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INTERACTIVE DATA VISUALIZATION IN ACCOUNTING CONTEXTS: IMPACT ON USER ATTITUDES, INFORMATION PROCESSING, AND DECISION OUTCOMES

by

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Kenneth G. Dixon School of Accounting in the College of Business Administration at the University of Central Florida Orlando, Florida

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ABSTRACT

In 2009, The United States Securities and Exchange Commission (SEC) issued a mandate requiring public companies to provide financial information to the SEC and on their corporate Web sites in an interactive data format using the eXtensible Business Reporting Language (XBRL). This dissertation consists of three separate, but interrelated studies exploring issues related to interactive data visualization in financial reporting contexts. The first study employs theories in information systems (task-technology fit and the technology-performance chain model) and cognitive psychology (cognitive load) to examine the link between characteristics of interactive data visualization and task requirements in a financial analysis context, and the impact of that link on task performance and user attitudes towards interactive data technology use. The second study extends the first by examining the effects of prior interactive data technology use on future choice to use an interactive technology. This study uses the IS continuance model to examine antecedents to continued interactive technology use based on previous assessments of task-technology fit and performance impacts from the first study. The third study employs an elaboration likelihood model (ELM) to understand the interactivity concept and its impact on information processing and belief/attitude formation. This study examines the impact of increasing interactivity on investor perceptions of forecast credibility and on a firm's attractiveness as a potential investment choice. Overall, these three studies provide insights on factors that impact decision-making in interactive financial reporting contexts, and how characteristics of interactive data visualization impact information processing, user perceptions, and task performance.

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GENERAL INTRODUCTION

Dilla et al. (2010, p. 1) define interactive data visualization as "computer-supported visual representation of data that allows users to select the information they wish to view and its format". Interactive data visualization has become more salient in the financial reporting arena due to the Securities and Exchange Commission's (SEC) 2009 mandate requiring public companies to provide financial information to the SEC and on their corporate Web sites in an interactive format using the eXtensible Business Reporting Language (XBRL). The XBRL mandate is intended to provide a financial reporting standard that enables more efficient retrieval and analysis of financial information (SEC 2009). XBRL is an eXtensible Markup Language (XML)-derived framework for communicating financial information (Baldwin et al. 2006). As an XML-based standard developed for business reporting, XBRL's structure enables the recognition, exchange, and processing of financial information across multiple platforms including software applications, databases, and financial reporting systems (www.xbrleducation.com; SEC 2009). In defining XBRL, EDGAR Online (2006, p. 4) noted, "think of XBRL as bar coding for financial statements. Every piece of data is linked to explanatory information. You don't just get numbers; you get context".

Proponents of XBRL note that it provides several benefits to investors, financial analysts, and others in the business community. For example, since related information will be similarly tagged, XBRL provides more relevant and accurate searches for financial information. In addition, XBRL eliminates the need for third-party intermediaries to extract and format financial information for use by analysts. Other proposed benefits of XBRL include improving

communications with investors, partners, and stockholders, reducing the costs of automated data gathering and evaluation, increasing financial reporting transparency, and improving the comparison of financial information across multiple periods and multiple companies.

According to Paredes (2003), in order for the benefits of disclosure requirements to be realized, securities market participants must be able to effectively acquire and process the disclosed information. Companies now use interactive data visualization techniques in an effort to facilitate access to, and analysis of, the vast amount of financial information being produced by their information systems (Kelton and Yang 2008; Dilla et al. 2010). However, we have very little knowledge of the impact of interactive data visualization on decision-making in a financial reporting context. Debreceny and Gray (2001) assert that the provision of XBRL-enabled reports should fuel the development of interactive data viewers and research is needed on developing such tools and understanding user-machine interaction in this context. Tang et al. (2014) present an initial examination of the effects of interactivity and visualization in a financial decision-making context and their findings indicate that both interactivity and visualization do positively impact decision accuracy and perceptions of confidence during a financial analysis task.

Following Dilla et al. (2010), the current research identifies two characteristics or elements of interactive data visualization that are likely to affect decision-making in accounting contexts¹. The first is interactivity or interaction, which is defined as the extent to which a user is able to manipulate information views or restructure information during decision making (Yi et al.

¹ Dilla et al. (2010) identify three elements of interactive data visualization – interaction, selection, and representation. However, Dilla et al. (2010, p. 4) further discusses that their review is based on three aspects of interactivity (i.e. navigation, selection, and how information is represented), and group navigation and selection techniques together. For simplification purposes, this research identifies selection as an interaction technique and identifies two primary elements of interactive data visualization.

2007; Lurie and Mason 2007). Interactivity involves giving the user active control over what and how information is viewed in the decision environment. The second characteristic or element of interactive data visualization is visualization or representation, which is defined as "the manner in which data are depicted or portrayed" (Dilla et al. 2010, p. 2-3). Characteristics of interactive data visualization potentially influence decision processes and outcomes by changing the decision-making frame, i.e. what information a decision-maker uses, and how it is used to gain insights and make decisions. Lurie and Mason (2007) assert in their review that interactive data visualization might improve decision-making performance by facilitating information acquisition due to the ability to select, navigate, and restructure complex data². However, interactive data visualization may also lead to overconfidence and biases in decision-making by increasing the salience of less diagnostic information. Finally, previous research suggests that investors might choose not to use interactive financial reporting technology even when use facilitates financial statement analyses (e.g. Hodge et al. 2004).

This research consists of three separate, but interrelated studies exploring issues related to the use of interactive data technology in financial reporting contexts. Drawing on theories from information systems, social psychology, and cognitive psychology, these three studies investigate 1) the link between characteristics of interactive data visualization and task requirements in a financial analysis context, and the subsequent effect on task performance, user attitudes, and user beliefs regarding the use of interactive data technology, 2) the influence of the experiential feedback from prior interactive data technology use on future interactive data technology choice, and 3) the effects of the increase in interactivity on perceived forecast

² Lurie and Mason (2007) use visual representation to refer to the same concept.

credibility and a firm's attractiveness as a potential investment. Further details on each study are provided in the following three subsections.

Study One: Interactive Data Visualization: A Model of Task-Technology Fit and the Technology-Performance Chain

The purpose of the first study is to examine the link between characteristics of interactive data visualization and task requirements in a financial analysis context, and the impact of that link on task performance and user attitudes and beliefs towards interactive data technology use. Critical to interactive data technology providing performance impacts is that there must be a match between characteristics of interactive data visualization and task requirements, and potential users must use the technology. Using Goodhue and Thompson's (1995) technology-performance chain model as a theoretical foundation, a research model is developed to investigate the effects of interactivity and visualization on task-technology fit, performance, perceived usefulness, and behavioral intention to use interactive data visualization technology. In addition, the effects of interactivity and visualization on cognitive load, and the subsequent effect of cognitive load on performance are also considered.

The research in this study employs both an experimental design and a survey of perceptual measures based on the experimental manipulations. The experimental design enables the examination of the manipulated independent variables on the primary dependent variables of interest. On the other hand, individual perceptions of the manipulated independent variables and the dependent variables are collected to facilitate the examination of the user's experience while

completing the experimental task and the simultaneous examination of the relationships among all of the variables in the research model.

