM has also been confirmed to corroborate the efficacy of employing students as substitutes for professionals in certain investigations, and possibly more generally (King & He, 2006). This makes it an excellent theory for my study. Consequently, I propose that job seekers who hold a perceived view of the ease and usefulness of technology will be more inclined to apply to a profession when they receive signals that accounting firms value technological acumen.

In summary, this theory offers insights into why individuals with technological skills may gravitate toward accounting. They enable us to predict behavior, suggesting that job seekers are more likely to apply to the accounting profession when they possess self-efficacy and believe in their ability to excel in the role due to their technological competence. I, therefore, contend that individuals proficient in technology will naturally be inclined to pursue employment in professions that embrace and utilize technology.

2.3. Hypotheses and Theoretical Framework

In their article, Hines and Tapis (2021) expressed that broadening the knowledge of high school and early college students regarding what accountants do, will help eliminate their negative perspective of the profession and interest them in the field. Furthermore, the accounting profession is changing due to technologies such as BDA, AI, ML, RPA, and BL and employers are looking for those with technological skills (Qasim & Kharbat, 2020; Tysiac & Drew, 2018) and prefer those who not only have technology skills, but also the ability to adapt to a changing technology landscape (Kroon et al., 2021; Tapis & Hines, 2021). As Liew et al. (2022) states, …"nowadays, for these roles, the firms are tending to employ university graduates with an IT major regardless of whether they have an accounting or business background" They also found that firms were increasingly recruiting students from STEM majors (Liew et al., 2022). However, there is the perception that the accounting profession is boring and does not carry the highest salaries, making it unattractive to job seekers (Karlsson & Noela, 2022). Also, accounting is very traditional, and it may be challenging to compete with younger professionals with technology acumen (Daniel, 2015) but job opportunities with high earning potential, and interest in the field will drive attraction to a profession and students in information technology would be strong competitors for accounting jobs (Adams, Pryor, & Adams, 1994).Additionally, in discussing behavioral intention, Bolodeoku, Igbinoba, Salau, Chujwudi & Idia (2022) studied what causes people to accept or reject technology and posited that people would use technology if they think it will help them perform better in their job duties (Bolodeoku, Igbinoba, Salau, Chukwudi, & Idia, 2022).

I use Signaling Theory as it shows how two parties communicate when they both have different information (Connelly et al., 2011) and how insiders or signalers (accounting firms) deliberately communicate information about their positive attributes (technology investments) to outsiders (job seekers).

Taken together, the theoretical arguments outlined above can be used to connect how a perception or orientation can result in the performance of another behavior. This leads us to our first hypothesis.

Hypothesis 1: A job seeker's signal of technology use by accounting firms will be positively related to his/her intention to apply to the Accounting profession.

Perceived ease of use (PEOU) and perceived usefulness (PU) are both arms of the Technology Acceptance Model (TAM) introduced by Davis (1989), and are widely accepted as one of the most valuable models for predicting human behavior of technology acceptance (F. D. Davis & Venkatesh, 2004; Horton et al., 2001; Moon & Kim, 2001). TAM posits that a user's intention is the best predictor of behavior of whether a user will accept technology (Fred D. Davis, 1989; F. D. Davis & Venkatesh, 2004).

PU is defined as the degree to which a person believes that using a particular system would enhance his or her job performance and will help them in the execution of their job, or the individual's perception of how technology or technologies may make someone's task more efficient or effective (Fred D. Davis, 1989). PEOU is defined as the degree to which a person believes that using a particular system would be free of effort (Fred D. Davis, 1989), meaning that the more a technology is deemed as easy to use and useful, the more likely it is for someone to use it. These two scales measure determinants of user's acceptance or rejection of technology. These constructs explore the perceptions of why some people accept or reject technology, a valid theory in predicting user behavior (Fred D. Davis, 1989) because "a system that does not help people perform their jobs is not likely to be received favorably despite careful implementation efforts, and a system that reduces rewards for users is likely to be met with disaster" (Robey, 1979).

Together, these constructs have been used in multiple studies – for example, evaluating software acceptance (F. D. Davis & Venkatesh, 2004), examining users' belief in World Wide Web acceptance (Moon & Kim, 2001); intranet use (Horton et al., 2001); physicians' decisions to accept telemedicine technology (Hu, Chau, Sheng, & Tam, 1999); and utilizing internet technologies for internet banking services (Schneider, Dai, Janvrin, Ajayi, & Raschke, 2015). These constructs are deemed to be valid and reliable (Dechow, Ge, Larson, & Sloan, 2011; Horton et al., 2001; Hu et al., 1999; King & He, 2006; Moon & Kim, 2001). The above discussion leads us to our next hypothesis:

Hypothesis 2a: The expected positive relationship between the signal of technology and a job seeker's intention to apply will be strengthened by higher perceived usefulness of technology.

Hypothesis 2b: The expected positive relationship between the signal of technology and a job seeker's intention to apply will be strengthened by higher perceived ease of use of technology.

Due to the importance of technology in society and in workplaces, it is critical that women and men have equal chances to participate in the field. However, despite technology's positive attributes, it is not a gender-neutral field (Bimber, 2000; Galyani Moghaddam, 2010; McGee, 2018; Reinen & Plomp, 1997) and there is still a gender imbalance in technology occupations (Annabi & Lebovitz, 2018; Trauth, 2002).

In recent decades, technology has culturally become associated with men and masculinity (Bimber, 2000; Gupta, 2015; Wajcman, 2007) even though computer programming was once dominated by women (Abbate, 2012) and the inventor of the computer language compiler which converts mathematical code into machine code was a woman (Little, 2017). Evidence suggests that technological jobs and computers were advertised, particularly in the 1980s, as primarily suitable for "geeky" boys/men, which started to shift the occupational composition of the technology field (Little, 2017), with these cultural masculine connotations continuing through the 2020s (Di Vaio, Hassan, & Palladino, 2023). The technology profession regularly incorporates these masculine symbols, values and connotations (Wajcman, 2007) and following gender stereotypes, many people still believe that computers and technology are more appropriate for boys/men than girls/women (Feeney & Fusi, 2021).

Additionally, people are affected by the attitudes of family, teachers, significant others (Trauth, 2002) and communities (Yücel & Rizvanoglu, 2019), who may influence whether someone feels that their gender identity aligns with an IT identity. This attitude is partially due to the fact that many still believe that women are better suited for other types of jobs that are more aligned with feminine stereotypes (e.g., teaching, health-related or care jobs). Accordingly, families, teachers, peers often help steer boys toward technology and girls away from it (Trauth, 2002; Vekiri & Chronaki, 2008; Yücel & Rizvanoglu, 2019). Cultural norms also dictate which gender has greater access to technology (Feeney & Fusi, 2021; Jackson, Zhao, Qiu, Kolenic, Fitzgerald, Harold, & von Eye, 2008b). For example, boys are more likely to have a computer in their room than girls (Fisher & Margolis, 2003) and boys are usually encouraged more to use technology by their parents which has a significant impact on the boys' choice to enter the technology field, unlike their female counterparts (Vekiri & Chronaki, 2008).

Moreover, numerous STEM workplaces, encompassing technology, have been identified as harboring hostile environments for women which may ostracize women from insider circles, permitting the prevalence of sexual harassment, bias, and discrimination (Scott, 2017). Consequently, girls and women often anticipate encountering great bias and discrimination in STEM jobs, which reduces their likelihood to pursue STEM subjects in school (Botella, Rueda, López-Iñesta, & Marzal, 2019) making them less prepared to enter the IT field. In her study, Trauth (2002) interviewed female IT professionals who were exposed to discrimination while attempting to navigate the male domain. They spoke about a need to earn a seat at the IT table while men can assume that they have a seat (Trauth, 2002) which partly explains why women are less attracted to the profession and have low retention rates. Indeed, women leave the IT field at a higher rate than their male counterparts (Annabi & Lebovitz, 2018; Holtzblatt & Marsden, 2018), due to social and cultural barriers such as stereotypes, work life balance, masculine environment, legitimacy questions (Annabi & Lebovitz, 2018; Galyani Moghaddam, 2010; Pretorius et al., 2015) and other negative experiences (Holtzblatt & Marsden, 2018).

Taken together, the theoretical arguments and empirical evidence outlined above suggest that women are less likely to be interested in technology jobs and, therefore, will have fewer intentions to apply to the accounting profession.

Therefore, we formulate our third hypothesis as follows:

Hypothesis 3:

The expected positive association between the technology signal and a participant's intention to apply to the accounting profession will be weaker for women.

Another factor that is likely to influence a job seeker's signal of technology use by accounting firms and a job seeker's intention to apply to the accounting profession is race. Information technology (IT) was initially hailed for being the gateway to the world and providing all users access to the gateway platform (Gunkel, 2003), but this was quickly squashed with the realization that access to the fruits of the internet was not as available to the populace (Gunkel, 2003). African Americans, Latinos, and other minorities are more likely to have little or no access to computers and technology than their Caucasian counterparts, even though they may have a positive attitude toward technology (Mossberger, Tolbert, & Gilbert, 2006). This makes them less likely to be comfortable with using technology. In a State of the Union speech, President Clinton mentioned the challenge of "the digital divide," a term coined by Lloyd Morrisett of the Markle Foundation, who used the term to indicate institutions were having difficulty finding qualified IT professionals. ("DeVry, Inc.: Bridging the 'Digital Divide' -- Computer Access for Minorities," 2000).