This study uses a 2x2 incomplete factorial design with interactivity and visualization as the manipulated variables. Interactivity is treated as a within-subject variable, while visualization is manipulated in the high interactivity condition alone. Interactivity is manipulated by varying the number of interactivity techniques available to users, based on the categories of interaction described in Yi et al. (2007) and attributes of interactivity described in Clements et al. (2011). In the low interactivity condition, the available interactivity techniques include exploring and filtering. However, in the high interactivity condition, the available interactivity techniques include filtering, selection, abstracting/elaborating, and exploring. Low interactivity was operationalized with the use of the SEC's Electronic Data Gathering Analysis and Retrieval (EDGAR) interactive viewer and high interactivity was operationalized with the use of Calcbench's online benchmarking and analysis tool. Visualization is operationalized by directing participants to use Calcbench's visualization tool, which allows a user to depict and see the trend for a financial statement item using line charts. In the no visualization condition, the visualization tool is not revealed to participants.

Data are collected from 170 graduate business students who serve as surrogates for nonprofessional investors³. The participants are asked to conduct two financial analysis tasks – one in the low interactivity condition and the other in the high interactivity condition. Following each analysis task, participants are asked to choose to invest in one of two companies. Next,

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³ Participants included 150 masters of accounting students, 16 masters of business administration (MBA) students, and 14 professional MBA students. The 16 MBA students have all taken their core accounting course.

participants are asked to evaluate and respond to several statements designed to measure their perceptions of task-technology fit, performance, cognitive load, interactivity, visualization, task complexity, perceived usefulness, and the behavioral intention to use interactive data technology. Finally, participants respond to ten questions related to financial reporting in order to measure their financial reporting knowledge. The data is evaluated using partial least squares (PLS) analysis and analysis of variance (ANOVA). The direct effect of the manipulated variables on task-technology fit, accuracy, and cognitive load are examined using ANOVA, while in subsequent analysis, all relationships are examined within the context of the overall path dependent model.

The experimental results indicate that higher levels of interactivity provide a better match between interactive data technology and task requirements in a financial statement analysis context. However, visualization does not appear to enhance task-technology fit based on the experimental results. The experimental results also indicate that interactivity and visualization do not have an effect on accuracy in the financial analysis task nor on the cognitive load experienced while completing the task. While the experimental analysis examined the direct effect of the treatment variables, the structural model is used to examine the simultaneous effects of perceptions of interactivity and perceptions of visualization on the interrelated constructs in the theoretical model.

The results from the structural model indicate that perceptions of both interactivity and visualization have significant and positive effects on assessments of task-technology fit. In addition, task-technology fit positively impacts user beliefs about using interactive data

technology and user attitudes towards interactive data technology use. Interactivity and visualization were expected to increase cognitive load due to the potential for the design of interactivity and visualization techniques to burden the decision-maker. However, the results from the structural model suggest that interactivity may, if anything, mitigate cognitive load as the relationship between interactivity and cognitive load is negative and statistically significant. Finally, examining the indirect effects of interactivity and visualization indicates that both interactivity and visualization affect perceptions of performance and the behavioral intention to use interactive data technology through their effects on task-technology fit.

<u>Study Two: Interactive Data Technology: Feedback from the Technology-Performance</u> <u>Chain and Future Technology Choice</u>

The second study extends the first by examining the effect of prior interactive data technology use on future choice to use the technology. Technology acceptance or use should not be limited to the initial adoption stage alone and the success of an IS implementation should be based on continued use of the technology (Limayem et al. 2007). Based on Goodhue and Thompson's (1995) technology-performance chain model examined in study one, the actual experience of using a technology will lead users to conclude if it had a better (or worse) effect on performance than anticipated, thereby affecting future utilization.

This study uses Bhattacherjee's (2001a) IS continuance model to examine how past experience with interactive data technology influences future beliefs and future technology choice during a financial statement analysis task. A research model is developed in which prior assessments of task-technology fit and performance are modeled as antecedents to satisfaction

with interactive data technology use, perceived usefulness of interactive data technology, IS continuance intention, and actual utilization of interactive data visualization technology.

Data are collected from 166 graduate business students who had previously participated in study one. The participants are asked to conduct a financial analysis task using their choice of two interactive financial reporting technologies. The two interactive technologies used are the same ones the participants are exposed to in study one (i.e. the SEC EDGAR interactive viewer and Calcbench). Participants are asked to assess their satisfaction and perception of usefulness with prior interactive technology use after making their choice of which technology to use. Participants then complete an analysis task using their choice of interactive data technology. Finally, participants are asked to respond to questions designed to examine their extent of utilization for the interactive reporting technology they chose. The collected data is evaluated using partial least squares (PLS) analysis.

The results provide support for all of the hypothesized relationships in the research model. Higher assessments of task-technology fit lead to increased satisfaction with interactive data visualization technology and increased assessments of the usefulness of interactive technology. In addition, the results indicate that user assessments of the performance impact of interactive data technology lead to increased perceptions of usefulness and satisfaction with interactive data technology use. Finally, perceptions of usefulness as well as satisfaction increase the intention to continue interactive data use, which in turn leads to an increase in the extent of utilization.

A further breakdown of the structural model into two groups based on interactive financial reporting technology choice showed that for participants who chose to use the low interactive viewer, task-technology fit and performance have positive effects on perceived usefulness, which in turn has significant positive effects on satisfaction. However, tasktechnology fit and performance do not impact satisfaction directly. In addition, satisfaction is the primary determinant of IS continuance intention and perceived usefulness no longer has a significant effect on IS continuance intention. On the other hand, task-technology fit and performance have significant effects on satisfaction and perceived usefulness for participants who chose the high interactivity software. However, perceived usefulness does not have an impact on satisfaction. Bhattacherjee (2001b) asserts that perceived usefulness represents the rational dimension of behavioral intentions, while satisfaction represents attitudes or the affective dimension. The results from the low interactivity group suggest that the affective dimension of behavioral intention supersedes the rational dimension in determining continuance intentions and ultimately, utilization for participants who chose the low interactivity software. On the other hand, for users who select the higher interactive software, both the rational dimension and the affective dimension of behavioral intentions represent complementary processes that motivate the intention to reuse and the choice to utilize interactive financial reporting technology. The interpretability of these results are limited, however, as only 40 participants chose to use the lower interactivity software when given a choice.

Study Three: The Effects of Interactivity on User Perceptions of Credibility and Investment Choice

The purpose of study three is to investigate the effects of the increase in interactivity in internet financial reporting on investors' perceptions of disclosure credibility and on a firm's attractiveness as a potential investment choice. Extant research on disclosure credibility suggests that the characteristics of a disclosure (e.g. venue, timing, precision, etc.) are a factor that can influence investor credibility assessments (Hodge 2001; Mercer 2004; Elliott et al. 2012).

Research in financial disclosure suggests that increased interactivity has a positive impact on investor perceptions of credibility and investment choices (e.g. Clements and Wolfe 2000; Elliott et al. 2012). This study examines disclosure credibility in the context of management's earnings forecasts. According to disclosure literature, management earnings forecasts are also an influencing tool in management's communication with investors. This study examines which of the two influence mechanisms (interactivity or the argument quality of management's earnings forecast) will most shape investor perceptions of credibility in a financial reporting context.

Using the elaboration likelihood model (ELM) as a theoretical foundation, a research model is developed to understand the interactivity concept and its impact on forecast credibility. ELM is a model of information processing and persuasion that specifies how beliefs or attitudes are formed or changed via two information processing routes – the central route and the peripheral route. In the central route, attitudes are formed as a result of careful scrutiny of relevant information in a message. On the other hand, attitude change occurs in the peripheral route as a result of cues associated with the message and not the message itself (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). The central route is operationalized using the

argument quality of management's earnings forecast, while the peripheral route is operationalized using varying levels of interactivity.

The research in this study employs both an experimental design and a survey of perceptual measures based on the experimental manipulations. The experimental design enables the examination of the manipulated independent variables on the primary dependent variables of interest. On the other hand, individual perceptions of the manipulated independent variables and the dependent variables are collected to facilitate the examination of the user's experience while completing the experimental task and the simultaneous examination of the relationships among all of the variables in the research model.

A 2x2 between-subjects experiment is conducted with interactivity and argument quality as the manipulated variables. Data are collected from 117 individuals recruited from Amazon's Mechanical Turk who proxy for nonprofessional investors. An experiment is conducted in which potential investors are asked to view financial information and conduct an analysis of a potential investment under varying levels of interactivity. Financial and nonfinancial information about the potential investment are presented online on the company's Web site. Following the analysis, participants are asked to view a press release, which detailed the company's most recent management's earnings forecast. Management issued a good-news forecast that included either verifiable forward-looking statements or "soft-talk" about the state of the company's business. Strong argument quality is manipulated as the use of verifiable forward-looking statements, while weak argument quality is manipulated as the use of "soft-talk" in the forecast. Interactivity is manipulated with two levels (low or high interactivity) by varying the ability of users to

interact with the information presented on the Web site. In the high interactivity condition, participants could hover over financial statement items and view definitions on each item, and view the financial statements with any software of choice (i.e. PDF, Excel, or Interactive). In addition, the interactive view used a drop-down list box which included available sections of the annual report and specific note information about any particular item on the financial statements. Participants in the low interactivity condition could only view the financial report in a PDF document. Investor perceptions of credibility and their final investment choice are measured following the press release. In addition, data is collected to measure two moderating variables (need for cognition and financial reporting knowledge) hypothesized to strengthen (weaken) the relationship between argument quality (interactivity) and forecast credibility. The data is evaluated using partial least squares (PLS) analysis and analysis of variance.

The results from the experimental analysis suggest that the experimental manipulations of argument quality and interactivity do not significantly impact forecast credibility. However, the research on interactivity suggests that a user's perception while engaging with an interactive medium is important in determining subsequent attitudes and outcomes. In addition, ELM research suggests that attitude formation or change is dependent on whether a message induces positive or negative thoughts when received. Taken together, these research streams both suggest that individual perceptions of actual interactivity and perceptions of argument quality are important in shaping perceptions of forecast credibility and behavior. Examining the structural model indicates that assessments of forecast credibility can be influenced by both perceptions of interactivity and perceptions regarding the information contained in management's earnings forecasts. Both perceived argument quality and perceived interactivity had significant and

positive effects on forecast credibility. However, perceived argument quality or the information content of the earnings forecast had a stronger effect on credibility than perceived interactivity. In addition, need for cognition and reporting knowledge do not significantly moderate the relationships between perceived argument quality and forecast credibility or perceived interactivity and forecast credibility. Finally, the results of this study indicate that the central route has a stronger impact on actual investment behavior than the peripheral route. While perceived argument quality and perceived interactivity both have positive and significant total effects on the investment decision, the regression coefficient of the total effect of perceived argument quality on the investment decision is higher, indicating that perceived argument quality has a greater impact on actual behavior.

Overall Contribution

The three studies contained in this dissertation examine interactive data visualization or interactive data technology within the context of financial reporting and analysis. Taken together, these studies advance the understanding of elements of interactive data visualization and how they affect financial statement analyses, perceptions of forecast credibility and investment choice, and user attitudes and beliefs towards the initial and continued use of interactive data technology. Consistent throughout these three studies is the influence of characteristics of interactive data visualization on the decision environment in a financial reporting and analysis context.

The first study examines whether characteristics of interactive data visualization (i.e. interactivity and visualization) provide a fit between interactive data technology and task

requirements during a financial statement analysis task. The effects of task-technology fit on performance and user attitudes and beliefs about interactive data technology are also considered. While previous studies have examined if reporting in XBRL facilitates financial statement analyses, interactive data visualization and characteristics of interactive data visualization are only recently emerging as a topic of interest (e.g. Dilla et al. 2010). Thus, the first study contributes to the research by examining how interactive data visualization impacts performance in a financial analysis context. In addition, previous research in accounting has reported that nonprofessionals may choose not to use interactive data technology (e.g. Hodge et al. 2004). The first study thus contributes to our understanding of the mechanism through which user attitudes and beliefs about interactive data technology use may be formed.

The second study extends our understanding of factors that may affect the adoption of interactive data technology by examining the antecedents to continued use or the choice to use a particular interactive data technology. Evidence from the first study showed that characteristics of interactive data visualization have a significantly positive effect on task-technology fit, which in turn has a positive impact on performance. This study examines how perceptions of task-technology fit and performance following the initial use of interactive data technology affects the future choice to use interactive data technology. Evidence from prior research suggests that the choice to use interactive financial reporting technology might be dependent on prior exposure or experience with the technology (Janvrin et al. 2013). This study makes a contribution to the research stream by contextualizing prior experience with interactive data technology in terms of prior assessments of task-technology fit and performance and investigating their impact on technology choice using the IS continuance model.

The third study examines the effect of interactivity on investor perceptions of forecast credibility and on a firm's attractiveness as a potential investment choice. Previous disclosure research has found that the venue of a disclosure is one factor that affects investor perceptions of disclosure credibility (see Mercer 2004 for a review). This study examines disclosure credibility in the context of management's earnings forecast and makes a contribution to the research stream by investigating a characteristic of internet financial reporting today, i.e. interactivity, and its potential to affect the decision-making environment and influence investor perceptions of forecast credibility.

Overall, these three studies contribute to our understanding of elements of interactive data visualization technology and how they impact nonprofessional investors in a financial reporting and analysis context. Although interactive data visualization has become more salient in various accounting contexts, there is a paucity of research examining how users interact with interactive data technology and how this interaction affects decision processes and outcomes. Evidence from research in various disciplines assert that elements of interactive data visualization could lead to improved decision making by facilitating information acquisition and information integration (Lurie and Mason 2007). On the other hand, interactive data visualization may lead to overconfidence if decisions are made from a limited number of observations, and emphasize biases by increasing the salience of less diagnostic information (Lurie and Mason 2007). These three studies present an in-depth examination of the process through which user-machine interaction with elements of interactive data visualization may lead to improved performance or emphasize biases in decision-making. The first two studies focus on the expectation that interactive data visualization may improve task performance during financial

statement analysis, and the subsequent effect of improved performance on beliefs and attitudes towards interactive data technology use. On the other hand, the third study considers the possibility that elements of interactive data visualization may emphasize biases and considers the role of interactivity as an influence mechanism in a financial reporting context. Taken together, these studies provide theory-driven empirical research on the influence of characteristics of interactive data visualization on the decision environment in a financial reporting and analysis context.

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STUDY ONE: INTERACTIVE DATA VISUALIZATION: A MODEL OF TASK-TECHNOLOGY FIT AND THE TECHNOLOGY-PERFORMANCE CHAIN

Introduction

In recent years, interactive data visualization has become salient in the financial accounting arena due to the prevalent use of the Internet as a disclosure and financial reporting venue, and the recent mandate by the U.S. Securities and Exchange Commission (SEC) (Dilla et al. 2010). In 2009, the SEC issued a mandate intended to address the issue of improving the usefulness of financial statement information to investors and promoting efficient and transparent capital markets. According to the SEC's final rule 33-9002, public companies are required to provide financial information to the SEC and on their corporate Web sites using the eXtensible Business Reporting Language (XBRL) (SEC 2009). Proponents of XBRL have presented it as the solution to both the resource discovery⁴ and attribute recognition⁵ problems that plague the current exchange of financial information (Debreceny and Gray 2001; Doolin and Troshani 2004). As an XML-based standard, XBRL's structure enables the recognition, exchange, and processing of information across multiple platforms including software applications, databases, and financial reporting systems (www.xbrleducation.com; SEC 2009).