The digital divide has been defined as the gap between those with the resources and skills to access and use technology versus those without (P. D. L. Hoffman & Novak, 1999; Jackson, von Eye, Fitzgerald, Zhao, & Witt, 2010; Jackson, Zhao, Kolenic, Fitzgerald, Harold, & Von

Eye, 2008a; Mossberger et al., 2006). It is also defined as "the fashionable term for indicating the Internet's failure, not only to reduce gaps between the information-rich and the information-poor but for accentuating them" (Norris, 2001). In addition, according to the US Department of Education, non-minorities are more likely to be enrolled in college than minorities (Fairlie, 2012). This contributes to why minorities are exposed to technology less than Whites. Differences in income, education, occupation, and language also contribute to what is referred to as the 'digital divide.'

However, Mossberger et al. (2006) found that racial inequities in technology use were not always a result of education, income, or negative attitudes in minorities, but also as a result of the place they live. Demographics play a prominent role, and those areas with concentrated poverty levels, racial discrimination, low educational attainment, social immobility, and low socio-economic status were more likely to be digitally disadvantaged (Mossberger et al., 2006). Contrary to belief, racial minorities are not low on motivation and have positive attitudes towards technology; however, they still fall low on the technology access radar (Mossberger et al., 2006). Racial disparities to home computers continue to exist, and it is less likely that Blacks and racial minorities will own computers (Fairlie, 2012; Mossberger et al., 2006) plus they are less likely to use the internet and other technologies as intensely as whites, even when they have access (Jackson et al., 2008a).

It is important to note that there are many misconceptions of the digital divide. It is not only a case of the haves and the have-nots (Graham & Smith, 2010; Mossberger et al., 2006) but more answers are needed as to whether the digital divide is triggered by unequal access to technology and communication, or whether it is a development and diffusion problem or an economic problem (Graham & Smith, 2010; Mossberger et al., 2006). Minorities are more likely to believe that good jobs in the future will not all require computer skills, while whites think the opposite – that computer skills will be essential for future jobs and would help to give them control of their lives (Jones, Johnson-Yale, Millermaier, & Pérez, 2009). However, digital inequities continue to plague societies as literacy in technologies and studies have found that more white households generally own home computers than their racial minority counterparts, even in the same income bracket (Chakraborty & Bosman, 2005) and levels of education (D. L. Hoffman, Novak, & Schlosser, 2000). Digital citizenship, or the lack thereof, restricts minorities from participating in a technology world, leading to a sense of community and inclusion (Mossberger et al., 2006).

Taken together, the above arguments suggest a digital divide, which is the gap between those who have the resources and skills to access and use technology versus those who do not. This digital divide negatively impacts minorities more than non-minorities and limits their ability to be technologically oriented. Therefore, minorities will have less perceived usefulness of technology and would, therefore, have fewer intentions to apply to the accounting profession. We therefore define our final hypothesis as follows:

> **Hypothesis 4:** The expected positive association between the technology signal and a participant's intention to apply to the accounting profession will be weaker for racial minorities.

CHAPTER 3: RESEARCH DESIGN AND METHODOLOGY

3.1. Study Design and Experimental Manipulations

Chapter 3 delineates the methodology employed to evaluate both the model and hypotheses as presented in previous chapters. It begins with an overview, followed by a section detailing the respondent population and the frequency of responses. Subsequently, the survey provides an outline of the measurement techniques and scales utilized for each variable. Finally, the chapter concludes with a description of the methods employed.

This research was conducted to examine the relationship between technology signals by accounting firms and a job seeker's intention to apply to the accounting profession. This research was a survey which included two scenarios or stories to which participants were randomly assigned. One story highlighted a general information condition about the accounting profession, such as, the different areas of accounting and the favorable job prospects in the profession. The other story had specific information about technology. Participants in the general information about accounting condition, received the same information as those in the specific condition; however, those in the latter group also received information about the affinity of accounting employers to technology, how they have embraced technology and now prefer to hire those who are more adept at technology skills. The manipulation was based on specific information about technology in accounting, and not just general information about the accounting profession. I provided definitions of the specific technologies that I am studying which are Blockchain, Artificial Intelligence, Machine Learning, Robotic Process Automation and Big Data Analytics.

My survey asked participants about their intention to apply for an accounting job based on the story they read. It also had questions about how they perceived technology and what they thought that accounting salaries should be. Participants also had to respond to open-ended questions about why (or why not) they would apply to the profession, their thoughts about the opportunities for career advancement in accounting and what would influence them for or against working in accounting. This information will help to give a rich perspective of their views, without the boundaries of the closed ended questions. They also had to provide demographic information, such as their race, gender, major, university and classification. To read the full stories, please see the Appendix below which contains the full survey. The survey was developed using the online Qualtrics XM platform which is password protected. Survey material and the overall survey process were approved by Office of Research Protections and Integrity at The University of North Carolina at Charlotte.

3.2. Sample

The survey was administered at North Carolina Agricultural and Technical State University, a Historically Black College/University (HBCU) and The University of North Carolina at Charlotte (UNCC), a Predominantly White University Institution (PWI). This is important as the model had a racial component and it was important that I received representation from both racial populations. Participants were at least 18 years old and obligated to read and acknowledge an informed consent notice.

The survey was conducted online on Qualtrics XM platform and yielded 595 results. This was achieved by contacting professors at both universities to request their assistance, including follow ups. Additionally, I visited professors during their classes so that they would encourage their students to complete the survey. At the completion of the survey, I exported the results from Qualtrics to Excel and cleaned the data by checking for and deleting incomplete or missing information and errors.167 responses were deleted from the final sample at this step.

There were 17 surveys where the respondent omitted only one response on the intention, perceived ease of use and perceived usefulness questions. I did not delete these responses, instead, I replaced the missing response with the mean response for that variable. I also deleted the responses of all respondents who identified their majors as accounting as the research did not require accounting students. 45 responses were deleted at this step. After deletions for missing information and accounting majors, the final sample included 383 surveys from undergraduate students who were Business, Science, Technology, Engineering or Mathematics majors.

I used the G*Power 3.1.9.7 software to determine a post hoc analysis of the power for my sample size of N=383, with statistical significance of $\alpha = .05$ and effect size of 0.2 and five predictors. The small effect size was chosen using Cohen's d, estimate of effect sizes (Jacob Cohen, 1977). This analysis resulted in an achieved power of 0.79 which is moderately high providing strong evidence of the existence of a meaningful difference or relationship between my variables. (see Figure1).

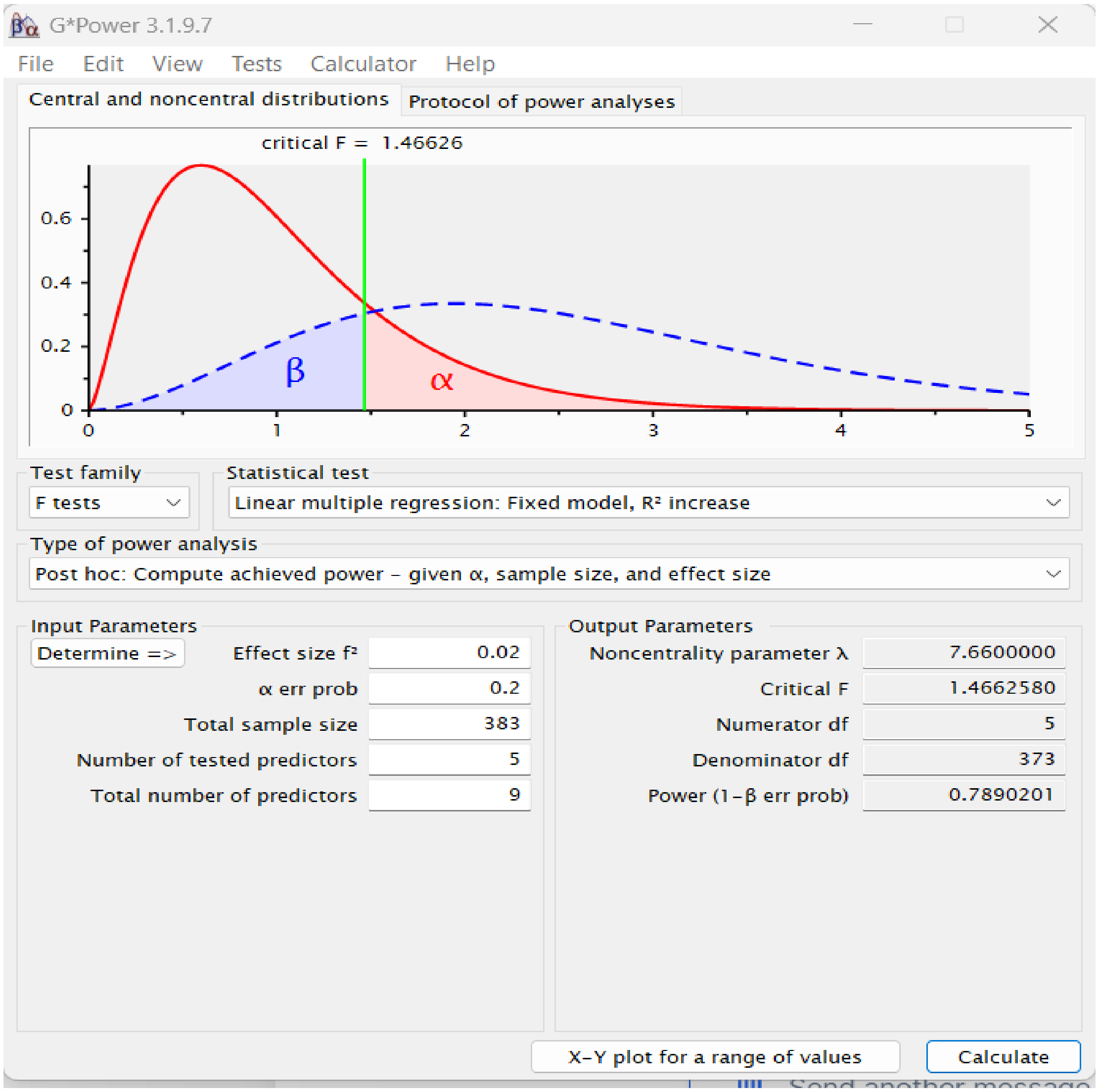

Figure 3.1-GPower analysis

3.3. Measures

This study examined whether job seekers who were technologically savvy will apply to the accounting profession if they receive signals of technology usage from accounting firms. The study also examined whether the perceived ease of use (PEOU) and perceived usefulness (PU) of technology, measures introduced by Fred Davis (1989) influenced the decision. Additionally, I also tested whether race and gender will influence the relationship.