The development of XBRL is expected to change the way financial information is rendered, acquired, and processed. Advancements in technologies and electronic data communication have significantly facilitated access to companies' financial information via the

⁴ Resource discovery refers to the difficulty in locating financial information, relevant to a particular user's interests (Bowman et al. 1994; Debreceny and Gray 2001).

⁵ Attribute recognition refers to identifying financial attributes or elements within financial statements (Debreceny and Gray 2001).

Internet. However, this information is typically presented in static data formats such as PDF documents. The limitation of this form of access is that financial information cannot be easily incorporated into decision-making without the addition of inefficient, extra steps. For instance, analysts often rekey data from financial statements into spreadsheets and other analysis tools before evaluating investment choices (Schmerken 2000; Boritz and No 2003). In theory, XBRL uses a set of tags to consistently identify data so that software applications will automatically recognize the information, making it easier to acquire and analyze financial information in a variety of formats, and thereby reducing the costs and efforts associated with current financial data analysis (SEC 2009). XBRL is thus generally referred to as interactive data (Cox 2006).

Dilla et al. (2010, 1) define interactive data visualization as "computer-supported visual representation of data that allows users to select the information they wish to view and its format." Companies now use interactive data visualization techniques in an effort to facilitate access to, and analysis of, the vast amount of financial information being produced by their information systems (Kelton and Yang 2008; Dilla et al. 2010). In order for the benefits of recent disclosure requirements to be realized, securities market participants must be able to effectively acquire and process the information produced by interactive data (Paredes 2003). Interactive data visualization techniques are essential in achieving this objective.

Drawing from research reviews in accounting, marketing, and computer science (Yi et al. 2007; Lurie and Mason 2007; Dilla et al. 2010), this paper identifies two primary characteristics of interactive data visualization (i.e. interactivity and visualization) that can potentially influence financial decision-making. Debreceny and Gray (2001) assert that the provision of XBRL-enabled reports should fuel the development of interactive data viewers and research is needed

on developing such tools and understanding user-machine interaction in this context. However, there is a lack of research that specifically examines the effect of interactive data visualization and interactive financial reporting on financial decision-making. The exception is Tang et al. (2014), which presents an initial examination into the impact of interactivity and visualization on financial decision-making and finds that both interactivity and visualization are important in improving financial decision-making accuracy and user calibration. However, Tang et al. (2014) did not attempt to investigate the process through which interactivity and visualization affect financial decision-making. Previous research in marketing and computer science (e.g. Teo et al. 2003; Sundar and Kim 2005; Yost 2006; Heer and Robertson 2007; Cyr et al. 2009) has also examined the impact of interactivity and visualization on decision-making. However, these studies have predominantly investigated either the interactivity element alone or the visualization element alone rather than allowing for the joint effect of both elements. To advance our understanding of the impacts of interactive data visualization on financial decision-making, it is important to consider the contribution of both elements of interactive data visualization on usermachine interaction within the interactive financial reporting context.

The purpose of this study is to examine the link between characteristics of interactive data visualization and task requirements in financial decision-making contexts, and the impact of that link on task performance and user attitudes towards interactive technology use. This research study therefore examines the efficacy of interactive data visualization in a financial decision-making context, particularly, the effect of interactive data visualization on decision-making performance for nonprofessional investors. The existing literature on interactive data visualization suggests that interactive financial reporting may positively affect decision-making

performance for nonprofessional investors by facilitating information acquisition and information integration, thereby enabling better-informed investment decisions (Hodge et al. 2004; Arnold et al. 2012). Evidence from previous research suggests that nonprofessional investors are more likely to benefit from interactive financial data reporting because in comparison to professional analysts, nonprofessional investors do not possess the relevant knowledge about the relationship between different financial statement items and typically follow a sequential search strategy while looking for information (Hunton and McEwen 1997; Maines and McDaniel 2000). The tagging of related financial information will thus be more beneficial to non-professional investors rather than professional investors. Prior evidence has shown that tagged data enables nonprofessional investors to become more directed in their search strategy, thereby leading them to behave more like professional investors (e.g. Arnold et al. 2012).

This study also examines the effect of decision-making in an interactive data visualization environment on user attitudes towards using interactive data visualization technology. Despite the SEC mandate and proposed benefits of interactive financial reporting to nonprofessional investors, previous research suggests that nonprofessional investors may choose other financial reporting technologies (e.g. Hodge et al. 2004). In Hodge et al. (2004), participants did not choose to use an XBRL-enabled technology although the technology facilitated increased information acquisition and integration. However, Janvrin et al. (2013) find that most users in their experimental study preferred XBRL to Excel and PDF after going through a tutorial using the three reporting technologies. It is therefore important to understand

the factors influencing user attitudes and beliefs in the context of interactive data visualization technology as the purported benefits cannot be realized without actual use.

There is a body of research in human-computer interaction (HCI) and information systems (IS) aimed towards a better understanding of the link between information technology (IT) and individual performance. This research stream typically employs one of two complementary theoretical models – a utilization focus based on user attitudes towards using the technology (e.g. Davis 1989, Venkatesh et al. 2003), or a task-technology fit focus based on the fit between task characteristics and the technology as a determinant of performance (e.g. Benbasat et al. 1986; Jarvenpaa 1989; Vessey 1991). Goodhue (2006) suggests that in order to adequately examine the impact of technology on performance, models of information systems and performance should incorporate both the utilization focus and the task-technology fit focus. This argument is based on the premise that for a technology to provide positive performance impacts, it must both be used, and be a good fit for the task. Combining the utilization and fit focus considers the interactions between characteristics of the task, technology, and the individual in models of technology performance. This study examines the effects of characteristics of interactive data visualization (interactivity and visualization) on decision processes and outcomes (cognitive load, performance), and user beliefs about interactive technology use.

The research in this study employs both an experimental design and a survey of perceptual measures based on the experimental manipulations. The experimental design enables the examination of the manipulated independent variables on the primary dependent variables of

interest. On the other hand, individual perceptions of the manipulated independent variables and the dependent variables are collected to facilitate the examination of the user's experience while completing the experimental task and the simultaneous examination of the relationships among all of the variables in the research model. An experiment is conducted where interactivity and visualization are manipulated in a 2 x 2 incomplete experimental design. Interactivity is manipulated within-subjects and participants are asked to conduct two financial analysis tasks – one in the low interactivity condition and the other in the high interactivity condition. Low interactivity is operationalized with the use of the SEC's Electronic Data Gathering Analysis and Retrieval (EDGAR) interactive viewer, while high interactivity is operationalized with the use of Calcbench's online benchmarking and analysis tool. Visualization is manipulated (no visualization/visualization) between-subjects in the high interactivity condition alone, and operationalized as the use or nonuse of a visualization tool to convert financial statement items displayed in tabular form into graphical representations with line charts. Each analysis task involved participants calculating financial ratios for two companies in the same industry and making a choice to invest in one of the two companies. Following both analyses tasks, participants are asked to evaluate and respond to several statements designed to measure their perceptions of the task and the interactive data visualization technology used.