3.31. Independent Variable

My study adopts a design akin to that employed by Drewery et al. (2022), where students were recruited to respond to a fabricated job advertisement and randomly assigned to different conditions (Drewery, Pretti, & Church, 2022). Likewise, respondents in this study were allocated to one of two conditions: one receiving a general narrative about the accounting profession, and the other supplemented with information on technology. This included statements like such as, ‘technology has significantly transformed the accounting profession by introducing cutting-edge advancements’ and ‘accounting firms are increasingly embracing these technologies, heavily investing in tech tools,’ and ‘recruiting non-accounting majors with strong technological skills.’ Definitions of these technologies such as Artificial Intelligence and Machine Learning, Blockchain, Big Data Analytics, and Robotic Process Automation were also included. Consequently, the variable is binary, with individuals exposed to the story without technology coded as no signal=0 and those exposed to technology information coded as signal=1, using IBM SPSS 29.

Independent variable: Condition or Signal

The assignment of the technology story was originally configured to present Condition 1 and Condition 2 equally. However, after the data was scrubbed, I ended up with 178 (46.5%) respondents in Condition 1 (who did not read about technology) and 205 (53.5%) in Condition 2 (who read about technology). See Panel A of Table 3.1.

3.32. Dependent variable

The focal variable under examination is students’ "intention to apply," assessed through participants' responses regarding their inclination to pursue a career in accounting subsequent to reading the narrative. Intention to apply may be measured through many theoretical frameworks.

However, most of them have several survey items. One such popular framework is the Theory of Planned Behavior (TPB) (Ajzen, 1991) which has about 28 survey items. However, because my population was students, there is a high likelihood that they will skip some of these questions due to survey fatigue, which occurs when participants experience fatigue or disinterest during the survey process, leading to less thoughtful responses or incomplete surveys. reducing the sample size significantly (Brown, St. John, Hu, & Sandhu, 2024; Le, Han, & Palamar, 2021).

On the other hand, there are some studies, such as those by De Kock & Adams (2015) and Asseburg & Homberg (2020), that have utilized one- or two-question measures to capture intention to apply (Asseburg & Homberg, 2020; De Kock & Adams, 2015). My measure was adapted from Highhouse, Thornbury & Little (2007), who employed a five-item scale to assess intention to pursue, in evaluating organizational attractiveness (Highhouse, Thornbury, & Little, 2007). Three items from the scale were modified to align with my study, while two unrelated items were omitted. (see full survey in Appendix). Respondents rated these questions on a seven-point Likert scale, ranging from strongly disagree=1 to strongly agree=7. The ratings were amalgamated into a composite variable for integration into a regression model.

There was a three-question measure to evaluate the dependent variable, intention to apply. Responses to these questions ranged from strongly disagree to strongly agree. They were coded as Strongly disagree=1, Disagree= 2, Somewhat disagree = 3, Neither disagree nor agree = 4, Somewhat agree = 5, Agree = 6 and Strongly agree =7. They were then calculated into a composite score to fit into the regression model. Reliability analysis returned a Cronbach Alpha score of 0.92 (see Table 3.2 below) for this measure which validates internal consistency of the scale. I looked at several variables that would describe the makeup of my sample which are described below.

3.33. University

I separated the sample based on the university the respondent attended. I coded NCAT=1 and UNCC and all other variables=0. Results show that 173 (45.2%) of the respondents were from NCAT and 210 (54.8%) were from UNCC. The results can be found in *Panel B* of Table 3.1. The demographics table below also shows the breakdown of race, gender and classification among universities. This separation serves merely for descriptive purposes since both university and race are likely to be confounded, making it challenging to disentangle their effects. However, I used a Chi-square test to assess their relationship and results for university and gender was $\chi^2 = 7.189$, df = 1, $p < .007$;.and for university and race was $\chi^2 = 110.067$, df = 1, $p < .001$ indicating an association in both cases.

3.34. Classification

I also captured university classification to understand the university level of my respondents. There were 29 (7.6%) freshman respondents, 57 (14.9%) sophomore respondents, with the largest classification group of 191 (49.9%) junior respondents and 106 (27.7%) senior respondents. University classification is categorical and was coded as, Freshman = 1, Sophomore =2, Junior = 3 and Senior = 4. See *Panel C in Table 3.1*

The survey also requested students' majors. This yielded about 40 different majors. The pie chart in the Appendix captures the various responses.

3.4. Moderating variables

3.41. Gender

My survey incorporated responses for gender such as Female and Trans Female, Male and Trans male, and Other categories. This was to make respondents feel inclusive as criticism has been directed towards survey measures of gender, citing their failure to adequately represent the diverse spectrum of the population other than the binary classifications of female or male and proposing that additional categories, such as transgender be included to more accurately capture gender diversity and refine models of gender inequality (Magliozzi, Saperstein, & Westbrook, 2016). I coded Female or Trans Female =1, and all others =0.

Gender is a moderating variable in the model and of the survey respondents, 164 (42.8%) identified as Female or Trans Female and 219 (57.2%) identified themselves as Male or Trans Male, or other. See table below. I dummy coded gender as, Female or Trans Female= 1, and Male or Trans Male and others = 0. I put 12 non responses or ‘other’ in the male category as the female variable was my reference category and my hypothesis was testing whether the association between technology signal and intention would be weaker for women. Similar to Race, I also ran a Chi-square test to assess the relationship between university and gender. The Chi-square test results indicate a statistically significant association between university attended and gender (Pearson Chi-Square = 7.189, df = 1, p = 0.007) indicating that the distribution of gender differs significantly across universities, suggesting that gender may influence university attendance or vice-versa. Other correlation tests also corroborated these results.

3.42. Race

My survey included an extensive list for race categories (see survey in Appendix) specifically to foster inclusivity (Magliozzi et al., 2016). However, for analysis, I collapsed them to a few categories of Black or African American/Latino or Latina, White, and Other categories. I coded the categories as follows, Black or African American/Latino/Latina = 1, and Whites and others= 0.

In terms of racial demographics, 188 participants (50.9%) identified themselves as Black, African American, or Latino/Latina (considered racial minorities), whereas 195 individuals

(49.1%) identified as White or belonging to other racial groups. Since these data were categorical, I employed dummy coding to represent the racial categories. Specifically, I assigned a value of 1 to those identifying as Black, African American, or Latino/Latina, and a value of 0 to all other racial identities. This is because prior research indicates that the association between technology signal and intention to apply to the accounting profession would be weaker for racial minorities. Also, because they non-racial minorities were not the focus of the research. There were 59 'other' races, such as Chinese, Asian, Indian and a variety of mixed races. I utilized the Chi-square test to explore the relationship between university attended and race. The results indicated a significant association, with a Pearson Chi-Square value of 110.067, df = 1, and $p < .001$. Similar patterns were observed across other chi-square test statistics. This indicates that there is a strong relationship between race and university attended. See *Panel E* in Table 3.1.

3.43. Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

To examine the moderating variables of perceived usefulness (PU) and perceived ease of use (PEOU), I used constructs from the well-established Technology Acceptance Model (TAM) introduced by Fred Davis (1989) which is widely accepted as one of the most valuable models for predicting human behavior of technology acceptance (F. D. Davis & Venkatesh, 2004; Horton et al., 2001; Moon & Kim, 2001). PU is defined as the degree to which a person believes that using a particular system would enhance his or her job performance and will help them in the execution of their job, or the individual's perception of how technology or technologies may make someone's task more efficient or effective. PEOU is defined as the degree to which a person believes that using a particular system would be free of effort (Fred D. Davis, 1989), meaning that the more a technology is deemed as easy to use and useful, the more likely it is for someone to use it.

For each construct, there were six questions rated on a seven-point Likert scale, ranging from strongly disagree =1 to strongly agree=7. See Table 3.2 below. The responses were converted from a text format to a scale of 1 to 7 to maintain the ordinal nature of the data. A composite value was computed for each construct to facilitate integration into the model.

PU and PEOU are distinct constructs within the Technology Acceptance Model (TAM). I tested them separately to allow me to examine how each construct influences the outcome variable independently. This will allow me to assess the individual contributions of each variable to the dependent variable and to understand their relative importance in predicting the outcome.

Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) constructs, each had six questions rated on a seven-point Likert scale, ranging from Strongly disagree (1) to Strongly agree (7). The responses were recorded on a scale of 1 to 7 and a composite measure was computed for each of these constructs to facilitate integration into the model.