The experimental results indicate that higher levels of interactivity provide a better match between interactive data technology and task requirements (task-technology fit) in a financial statement analysis context. However, visualization does not appear to enhance task-technology fit according to the experimental results. The experimental results also indicate that interactivity and visualization do not have an effect on accuracy in the financial analysis task or on the

cognitive load experienced while completing the task. While the experimental analysis examined the direct effect of the treatment variables, a structural model is used to examine the simultaneous effects of perceptions of interactivity and perceptions of visualization on the interrelationships between task-technology fit, cognitive load, performance, and attitudes and beliefs about interactive data visualization technology as theorized in the TPC model. The results from the structural model indicate that perceptions of both interactivity and visualization have significant and positive effects on assessments of task-technology fit. In addition, tasktechnology fit positively impacts perceived performance, perceived usefulness, and the behavioral intention to use interactive data visualization technology. Although interactivity and visualization were expected to increase cognitive load, the results from the structural model suggest that interactivity may mitigate cognitive load and visualization did not have an effect on cognitive load. The indirect effects of perceived interactivity and perceived visualization on perceived performance and the behavioral intent to use interactive data visualization technology were also examined. The results indicate that both perceived interactivity and perceived visualization have an impact on perceived performance through their effects on task-technology fit. In addition, perceived interactivity and perceived visualization both impact the behavioral intent to use interactive data visualization technology through their effects on task-technology fit and perceived usefulness.

This study has important theoretical and practical implications. In a recent review, Dilla et al. (2010) call for more research on the impact of interactive data visualization on decision processes and judgments in accounting contexts. In addition, the effects of interactive data visualization tools (e.g. the SEC's EDGAR interactive viewer, Crossfire from Rivet Software,

and Calcbench's benchmarking and analysis tool) on decision processes and outcomes have not been fully explored in accounting research. This study makes a contribution to this research agenda by examining characteristics of interactive data visualization in a financial statement analysis context. The results suggest that considering the behavioral dimension of characteristics of interactive data visualization may be important in conjunction with examining the actual provision of interactive and visualization features when examining the impact of interactive data visualization on financial decision-making. Although the experimental results only revealed that interactivity had a positive effect on task-technology fit, examining user perceptions in a structural model shows that perceived interactivity and perceived visualization both affect task-technology fit and subsequently, perceived performance.

One of the proposed benefits of XBRL is that it could level the playing field among consumers of financial information by facilitating access to and analysis of financial information. XBRL serves as a means of achieving the goal of effective financial statement analysis.

However, low utilization may hamper the realization of the potential benefits of interactive financial reporting. This study contributes to this literature by examining user attitudes and beliefs that contribute to technology use and acceptance. The results of this study indicate that task-technology fit is an important determinant of user attitudes and beliefs towards the use of interactive data visualization technology. Results show that assessments of task-technology fit positively impact both perceived usefulness and the behavioral intention to use interactive data visualization technology.

Lastly, judgment and decision-making research in accounting (e.g. Libby and Luft 1993; Bonner and Walker 1994) has largely investigated the effect of task characteristics on performance while narrowly examining the effects of task and technology (Benford and Hunton 2000). However, IS theories (e.g. Task-Technology Fit [Goodhue and Thompson 1995]; Cognitive Fit Theory [Vessey and Galletta 1991]) suggest that the match between a task and technology are important determinants of performance. This study adds to this research stream by examining an expanded model of decision-making in a financial analysis context – one that incorporates a theory of IS and performance (i.e. task-technology fit). According to the research results, the match between characteristics of interactive data visualization and task requirements during a financial analysis task have implications for performance as both perceived interactivity and perceived visualization both indirectly influence perceived performance through their effects on task-technology fit. In addition, this study also considers the potential for the joints effect of task and technology to increase cognitive processing and negatively impact performance by examining the effect of characteristics of interactive data visualization on cognitive load. Examining the effect of the characteristics of interactive data visualization on cognitive load acknowledges the possibility that the positive effects of technology might be counteracted by increased mental workload (Benford and Hunton 2000). However, the results suggest that the interactivity element might reduce rather than increase cognitive load, while visualization does not appear to impact cognitive load.

The remainder of this paper is organized as follows. The next section discusses the background research, theoretical foundation, and develops the hypotheses. Section III discusses the study and experimental materials. Section IV and V include the results and a summary discussion of the study, respectively.

Prior Research and Hypotheses Development

Interactive Data Visualization

Following Dilla et al. (2010, p. 1), this study defines interactive data visualization as "computer-supported visual representation of data that allows users to select the information they wish to view and its format". Although interactive data visualization has only recently become salient in financial accounting contexts, research from marketing and computer science domains have examined interactive data visualization albeit using different terminologies. In marketing, the term visual representation has been used to refer to the presentation of information in visual form (Lurie and Mason 2007). On the other hand, research in computer science uses the term information visualization to refer to the same concept (e.g. Hornbaek and Frokjaer 2001; Heer and Robertson 2007). Regardless of the terminology used, there is a consensus from these streams of research that information visualization, visual representation, and interactive data visualization have two characteristics or elements in common (i.e. interaction/interactivity and visualization/representation) that potentially affect decision-making⁶. This study uses the terms interactivity and visualization.

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⁶ In a review of accounting research, Dilla et al. (2010) identify three elements of interactive data visualization – interaction, selection, and representation. However, Dilla et al.'s (2010) definition of interactive data visualization is based on research in information visualization, which identifies two primary characteristics of information visualization – interaction/interactivity and representation/visualization (e.g. Yi et al. 2007). In addition, Yi et al. (2007) identify 'select' as an interaction technique. Based on a review of marketing studies, Lurie and Mason (2007) use the term visual representation, and discuss two characteristics of visual representation – the visual perspective and the information context. The visual perspective is further broken down into two variables – interactivity and depth of field, which represent the extent to which the decision maker can manipulate the decision environment, and the amount of information presented (Lurie and Mason 2007). The information context is defined as the use of colors, data values, and shapes that affect the vividness, evaluability, and framing of presented information (Lurie and Mason 2007). Despite the different terminologies used, Lurie and Mason's (2007) review of the literature on depth of field and the information context is based on visualization research.

Interactivity

Interactivity typically involves active control by a user in the communication between the user and the system. Generally, interactivity refers to the user's ability to manipulate information views or restructure information during decision making (Yi et al. 2007; Lurie and Mason 2007). Interactivity is one element that primarily distinguishes interactive data visualization techniques from traditional, static representations.

Interactivity is a complex concept with multiple definitions and conceptualizations (Liu and Shrum 2002; Song and Bucy 2008). In addition, prior research has employed different operationalizations of interactivity and found conflicting results. For instance, prior research has found that interactivity led to positive attitudes towards a political candidate (Song and Bucy 2008), increased information processing (Sicilia et al. 2005), positive attitudes towards a Web site and increased memory of Web site contents (Chung and Zhao 2004), increased cognitive and affective involvement (Jiang et al. 2010), and increased decision accuracy (Tang et al. 2014). On the other hand, some studies report an absence of the effect of interactivity on learning (Haseman et al. 2002), and on perceptions of the informativeness of Website content and memory (Sundar et al. 2003).