Subsequently, all multi-item scales in the study underwent reliability analysis using Cronbach's Alpha, which is a widely used method for assessing the consistency of self-report items. Cronbach's Alpha values range from 0.0 to 1.0, with higher values indicating a stronger relationship among the individual scale items. An optimal range for composite Cronbach's Alpha falls between 0.7 and 0.9 (Creswell & Creswell, 2018). Results show that for the measures with multi scale items displayed in table below are reliable as designed. See Table 3.3

Table 3.1 Sample Demographics

Panel A – Signal/No Signal

	N	%
No Signal	178	46.5%
Signal	205	53.5%

Panel B – University

	N	%
NCAT	173	45.2%
UNCC	210	54.8%

Panel C- Classification and University

		University				Total	
		NCAT		UNCC			
		N	%	N	%	N	%
Classification	Freshman	21	12.1%	8	3.8%	29	7.6%
	Sophomore	47	27.2%	10	4.8%	57	14.9%
	Junior	65	37.6%	126	60.0%	191	49.9%
	Senior	40	23.1%	66	31.4%	106	27.7%
Total		173	100.0%	210	100.0%	383	100.0%

Panel D- University and Gender

		University				Total	
		NCAT		UNCC			
		N	%	N	%	N	%
Gender	Male or Trans Male	86	49.7%	133	63.3%	219	57.2%
	Female or Trans Female	87	50.3%	77	36.7%	164	42.8%
Total		173	100.0%	210	100.0%	383	100.0%

Panel E- University and Race

		University				Total	
		NCAT		UNCC			
		N	%	N	%	N	%
Race	Caucasian	37	21.4%	158	75.2%	195	50.9%
	Black or African American	136	78.6%	52	24.8%	188	49.1%
Total		173	100.0%	210	100.0%	383	100.0%

Table 3.2 – Measures for Perceived Ease of Use and Perceived Usefulness

Measure	Measurement	Author
Perceived Ease of Use (PEOU) PEOU is the degree to which a person believes that using a particular system would be free of effort (Strongly disagree=1, Disagree=2, Somewhat disagree=3, Neither agree nor disagree =4, Somewhat agree=5, Agree=6, Strongly agree=7	Learning to operate new technologies is easy for me. I find it easy to get technologies to do what I want it to do. My interaction with technologies in my future job will be clear and understandable. I find technologies to be flexible to interact with. It is easy for me to become skillful at using technologies. I find technologies easy to use.	Fred Davis (1989)
Perceived Usefulness (PU) PU is the degree to which a person believes that using a particular system would enhance his or her job performance and will help them in the execution of their job, or the individual's perception of how technology or technologies may make someone's task more efficient or effective (Strongly disagree=1, Disagree=2, Somewhat disagree=3, Neither agree nor disagree =4, Somewhat agree=5, Agree=6, Strongly agree=7	Using technologies in my future job will enable me to accomplish tasks more quickly. Using technologies will improve my future job performance. Using technologies in my future job will increase my productivity. Using technologies will enhance my effectiveness in my future job. Using technologies will me it easier to do my future job. I will find technologies useful in my future job.	Fred Davis (1989)

Table 3.3. Reliability Analysis

Construct	Number of Items	Cronbach Alpha
Dependent variable: Intention to Apply	3	0.920
Moderating variable: PEOU	6	0.938
Moderating variable: PU	6	0.957

3.44. Manipulation Check

There were three manipulation checks incorporated into the survey. Manipulation checks are considered a fundamental technique (Ejelöv & Luke, 2020), used to test construct validity to verify that the experimental manipulation has occurred as intended. It helps researchers confirm that participants in different experimental conditions perceive or experience the manipulation differently. My checks consisted of three questions which participants were required to answer based on the understanding of the story. The questions asked about new technologies in accounting firms, about accounting jobs being offered to non-accounting majors, and how non-accounting majors can be hired in accounting firms (see questions in Table 3.4 below), with the assumption that most of those who did not receive the technology story will be more likely to respond in the negative, while those who received the story with technology will be more likely to respond in the positive.

To test manipulation, I ran a Mann Whitney U test (in place of a traditional t-test), to evaluate the relationship between the independent variable, Signal, and the dependent variable, Manipulation Check. This test was used due to the categorical and ordinal nature of the variables. See results in Chapter 4.

Table 3.4: Manipulation Checks

Please indicate how much you agree with each of the following statements, based on the information you read. Responses may be recorded as Yes or No.

---

1. Accounting firms are using new technologies in the field.
2. Accounting jobs are now being offered to non-accounting majors.
3. Non-accounting majors can be hired in accounting firms.

3.45. Data Analyses

This section provides a brief overview of the data analysis that was used to evaluate my hypotheses. Results, data analysis, and review of hypotheses is presented in Chapter 4.

Using IBM SPSS 29, I conducted data analysis for this study. Initially, I conducted descriptive statistics and correlations among the variables of interest. Particular attention was given to assessing multicollinearity by examining correlations between independent variables, with a focus on any absolute correlation values exceeding 0.8 (Singh, Singh, & Paprzycki, 2023). Subsequently, hierarchical regression was employed to analyze the relationships between independent variables, moderating variables, and their interactions with the dependent variable.

Two sets of analyses were performed. Firstly, three regression models were assessed: Model 1 evaluated the impact of independent and dependent variables; Model 2 assessed the influence of moderating variables; and Model 3 examined the interaction between independent and moderating variables, representing the entire research model outlined in the Appendix.

Additionally, an extra analysis was conducted to individually evaluate the impact of two of the variables on the relationships. Both analyses were reviewed, focusing on the adjusted R-squared values to determine the amount of explained variance by each model. Changes in adjusted R-squared were examined to assess if increasing model complexity led to a greater explained variance. Finally, the results from hierarchical regression were reviewed to ascertain significant relationships between each variable and the dependent variable, including p-values. The comprehensive results are presented in chapter 4.

CHAPTER 4: RESULTS

In this chapter, I present the findings derived from analyzing the hypothesized relationships introduced in Chapter 3. I delve into the demographics of my respondents, and the descriptive statistics and correlation review along with checking for collinearity. I also review reliability testing using Cronbach Alpha to ensure that the scales were valid. With the measures confirmed to be valid, I utilized moderated hierarchical regression to test the hypothesis in this study. I later discuss the outcomes.

4.1. Study Design and Experimental Manipulations

Before full deployment of the survey, I conducted a pilot study of 19 respondents and requested their feedback to assess their understanding of the story and any unforeseen problems. Feedback from respondents confirmed their understanding of the stories as designed. After removing surveys that were incomplete or the respondent indicated they were an accounting major, the final sample included 383 responses.

I first examined the descriptive statistics and bivariate correlation. Table 4.1 displays the descriptive statistics for all variables in my model, including the mean and standard deviation. Mean for Intention was 4.0401, Signal was .5352, PU was 6.0989 and PEOU was 5.6788, Gender was .4282, Race was .4909 and Manipulation Check variable was .7894. It should be noted that the standard deviation is very low for all variables especially the signal variable indicating the technology signal has little influence on the respondent's views.

Table 4.1 below shows correlations for variables in the study. The Pearson correlation coefficient ranges from -1.0 to +1.0. A higher absolute value indicates a stronger correlation between two variables, while the sign indicates the direction of the correlation.

There was a low correlation between the moderator, PEOU and the dependent variable, Intention to apply at r=0.132, which was statistically significant at p = 0.010. Similarly, there was also a low correlation between Intention and PU at r=.147, p=.004. PU and PEOU were highly correlated at r=.722, p=<.001; Race and Gender were moderately correlated at r=.111, p=.03. The composite of the manipulation check score was very correlated with Signal at r=.395, p<.001; University was negatively correlated with both Gender and Race at r=-.137, p=.007 and r= -.536 at p=<.001 respectively.

Table 4.1. Statistics, Correlation and Scale Reliabilities

	Mean	Std. Deviation	Intent	PU	PEOU	Signal	Gender	Race	Mani Check
Intent	4.0401	1.70148	(.920)						
PU	6.0989	1.07045	.147**	(.957)					
PEOU	5.6788	1.06484	.132**	.722**	(.938)				
Signal	0.5352	0.49941	-0.003	0.031	0.019	--			
Gender	0.4282	0.49546	-0.069	0.008	-0.020	0.066	--		
Race	0.4909	0.50057	-0.008	-0.003	0.019	-0.007	.111*	--	
Mani_ Check	0.7894	0.32047	0.077	0.003	0.054	.395**	0.064	0.048	--
Univ	0.5483	0.49831	-0.039	0.039	-0.070	-0.004	-.137**	-.536**	-0.062

4.2. Manipulation Checks

A Chi-Square test, of independence was conducted to examine the relationship between signal and the manipulation questions, to determine if the manipulation worked. The analysis indicated a substantial disparity in the two groups, with the following results:

Manipulation question 1 and signal: $\chi^2 = 56.701$, df = 1, p < .00;

Manipulation question 2 and signal: $\chi^2 = 27.714$, df = 1, p < .001.

Manipulation question 3 and signal: $\chi^2 = 38.313$, df = 1, p < .001.

These results reflect a strong association between Signal and the Manipulation variables. Notably, the No Signal group exhibited significantly lower values on manipulation checks compared to the Signal group, implying the efficacy of the manipulation checks.

4.3. Regression Results

A moderated hierarchical linear regression analysis was conducted in IBM SPSS 29 to evaluate the relationship between technology signal and a job seeker's intention to apply to the accounting profession and the moderating effects of PU, PEOU, Gender, and Race. The first model examined the relationship between the independent variable, Signal, and the dependent variable, Intention. I then added moderators of PU or PEOU, Gender and Race to the model. PEOU and PU were included in separate models because these two variables were highly correlated. Lastly, the interaction variables for PU or PEOU, Gender, and Race were added to the model. Model 2 and 3 include the moderating variables PU, Gender and Race, while Model 4 and 5 include PEOU, Gender and Race.