In defining interactivity, previous marketing research has differentiated between the loci of interactivity or where interactivity actually resides. There are three predominant definitions of interactivity – the functional/mechanic view, the contingency view, and the perceptual view (Liu and Shrum 2002; Song 2008; Jiang et al. 2010; Voorveld et al. 2011). The functional view or mechanic view of interactivity is objective in nature and defines interactivity based on the actual provided opportunity for interaction via technological features or dimensions of control (Liu and

Shrum 2002; Song 2008). The contingency view is primarily concerned with the two-way communication between an interactive media and a user, and defines interactivity as the "degree of responsiveness of messages exchanged between two users or between a user and a media system in a mediated communication situation" (Song 2008). The perceptual view of interactivity is based on a user's perception of their interaction during a communication process and their perception of control over information and communication flow (Liu and Shrum 2002, Chung and Zao 2004; Wu 2005; Voorveld et al. 2011).

Jiang et al. (2010) advocate conceptualizing interactivity to match the context of a study. Previous accounting research that examines the effect of interactivity on decision-making is limited. However, Tang et al. (2014) examines the effect of interactivity in financial decision making and adopt the mechanic view of interactivity by investigating the effect of interactive features on decision-making accuracy. Although interactivity is not directly examined, evidence from prior accounting research can be extended to the concept of interactivity. For instance, Hodge (2001) compares investor judgments and credibility assessments when participants utilized a hyperlink display versus static hard copy displays to view unaudited financial information. In addition, Hodge et al. (2004) use PDF versus an XBRL-enabled search engine to examine differences in the information acquisition and information integration of nonprofessional investors. The concept of interactivity in these studies is consistent with the mechanic view. This study adopts the mechanic or functional view to operationalize interactivity in examining the effect of interactivity on financial decision-making performance. Interactivity techniques involve providing users with the ability to manipulate information views by selecting or marking items of interest, exploring different sets of data via panning or hyperlinks,

reconfiguring or showing different perspectives of data, manipulating representation views, changing the level of abstraction from detailed to a contextual overview, filtering data based on a set of criteria, and highlighting relationships between data items that would otherwise be unknown (Yi et al. 2007; Dilla et al. 2010).

This study also adopts the perceptual view of interactivity in examining the effects of interactivity on user assessments of the match between technology and task requirements, and the subsequent effects on user attitudes and beliefs. The perceptual view posits that interactive features may influence perceptions of interactivity which in turn impact an individual's judgments and decisions. In addition, while interactive features may remain constant, individual differences may cause user perceptions of interactivity to vary. Interactivity is defined in this view as perceived interactivity, which is "the degree to which users actually experience a sense of reciprocal involvement (regardless of the number of technological features) during engagement with information and communication technologies" (Song 2008, 17-18). Several marketing research studies (e.g. Cho and Leckenby 1999; Wu 1999, 2005; Chung and Zhao 2004; Song and Bucy 2008; Yoo et al. 2010; Noort et al. 2012) have found a positive relationship between perceived interactivity and outcomes such as attitude toward the site and/or the brand, intent to purchase, online flow experience, and satisfaction.

Visualization

Card et al. (1999) defines visualization as visual data representations that are used to enhance cognition. Visualization typically refers to the form in which information is portrayed. Prior research on visualization primarily focused on comparing the effects of tables versus graphs on decision-making (Kelton et al. 2010). This research was primarily based on cognitive

fit theory (Vessey 1991; Vessey and Galleta 1991), which differentiated between graphs or spatial representations and tables or symbolic representations. The collective evidence from this research stream (e.g. Frownfelter-Lohrke 1998; Wilson and Zigurs 1999; Speier and Morris 2003; Speier 2006; Shaft and Vessey 2006) is consistent with the tenets of cognitive fit theory, and suggests that task requirements are important in considering the appropriate representation type, and performance is enhanced when task requirements and representation types are matched (Vessey 1991). For example, Shaft and Vessey (2006) find that performance on a modification task is dependent on the cognitive fit between a software developer's mental representation of the software and the mental representation of a modification task. Tang et al. (2014) presents an initial investigation of the effects of interactive data visualization in a financial reporting context and the results from their study indicate that high visualization has a positive effect on decision accuracy.

In the computer science domain, the research (e.g. Hornback and Frokjaer 2001; Yost et al. 2006; Heer and Robertson 2007) on information visualization is more developed and examines the effects of more advanced visualization techniques (e.g. high resolution displays, animated transitions between charts and graphs, and fisheye interfaces) on decision-making and user experience. The general consensus from this research stream suggests that more visualization enhances performance. For example, Hornback and Frokjaer (2001) find that students who were provided with an overview and detail visualization interface received higher grades on a reading activity task.

Models of Technology and Individual Performance

There is a large body of IS research aimed towards a better understanding of the impacts of IS on individual performance. Early researchers have identified a "productivity paradox," citing a minimal and even negative impact of IT on performance. Two complementary streams of research have been predominantly used in models of IS and individual performance: a utilization-focus and a task-technology fit focus. The utilization focused studies emphasize user attitudes as predictors of utilization, which in turn is an antecedent to performance, while the "fit" focused studies cite task-technology fit as a determinant of performance. Utilization focused studies posit that in order for new technologies to enhance performance, a critical element is that users must accept and use the new technology. Several models have been used to explain user acceptance of new technology (e.g. Technology Acceptance Model [Davis et al. 1989), Unified Theory of Acceptance and Use of Technology [Venkatesh et al. 2003]). A precursor to users accessing and utilizing interactive data is whether investors perceive the value of interactive technologies on decision making. Prior research in accounting has shown that users do not necessarily use interactive technology even though it might aid in information acquisition and integration (Hodge et al. 2004). This might be due to a lack of prior exposure or knowledge of the expected performance impacts of interactive data technology. The task-technology fit perspective considers the effect of both task and technology characteristics on individual performance. This perspective emphasizes that a match between task requirements and technology functionality is positively associated with performance (Goodhue and Thompson 1995).

Goodhue and Thompson (1995) and Goodhue (2006) advocate a combination of both the utilization and task-technology fit models of performance. Utilization focused models of technology performance might be limited because use could sometimes be mandatory and based on job functions while not necessarily being a function of system performance. In this scenario, performance impacts actually depend more on task-technology fit than utilization (Goodhue and Thompson 1995). In addition, even when use is voluntary, other factors (e.g. availability, ignorance, etc.) could potentially lead to continuous use of a system with low task-technology fit and negative impacts on performance (e.g. Pentland 1989; Goodhue and Thompson 1995). On the other hand, task-technology fit models largely ignore the fact that technology must be used before it can have an effect on performance (Goodhue and Thompson 1995). Goodhue and Thompson (1995) thus develop a new model, namely the technology-to-performance chain model, which combines insights from both utilization focused theories and theories of task-technology fit.

Determinants of Performance: The Technology to Performance Chain Model (TPC)

Goodhue and Thompson (1995) develop a theoretical model of technology and individual performance which posits that for technology to have a positive effect on performance, the technology must be utilized, and the technology must be a good fit for the task that it supports. According to the technology to performance chain model (TPC), the interaction between the task, technology, and the individual influences task-technology fit. Subsequently, task-technology fit directly impacts precursors to technology use (e.g. expected consequence of use, affect towards use, etc.) and performance. Finally, attitudes and beliefs towards utilization impact actual use which also influences performance. The following subsections discuss the

items in the TPC model in further detail. Figure 1 depicts the TPC as developed by Goodhue and Thompson (1995).