Model 1

The first model is the baseline model and evaluated the independent variable, signal of technology with the dependent variable, intention to apply. The R Square and Adjusted R square values were close to 0, indicating that the model did not explain much variance in the dependent variable. The p-value for the model was 0.959 indicating that the model itself was not statistically significant. In addition, the t-statistic for signal was not statistically significant. This result indicates the technology signal did not increase the respondents' likelihood that they would apply for an accounting job, thus, offering no evidentiary support for Hypothesis 1.

Models 2 and 3

In Model 2 the moderating variables of PU, Gender and Race were added while Model 3 added the interaction terms. As noted earlier, PU and PEOU were introduced separately to test their individual significance. PU and PEOU are highly correlated at r=.722 at a statistically significant level of .000. In addition, they are distinct constructs within the Technology Acceptance Model (TAM). Testing them separately allows me to examine how each construct influences the outcome variable independently. First, I performed an analysis including Signal, Intention, Race, Gender, and PU. The results indicated that the model was statistically significant ($p = .037$) with an F-statistic of 2.583. In addition, the PU variable was significant at the .001 level. When the interaction variables were added to the model, the model was no longer significant ($p=.158$) and an F-statistic of 1.524. However, the PU variable remained significant with a t-statistic value of 1.932 and a p-value of .054. See Table 4.2.

Table 4.2- Panel A Model 2 - Moderators of PU, Gender, Race

	Coefficients	*t Stat*	*P-value*
Intercept	2.714	5.262	<.001
Signal	-0.009	-0.052	0.959
Race	.002	0.010	0.992
Gender	-0.241	-1.372	0.171
PU	0.235	2.912	0.004**
Regression Statistics			
R Square	0.027		
Adjusted R Square	0.016		
F-statistic	2.583		
P-value	.037*		

Table 4.2- Panel B Model 3 - Moderators of PU, Gender, Race Plus Interactions for PU, Gender and Race

	Coefficients	*t Stat*	*P-value*
Intercept	2.797	3.775	<0.001
Signal	-0.197	-0.192	0.848
Race	-0.056	-0.252	0.802
Gender	-0.309	-1.167	0.244
PU	0.230	1.932	0.054*
Sig x PU	0.012	0.073	0.942
Sig x Gender	0.131	0.368	0.713
Sig x Race	0.146	0.471	0.638
Regression Statistics			
R Square	0.028		
Adjusted R Square	0.010		
F-statistic	1.524		
P-value	.158		

**. Significant at the 0.01 level
*. Significant at the 0.05 level

Model 4 and 5

In Model 4 the moderating variables of PEOU, Gender and Race were added while Model 5 adds the interaction terms. The result indicated that the model was not statistically significant ($p=0.78$), which was slightly over the statistically significant threshold with an F-statistic of 2.115. However, the PEOU variable was significant at the .01 level. See Table 4.4 below. When the interaction variables were added to the model, the model was no longer significant ($p=.262$) and an F-statistic of 1.274 and the PEOU variable was not significant either at $p=0.117$ and a t-statistic of 1.573. See Table 4.3 below.

Table 4.3- Panel A Model 4 - Moderators of PEOU, Gender, Race

	Coefficients	*t Stat*	*P-value*
Intercept	2.956	6.053	<0.001
Signal	-0.003	-0.016	0.987
Race	-0.010	-0.057	0.954
Gender	-0.227	-1.287	0.199
PEOU	0.209	2.572	0.011
Regression Statistics			
R Square	0.022		
Adjusted R Square	0.012		
F-statistic	2.115		
P-value	.078		

**. Significant at the 0.01 level
*. Significant at the 0.05 level

Table 4.3- Panel B Model 5 - Moderators of PU, Gender, Race Plus Interactions for PU,

Gender and Race

	Coefficients	*t Stat*	*P-value*
Intercept	3.124	4.485	<0.001
Signal	-0.367	-0.380	0.704
Race	-0.050	0.220	0.826
Gender	-0.321	-1.211	0.227
PEOU	0.190	1.573	0.117
Signal x PEOU	0.042	0.257	0.797
Signal x Gender	0.183	0.513	0.608
Signal x Race	0.113	0.364	0.716

Regression Statistics	
R Square	0.023
Adjusted R Square	0.005
F-statistic	1.274
P-value	.262

In addition to the close ended survey questions, I also incorporated open-ended questions to capture the diverse perspectives of my survey participants. These perspectives, which are often challenging to quantify using quantitative tools, went through an inductive analysis, aligning with the foundational principles of grounded theory (Glaser & Strauss, 1967). Grounded theory suggests that information should organically arise from the underlying concepts without imposing or aligning it with preconceived theoretical frameworks. Consequently, the data was carefully examined and organized into thematic codes that naturally emerge from the data itself, rather than relying on predefined rules. This process, known as open coding, facilitated the identification of emerging themes and a comprehensive understanding of our participants' diverse viewpoints regarding the accounting profession, enabling meaningful insights.

I asked respondents about whether they had worked in accounting or a similar role and found that 91% had never worked in accounting while only 8.6% has worked in an accounting role. Additionally, the median amount that respondents thought that an entry-level accountant should earn was $75,398, with suggested amounts ranging between $36,134 all the way to $120,000 annually which is a wide range indicating that students do not know how much the profession pays for entry level accountants.

Responses to the question of what respondents thought about the opportunities available for accountants yielded positive results with most respondents indicating that they believed that accounting had plentiful opportunities. However, the question about what would influence the respondents for or against working in Accounting, overwhelmingly pointed to salary, benefits/compensation and work life balance. Over 30% of respondents say that they will consider working in Accounting if the field was lucrative. This aligned with the (high) mean value of $75,398 that was expected for entry-level accountants. Some responses were as follows:

“To work in Accounting, the pay and benefits would heavily influence me”.

“Stability and a livable salary would influence me”.

“Money and opportunity would influence me.”

“I would work in Accounting if the entry-level salary was higher.”

A number of people thought accounting was boring. “I think accounting, to me, sounds boring. It would need to be more exciting than I make it out to be and be able to pay equal to or more than what I could make with my current degree.”

“It's just confusing to me and seems pretty boring.”

Yet, others had responses such as:

“What would influence me for working in accounting are my technological skills being used appropriately and effectively. What would influence me against it are my technological skills not being used on the job.”

“What would influence me against working in Accounting is if it is hard to have opportunities for growth, a raise, and promotion within the field.”

“The only way to influence me to go into the accounting industry would be the economic benefits and less education requirements like requirement to have a masters.”

“The biggest thing that would influence me against working in Accounting would be the reputation of long days and long hours working for the larger accounting firms, coupled with the competitive nature of the job when it comes to advancement.”

“Nothing could influence me to work in accounting. The number of laws that are required to be kept up with are too many.”

“I think knowing more about accounting would influence me for working in that field.”

Other responses included long hours, poor work/life balance, too many requirements, too much math, not enough opportunities, not very interesting.

CHAPTER 5: DISCUSSION AND CONCLUSION

This chapter serves as a comprehensive conclusion to the study. Initially, it offers a broad overview of the research conducted. Subsequently, it delves into a thorough examination of the research findings and their corresponding interpretations. Following this, it highlights the contributions made by this study. Lastly, it critically evaluates the limitations encountered in the study, and outlines potential avenues for future research.

It is widely recognized that technology has fundamentally transformed various industries and sectors, becoming an integral part of modern society (McAfee & Brynjolfsson, 2012). Particularly, technology plays a crucial role in the success of companies (Hannah, 2017; Manita et al., 2020). Despite this, accounting firms have been relatively slow to embrace technological advancements (Damerji & Salimi, 2021), but are gradually incorporating them into their operations. These firms are now leveraging technologies such as Artificial Intelligence, Machine Learning, Blockchain, Big Data Analytics, and Robotic Process Automation to enhance their efficiency and competitiveness. Consequently, there's a growing demand for individuals skilled in these technologies (Gulin et al., 2019; Lawler & Joseph, 2017). Accounting firms are increasingly recruiting students with a background in technology (Hannah, 2017). Therefore, my study aims to investigate whether traditional accounting students face potential challenges in recruitment due to this shift towards technology-focused hiring practices. My study sought to answer the following questions:

1. If job seekers (other than accounting majors) get a signal that accounting firms are recruiting those with technology background, would they be open to applying?
2. How does the perception that technology is easy to use and useful affect the relationship between technology signal and intention to apply?

3. Technology is usually a male's domain. How does this play a role in the relationship?
4. **4.** There is a digital divide in technology as relates to race. How does this affect the relationship?

5.1. Findings and Discussion

The regression analysis aimed to investigate the relationship between technology signal of firms and the intention to apply to the accounting profession. The model summary did not reveal notable findings. Model 1, comprising solely the Signal variable, did not demonstrate a relationship with the dependent variable, evident from low R Square and Adjusted R Square values (R Square = 0.000, Adjusted R Square = -0.003) which were at an insignificant level of p=.959.

Subsequent models, incorporating Perceived Ease of Use, Perceived Usefulness, Gender and Race variables, notably improved the model's explanatory power. For instance, Model 2 exhibited a significant increase in R Square and Adjusted R Square values (0.028 and 0.015, respectively) which improved the model, but was slightly over the statistically significant threshold at p=.058, indicating that some type of relationship existed amongst these variables. The interaction terms in Model 3, did not notably enhance the model beyond Model 2, indicating that the inclusion of interaction terms may not significantly augment the models' predictive ability.

Due to the strong correlation between the PU and PEOU variables, additional analyses were conducted using each of these variables at a time. Interestingly, in each case, both PU and PEOU emerged as statistically significant predictors. This suggests that a student's perceived ease of use of technology and their perceived usefulness of technology both contributed to an increase in a job seeker's intention to apply.

Overall, aside from the variables PU and PEOU that exhibited some relationship, none of the others were supported as stated. The signal of technology did not affect a job seeker’s intention to apply to the profession at a statistically significant level. A post hoc analysis using manipulation checks as the independent variable instead of signal did not produce any statistically significant results. It is possible that beliefs about accounting and technology did not influence a job seeker’s intention to apply . Perhaps due to the fact that the majority of respondents had no prior experience in accounting, there might be a fear of the unknown associated with it. Additionally, survey responses indicated that some were deterred from pursuing accounting because they perceived it as dull, offered low entry-level salaries, and provided a poor work-life balance. Moreover, many expressed excitement about potential careers in their respective fields post-college. It's plausible that negative preconceptions about the accounting profession played a role in rejecting the null hypothesis.

Despite the study not confirming all of the hypotheses, there is evidence that technology has indeed disrupted the accounting profession. The literature review confirms this disruption; however, the empirical findings of this study suggest that this disruption may not necessarily result in significant changes in the hiring of non-accounting majors by accounting firms. While some technology students may pursue this career path, and certain accounting processes may become less necessary, the overall impact may not be as profound as initially thought. If accounting firms cannot attract non-accounting majors for technology tasks, they may have to train their accounting staff or fund programs to give them more exposure to technology tasks.

Consequently, it is unlikely to displace traditional accounting students, meaning that job seekers in this field are not significantly vulnerable to job loss. Notably, the responses to the question about what would influence someone to work in accounting, overwhelmingly leaned to compensation and benefits. Maybe more of these job seekers would be more willing to work for the company if the salaries were attractive.

5.2. Contribution

This research contributes to the extant accounting literature on how technology impacts the accounting profession as there has been a gap in research between the relationship between accounting and applied technologies in the industry (Al-Htaybat et al., 2018). This research gives a small peek into some of the technologies used in the industry. It reinforces existing literature indicating that accounting is commonly perceived to offer lower salaries and was boring (Karlsson & Noela, 2022) and indicates that job seekers who perceive that their knowledge of technology will make them do their jobs more effectively, will be likely to apply.

It also has practical implications for both academia and the practitioner. Accounting firms have signaled that they will continue to move to technology platforms as they continue to invest significantly in technology tools to get a competitive advantage (Agnew, 2016; Y Zhang et al., 2020). The study revealed that perceived ease of use and perceived usefulness of technology may encourage non-accounting majors to apply to the accounting profession. Therefore, attention has to be paid to what can be done in the classroom, to better give students more tools in their tool belts. It also brings an awareness to the issue and practitioners could partner with universities to give technology scholarships to racial minorities and women in order to produce a diverse workforce, which increases productivity. Failure to turn the proverbial blind eye may lead to the graduation of students who may not be as technologically savvy as jobs might need, and a skewed workforce in gender and race.

5.3. Limitations and Future Research

Like many studies, this research is not without its limitations. Firstly, it focused on university students as the sample population, which may not fully represent the broader spectrum of job seekers. Additionally, restricting the study to just two universities could affect the generalizability of the findings. Moreover, employing an experimental design poses inherent challenges; participants might modify their behavior in response to perceived expectations within the context or their surroundings. There's also a possibility that students responded based on their personal experiences rather than the provided story, despite instructions to the contrary.

More research is needed to explore other technologies that affect the accounting profession and the potential impact. While this study centered on non-accounting students, additional research is needed to gauge the perceptions of accounting students regarding the emergence of technology and their viewpoints on the trajectory of the profession.

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APPENDIX

Survey Instrument

The purpose of this research is to examine the impact of certain technologies on the accounting profession. Please indicate your response based on the scenario. Participation in this study is voluntary and you are free to withdraw at any time.

This invitation is for voluntary participation in a research study examining influences on career decisions. The study involves a survey focusing on perceptions related to the accounting profession, requiring demographic details like school affiliation and major.

The survey is anticipated to take 9-10 minutes to complete and does not involve sensitive questions. There are no apparent risks known. Participants would not gain personal benefits, but the study aims to benefit others by understanding career decision-making factors.

Privacy protection measures include data encryption and confidentiality. Data may be shared with other researchers without identifiable information. Participation is voluntary and can be stopped at any time.

If you have questions concerning the study, contact the principal investigator, Helen Buck by email at hbuck1@uncc.edu. If you have questions or concerns about your rights as a participant in this study, contact the Office of Research Protections and Integrity at (704) 687-1871 or uncc-irb@charlotte.edu.

Please indicate that you are 18 years of age or older and have read and understand the information provided. You understand that you may contact the researcher listed above if you have any questions. You freely consent to participate in the study.

Click on continue to indicate agreement and proceed with the survey or close and exit if you decide not to participate.

Click on yes or next page to continue or no to exit the survey if you decide not to participate.
Yes
No

Please read the following scenario and then complete the questions that follow.

[Story 1 and story 2 will be randomized in Qualtrics]

[Story 1 – General information about accounting]:

The accounting profession, with a longstanding history, demands critical thinking, problem-solving, collaboration, and teamwork. Professionals in this field are highly sought-after across diverse industries like retail, manufacturing, corporate, entertainment, government, and non-profit sectors. Job prospects remain robust due to the ongoing need for accounting personnel across organizations, ensuring a steady growth in opportunities within various accounting roles. Accounting staff are integral to the functioning of most workplaces, particularly in public companies, emphasizing their essential role in organizational operations. This profession is appealing due to its widespread job opportunities, stability across industries, and avenues for professional advancement, including leadership positions.

Working in accounting firms not only provides exposure to diverse industries but also equips individuals with valuable insights into running a successful business, potentially facilitating entrepreneurship. Moreover, accounting roles often offer opportunities for international travel and global experiences, especially within firms with international offices, adding an extra dimension to career possibilities within the accounting profession.

[Story 2 – same as Story 1 with additional information on technology]:

The accounting profession, with a longstanding history, demands critical thinking, problem-solving, collaboration, and teamwork. Professionals in this field are highly sought-after across diverse industries like retail, manufacturing, corporate, entertainment, government, and non-profit sectors. Job prospects remain robust due to the ongoing need for accounting personnel across organizations, ensuring a steady growth in opportunities within various accounting roles. Accounting staff are integral to the functioning of most workplaces, particularly in public companies, emphasizing their essential role in organizational operations. This profession is appealing due to its widespread job opportunities, stability across industries, and avenues for professional advancement, including leadership positions.

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[Additional information in Story 2 that is not included in Story 1]

Technology has significantly transformed the accounting profession by introducing cutting-edge advancements like Artificial Intelligence, Machine Learning, Blockchain, and Robotic Process Automation. Accounting firms are increasingly embracing these technologies, heavily investing in tech tools, and even going to college campuses to recruit non-accounting majors with strong technological skills. Such individuals bring creative mindsets that synergize with technology, allowing for innovative task execution using artificial intelligence and other tech solutions.

See definitions below of some of the technologies that are becoming more and more important in the accounting field:

Artificial Intelligence (AI) is the development of computer systems able to perform tasks that normally require human intelligence.

Machine Learning (ML) development of computer systems that are able to learn and adapt without following explicit instructions.

Blockchain Technology (BT) is defined as shared, distributed ledgers that facilitates the process of recording transactions and tracking assets in a business network.

Big Data Analytics (BDA) is a process that systematically extracts information from data sets that are too large or complex to be dealt with by traditional data-processing application software.

Robotic Process Automation (RPA) is a process where programmable robots are used to automate processes, imitating keyboard strokes that were previously performed by humans.

[Next 3 questions are manipulation checks –used for both stories. The expectation is that Story 1 readers will answer No to at least 2 of 3 questions and Story 2 readers will answer 'Yes' to at least 2 of 3 questions]

1). Based on the information, accounting firms are using new technologies in the field.
  Yes
  No

2). Based on the information, accounting jobs are now being offered to non-accounting majors.
  Yes
  No

3). Based on the information, non-accounting majors can be hired in accounting firms.
Yes
No

Please answer the following questions based on your intent after reading [will appear as matrix in Qualtrics].

1. Strongly disagree 2. Disagree 3. Somewhat disagree 4. Neither agree nor disagree
5. Somewhat agree 6. Agree 7. Strongly agree

4). I would be interested in applying for a job in accounting if an opportunity arose.

5). I would be interested in visiting a career booth on accounting jobs at my university's career fair.

6). I would be interested in speaking with Human Resources Recruiters about jobs in accounting.

[Questions 4-6 address the intention to apply].

5). What do you think should be the starting salary for an entry-level position in accounting?

Between $30,000 to $120,000. [These amounts will be on a slider scale in Qualtrics]

6). What would influence you for or against working in accounting?

____
____
____

7). What do you think about the opportunities for career advancement in accounting?

____
____
____

8). Have you ever worked in an accounting or similar role?

____
____

Below, you will be asked questions about how easy it is for you to use technology in your future career and your technological skills/abilities.