Within the TPC, the match between task-requirements and technology functionality is captured with user evaluations of task-technology fit. Task-technology fit is defined as "the correspondence between task requirements, individual abilities, and the functionality and features of the technology" (Goodhue 2006, 190). Task-technology fit is primarily concerned with predicting the performance impact of an IS (Cane and McCarthy 2009). In the context of interactive data visualization technology, prior research (e.g. Tang et al. 2014) has identified two elements that represent different facets of interactive data visualization (i.e. interactivity and visualization) and have been shown to impact decision-making. This study contextualizes technology characteristics in the TPC model with two constructs from the research on interactive data visualization – interactivity and visualization.

This study also extends the contextualized model by incorporating insights from cognitive load theory. Cognitive load is the burden placed on working memory while problem-solving (Sweller et al. 1998). Due to limited cognitive resources, extra burdens can be placed on working memory due to the complexity of a task, problem representation, and an individual's prior knowledge or experience with the task. High cognitive load is associated with suboptimal performance (Chandler and Sweller 1992). The contextualized TPC model is extended by incorporating cognitive load as a consequence of technology characteristics and as an antecedent to performance. The TPC is a relatively comprehensive model and would be difficult to test in a single study primarily because the model considers the effects of the interaction between a task, a

the effects of characteristics of interactive data visualization (a technology) on task-technology fit, attitudes towards utilization, and performance. The interaction between technology characteristics, task characteristics, and decision-maker characteristics is beyond the scope of this study. Figure 2 depicts the extended and contextualized research model. The following subsections discuss the theorized effects in the research model in further detail.

Technology Characteristics

Goodhue and Thompson (1995, p. 216) define technologies as "tools used by individuals in carrying out their tasks". In the context of interactive data visualization, the technology characteristics that theoretically affect decision processes and outcomes include interactivity and visualization.

Prior accounting research suggests that the judgment processes of financial report users during a financial analysis task typically involve three stages: information acquisition, information evaluation, and information assimilation/combination (Hogarth 1980; Maines and McDaniel 2000; Hodge et al. 2004; Arnold et al. 2012). Information acquisition refers to the search for and identification of relevant pieces of information. Information evaluation is the process of assessing the implications of information on a particular decision or judgment, and information assimilation or combination refers to the process of considering and weighting the implications of various pieces of information in order to arrive at an overall judgment (e.g. an investment decision). Hodge et al. (2004) combine information evaluation and combination into one task: information integration. Incorporating the above discussion into the TPC model suggests that for task-technology fit to be enhanced in the context of interactive data

visualization, the capabilities of interactive data visualization technology must support information acquisition and information integration.

Interactivity should assist in information acquisition and integration by enabling users to actively control the identification and selection of information they wish to view, and the format in which to display this information in order to quickly and easily develop insights. The link between interactivity and task-technology fit has not been directly examined in prior research. However, evidence from Hodge et al. (2004) and Arnold et al. (2012) suggest that interactive features (e.g. an XBRL-enabled search tool, tagged presentation of qualitative financial information) facilitates information acquisition and information integration. In addition, the evidence from Jiang et al. (2007) indicate that interactivity has positive effects on the extent to which consumers believed a website facilitated product understanding. This leads to the following hypothesis:

H1a: Interactivity will have a positive effect on user assessments of task-technology fit.

Previous accounting studies suggest that interactivity may positively affect performance in accounting tasks by aiding in information acquisition and information evaluation/integration. In Hodge et al. (2004), participants who used an XBRL-enabled search engine were more likely to acquire and integrate information about stock option compensation disclosed in the footnotes, which resulted in different investment decisions compared to participants who did not use the XBRL-enabled search technology. Arnold et al. (2012) examine the impact of information tagging of complex narrative disclosures on investor decision making and find that investors are better able to integrate key information into their investment model and stock price predictions.

Hodge et al. (2004) and Arnold et al. (2012) do not directly examine the interactivity concept. However, the results of their research can be extended to inform the relationship between interactivity and performance. Both studies provide indirect evidence suggesting that increased control over information flow (e.g. via an XBRL-enabled search engine) will have positive effects on performance in a financial analysis task. Tang et al. (2014) does examine the effect of interactivity on decision making accuracy in a financial analysis task. The results from Tang et al. (2014) indicate that interactivity can increase decision accuracy. This leads to the following hypothesis:

H1b: Interactivity will have a positive effect on performance in a financial analysis task.

Although prior research has not examined the relationship between visualization and task-technology fit, the empirical evidence from other fit-focused theories can be extended to the link between visualization and task-technology fit. Previous research on information representation (e.g. Frownfelter-Lohrke 1998; Wilson and Zigurs 1999; Speier and Morris 2003; Speier 2006; Shaft and Vessey 2006) suggests that performance is enhanced when task requirements and problem representation types are matched (Vessey 1991). In this study, visualization is defined similar to Tang et al. (2014), who define high visualization as information presented to users in the form of both text and images. Visualization has the potential to facilitate information acquisition and integration due to the use of multiple channels to convey information (Tang et al. 2014). This leads to the following hypothesis:

H2a: Visualization will have a positive effect on user assessments of task-technology fit.

Visualization or information representation has also been shown to have an impact on decision processes and outcomes. Cognitive fit theory (e.g. Vessey and Galletta 1991; Vessey 1991) suggests that a match between problem representation and a decision-making task is an important determinant of task performance. Cognitive fit research (e.g. Vessey and Galletta 1991; Frownfelter-Lohrke 1998; Wilson and Zigurs 1999) has largely examined the effects of graphical/spatial versus tabular/symbolic representations of data. However, accounting research in this area is largely inconclusive as to representations that contribute to decision quality in various accounting tasks (Kelton et al. 2010). Indirect evidence from some studies suggests the superiority of visual or graphical representations for highly complex tasks (e.g. Speier and Morris 2003; Huang et al. 2006). In addition, Lurie and Mason (2007) assert that the evidence from their review of marketing JDM research suggests that representations that provide both context (i.e. graphs) and detail views (i.e. tables) may be superior to either strategy alone because it provides overall understanding of information and a decision-maker can focus on a subset of alternatives while remaining aware of others. Hornback and Frokjaer (2001) find that student grades were higher during a reading task for students who use an 'overview+detail' visualization interface. Taken together, the aforementioned studies seem to suggest that increasing visualization may be superior.

Dilla et al. (2010, p. 4) define visualization in an interactive environment as an "on demand visualization process that allows decision makers to navigate to selected data and display it at various levels of detail and in various formats". Visualization in an interactive environment provides the ability to manipulate information views and provides an opportunity for both context and detail information representations. Research examining the effect of

visualization in financial decision-making is very limited (Dilla et al. 2010). However, the recent evidence in Tang et al. (2014) indicates that financial decision-makers who view financial information in a high visualization environment have higher decision accuracy than those who do not. Using dual coding theory, Tang et al. (2014) suggest that visualization should improve decision-making accuracy and performance in a financial decision-making context because visualization allows a decision-maker to render financial items in numeric tables or charts, thereby activating the simultaneous processing of information in the imagery system and verbal system and leading to deeper information processing and better understanding. This leads to the following hypothesis:

H2b: Visualization will have a positive effect on performance in a financial analysis task.