Please respond to the following questions as follows: [Will be displayed in a matrix format]

1. Strongly disagree 2. Disagree 3. Somewhat disagree 4. Neither agree nor disagree
5. Somewhat agree 6. Agree 7. Strongly agree

Q1 PU- Using technologies in my future job will enable me to accomplish tasks more quickly.
Q2 PU -Using technologies will improve my future job performance.
Q3 PU- Using technologies in my future job will increase my productivity.
Q4 PU -Using technologies will enhance my effectiveness in my future job.
Q5 PU -Using technologies will make it easier to do my future job.
Q6 PU -I will find technologies useful in my future job.
Q 7 PEOU- Learning to operate new technologies is easy for me.
Q 8 PEOU- I find it easy to get technologies to do what I want it to do.
Q 9 PEOU- My interaction with technologies in my future job will be clear and understandable.
Q10 PEOU- I find technologies to be flexible to interact with.
Q11 PEOU- It is easy for me to become skillful at using technologies.
Q12 PEOU- I find technologies easy to use.

The final section will ask you to answer questions about your demographics and schooling.

1. What is your race? [Used to be inclusive – will be collapsed into Black, White, Latino, Asian, and Other]
   - White
   - Black or African Am.
   - Latino/Latina
   - American Indian or Alaska Native
   - Asian Indian
   - Japanese
   - Chinese
   - Korean
   - Filipino
   - Vietnamese
   - Other Asian, for example, Hmong, Laotian, Thai, Pakistani, Cambodian, and so on
   - Native Hawaiian
   - Guamanian or Chamorro
   - Samoan
   - Other Pacific Islander, for example, Fijian, Tongan, and so on.
   - Some other race

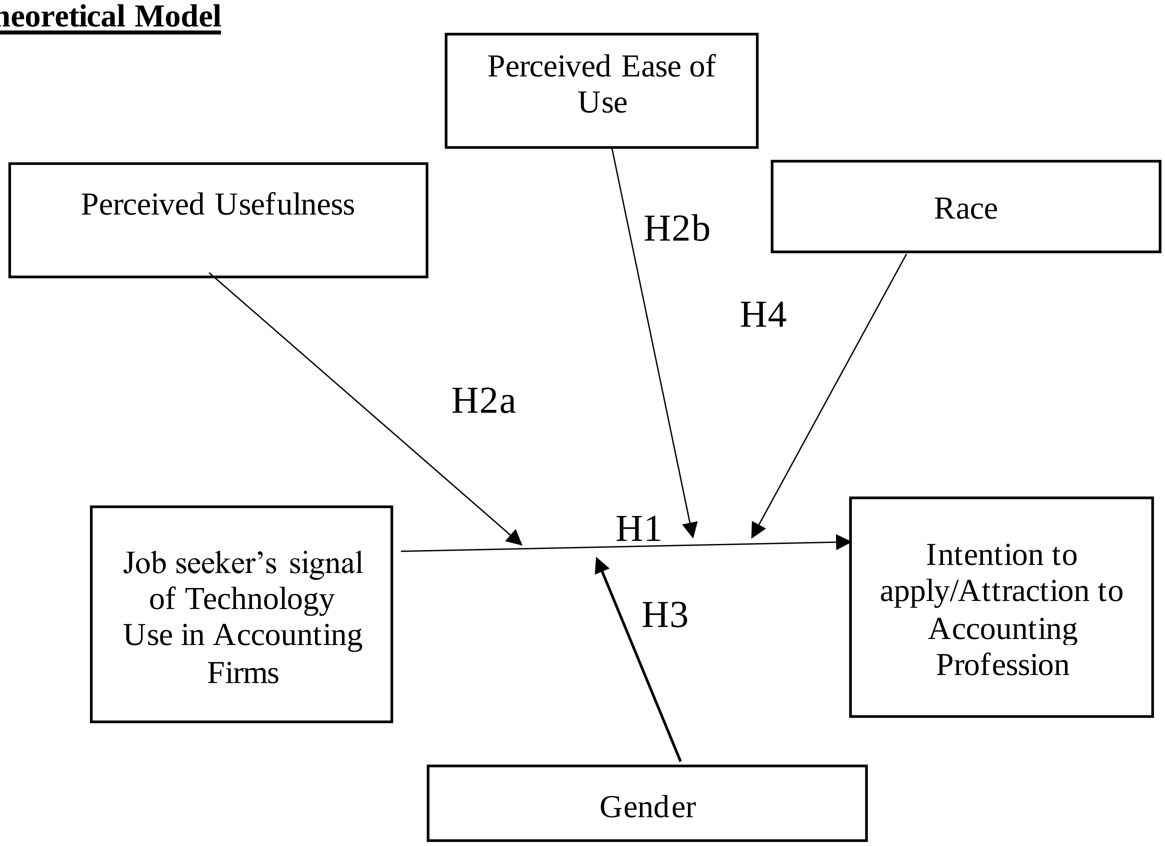
2. What is your current gender identity? [Will be collapsed to male, female and other]
   - Male or Trans male
   - Female or Trans female
   - Other (please state): ____________

3. What is the name of the university that you currently attend? _____________

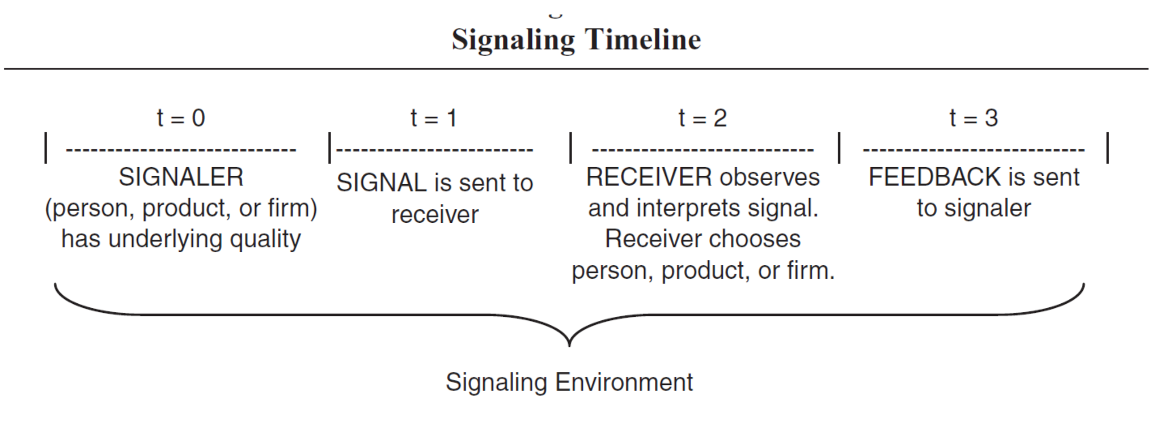
4. Current classification at the university?
   - Freshman
   - Sophomore
   - Junior
   - Senior

5. What is your major? _______________

Theoretical Model



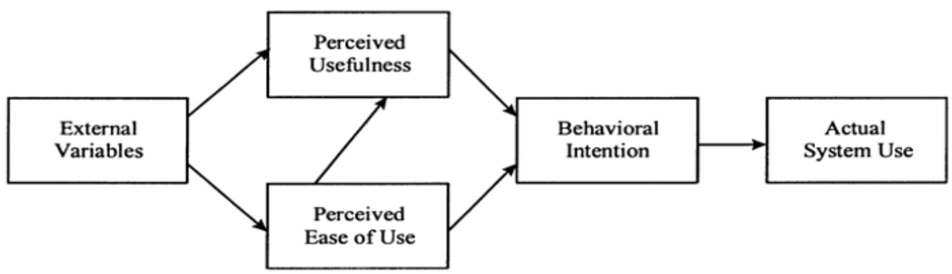
<u>Tables and Figures</u>



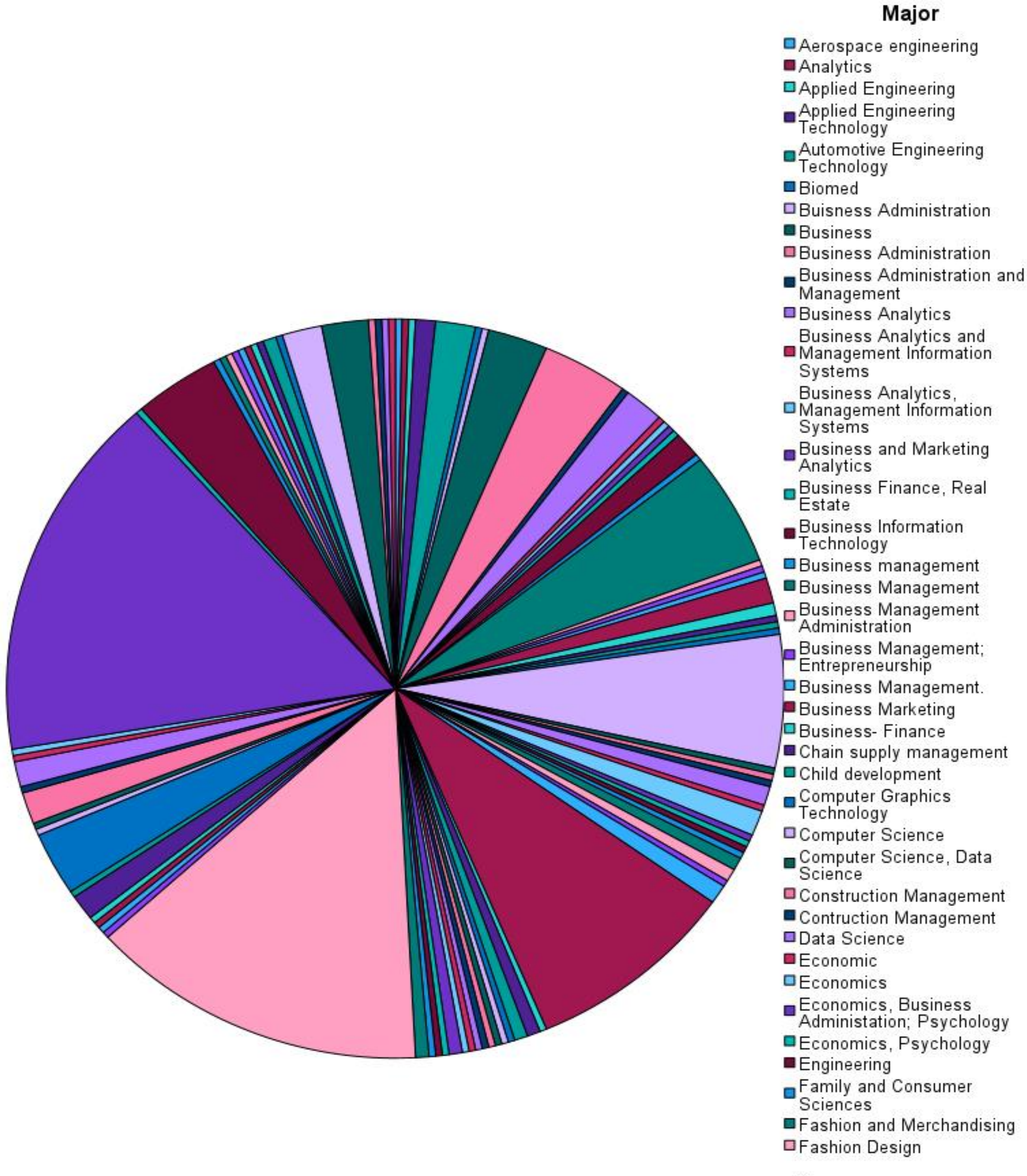
Note: t = time.

(Connelly et al.)

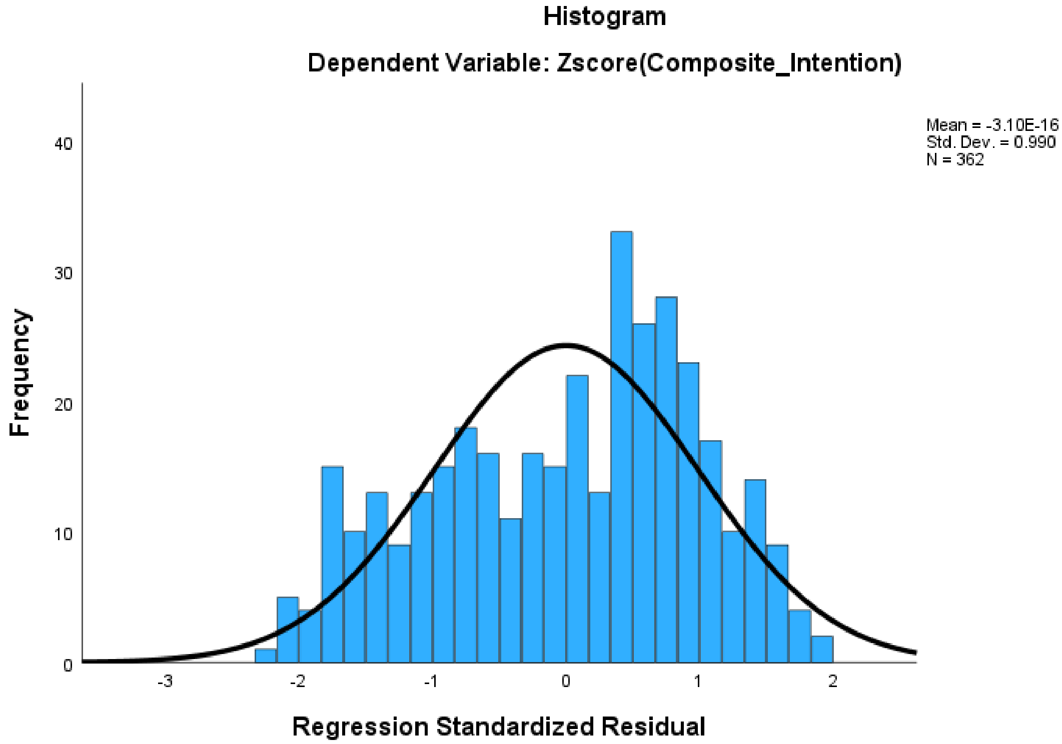
Technology Acceptance Model (TAM)

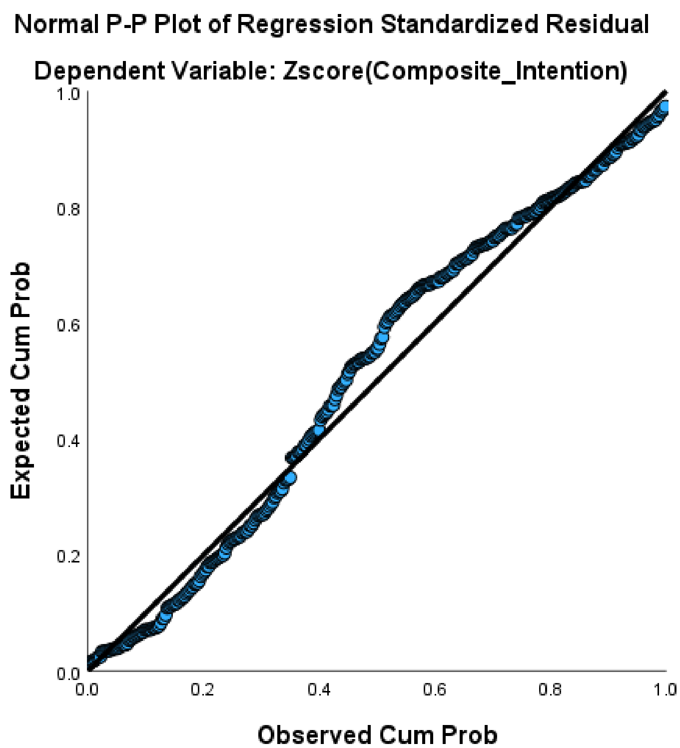


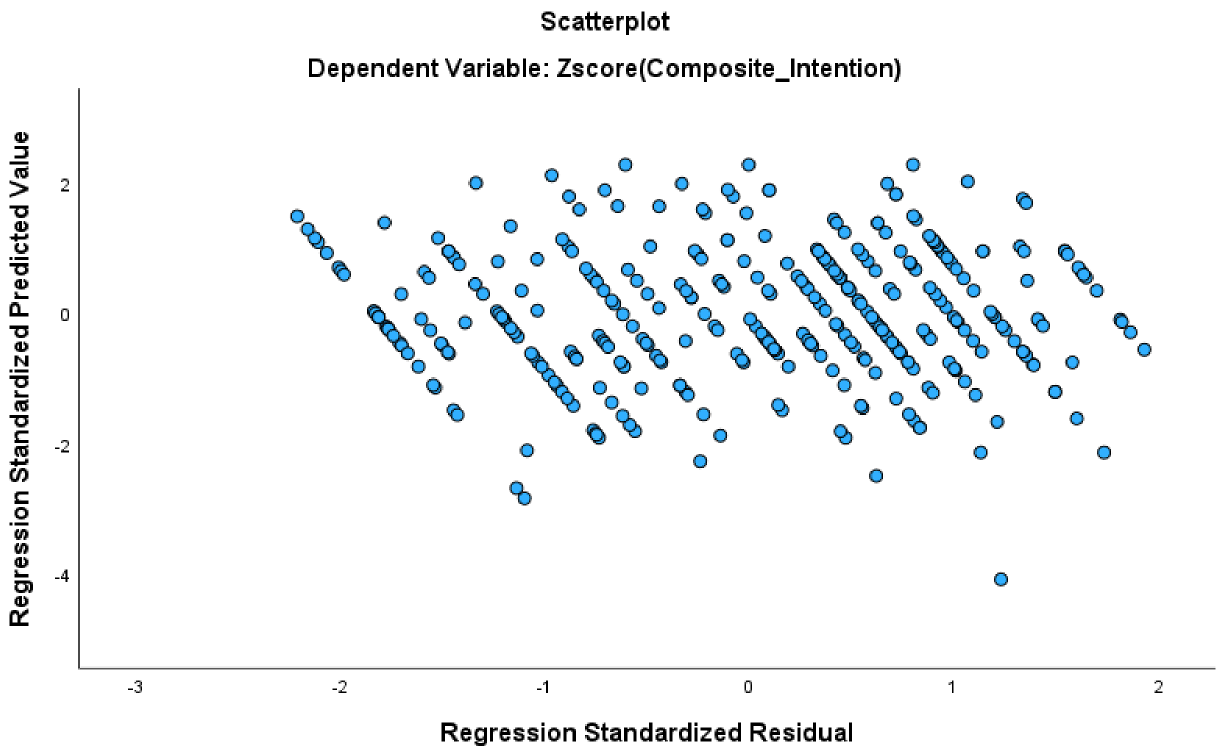
(F. D. Davis & Venkatesh, 2004)



Majors identified in the study


Histogram
Dependent Variable: Zscore(Composite_Intention)
Mean = -3.10E-16
Std. Dev. = 0.990
N = 362
Frequency
0
10
20
30
40
-3
-2
-1
0
1
2
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: Zscore(Composite_Intention)
Expected Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob


Scatterplot
Dependent Variable: Zscore(Composite_Intention)
Regression Standardized Predicted Value
2
0
-2
-4
-3
-2
-1
0
1
2
Regression Standardized Residual