Precursors to Utilization

Goodhue and Thompson (1995) define utilization as "the behavior of employing the technology in completing tasks". According to TPC, the impact of TTF on utilization occurs through the relationship between TTF and beliefs and attitudes about the consequences of using a system. Several theories on the precursors to utilization exist in the IS literature. These theories examine IT-specific user cognitions such as perceived usefulness and perceived ease of use as precursors to utilization (e.g. Technology Acceptance Model [Davis et al. 1989]; Unified Theory of Acceptance and Use of Technology [Venkatesh et al. 2003]). The Technology Acceptance Model (TAM) has been widely used to explain the attitudes and behaviors of IS users towards IT (for a review, see Venkatesh et al. 2003). TAM suggests two variables that are very important in influencing system use – perceived usefulness and perceived ease of use. Davis et al. (1989 p. 320) defines perceived usefulness as "the degree to which a person believes that using a

particular system would enhance his or her job performance", and perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort". TAM posits that individuals' perceptions of a system's ease of use and usefulness determine an individual's attitude towards using and intention to use a system, which in turn influences the likelihood that a user will quickly and efficiently adopt new technologies. In addition, perceived ease of use has a direct impact on perceived usefulness.

Goodhue and Thompson's (1995) TPC model is partly based on utilization focused research such as TAM, which suggests that technology affects performance via increased utilization. Collectively, utilization focused studies of IS and performance posit that characteristics of technology impact user beliefs and attitudes about use, which in turn affect user intentions towards using the technology and ultimately actual utilization (Goodhue and Thompson 1995). In the context of financial decision-making, interactivity and visualization are expected to positively impact task-technology fit, and high task-technology fit should increase the likelihood of utilization. Goodhue and Thompson (1995) advocate using reference theories about IS utilization and performance to inform the utilization portion of TPC.

The variables in TAM have been applied to different types of systems and users (for a review see Venkatesh et al. 2003). Venkatesh et al. (2003) subsequently develop the Unified Theory of Acceptance and Use of Technology (UTAUT) which consolidates the constructs of earlier models of IT acceptance and use in order to explain user intentions to use a system and subsequent usage behavior. The UTAUT simplifies the original TAM model by removing the attitude construct. This study uses the refined TAM model to inform the utilization portion of

TPC. According to the TPC model, task-technology fit will have a positive influence on the precursors to utilization from the TAM model. This suggests that task-technology fit will have a positive effect on perceived usefulness and the behavioral intent to use a technology. The results from prior IS research (e.g. Staples and Seddon 2004; Lu and Yang 2014) indicate that task-technology fit has significant positive effects on both perceived usefulness and the behavioral intent to use a technology. A relationship between task-technology fit and perceived ease of use is not proposed because Goodhue and Thompson's (1995) TPC model embeds perceptions of ease of use as a dimension of task-technology fit. This leads to the following hypotheses:

H3a: Task-technology fit will have a positive effect on perceived usefulness.

H3b: Task-technology fit will have a positive effect on a user's behavioral intention to use interactive technology.

H3c: Perceived usefulness will have a positive effect on a user's behavioral intention to use interactive technology.

Performance

Goodhue and Thompson (1995) define high performance as a mix of improved efficiency, effectiveness, and/or higher quality. According to TPC, high task-technology fit increases the performance impact of technology independent of why the technology is being used. High task-technology fit implies that a technology closely meets the needs of a user while performing a specific task. Thus, increases in fit will have a positive effect on individual performance. Previous IS research (e.g. Lee et al. 2005; El-Gayar et al. 2010; D'Ambra et al. 2013) has primarily examined the link between task-technology fit and perceptions of performance, and find strong support for this relationship. This study considers an objective measure of performance in addition to individual perceptions of performance as advocated by

Staples and Seddon (2004) and McGill et al. (2009). The results from McGill et al. (2009) suggest that task-technology fit positively impacts both perceived performance and actual performance. This leads to the following hypothesis:

H4: Task-technology fit will have a positive effect on performance.

The Impact of Cognitive Load

Although the Goodhue and Thompson (1995) TPC model does not consider cognitive load, previous research suggests that technology characteristics can impose additional workload on the decision maker (e.g. Rose et al. 2004). This study extends the TPC model by considering insights from cognitive psychology on problem-solving. Benford and Hunton (2000) develop a model of JDM in accounting that incorporates task-technology fit and considers that the layering of task complexities and technology characteristics may impose mental workloads on decision-makers and detract from performance. Cognitive load theory is primarily concerned with the ease with which information may be processed in working memory (Sweller et al. 1998) and is generally defined as the load that performing a task imposes on the decision maker's cognitive system (Paas et al. 2003). When an individual experiences high cognitive load, further information acquisition and integration is hampered due to limited resources in working memory.

Paas and Merrienboer (1994) discuss that cognitive load is multidimensional and its antecedents include the interaction between characteristics of the task (i.e. task complexity) and the decision maker. According to cognitive load theory, there are three different types of cognitive load: germane, intrinsic, and extraneous cognitive load. Germane cognitive load is

relevant to information processing and understanding a task and contributes to schema acquisition (Sweller et al. 1998). Intrinsic cognitive load is dependent on the nature of the task and task experience. Intrinsic cognitive load is low when the degree of element interactivity (the extent to which processing of new cues is dependent on referencing previously learned cues) is low, and high when the degree of element interactivity is high. The interaction between intrinsic load and the expertise of the person doing the task occurs when element interactivity is high because a high number of interacting cues for one person may constitute a single cue for someone with more experience (Sweller et al. 1998). On the other hand, extraneous cognitive load is imposed by poor design features and consists of activities that are irrelevant to understanding a task. For example, Rose et al. (2004) discuss that cognitive load can be imposed via the design of decision aids and information systems displays, in addition to the quantity of information cues. This study is particularly concerned with the potential for the design of interactive data visualization technology to increase extraneous cognitive load.

While interactive data visualization may possibly assist a decision-maker in completing a task, it may also place additional burdens on a decision-maker's cognitive resources by increasing the amount of extraneous cognitive load a user experiences during their utilization of interactive data visualization technology. Evidence from previous accounting research shows that cognitive load affects decision-making performance (e.g. Rose et al. 2004; Rose 2005). Specifically, increases in cognitive load are theorized to be associated with corresponding decreases in learning and performance (e.g. Rose and Wolfe 2000; Rose et al. 2004; Rose 2005). This leads to the following hypotheses:

H5a: Interactivity will be positively related to cognitive load.

H5b: Visualization will be positively related to cognitive load.

H6: Cognitive load will be negatively related to performance.

Research Design and Methodology

This study uses a 2x2 incomplete factorial design, with interactivity and visualization as the manipulated variables. All participants are exposed to both a low and high interactivity treatment. To address potential order effects, the order of the interactivity conditions are counterbalanced such that some participants are exposed to the low interactivity condition first and then exposed to the high interactivity condition, while the rest are exposed to the high interactivity condition first and then the low interactivity condition. The order in which each participant is exposed to an interactivity condition is determined by random assignment. In order to compare the differences between the two interactivity conditions, participant responses to the financial analysis questions in the second interactivity condition are used. Participants are also asked to refer to the last interactive technology used in the case when answering the postexperimental survey questions. The post-experimental survey questions are measured variables designed to capture individual perceptions of the key variables in the study. Participants are exposed to a no visualization or visualization condition. However, visualization is only manipulated in the high interactivity condition. Thus, the result is three experimental groups: a low interactivity/no visualization condition, a high interactivity/no visualization condition, and a high interactivity/visualization condition. In discussing interactive data visualization, Dilla et al.

(2010) define visualization within the context of high interactivity as "on demand" visualization or interactive representation, which allows the user to have active control in changing or reconfiguring the encoding of data. The visualization element is not identified as existing independent of interactivity. Accordingly, a low interactivity/visualization condition is not included in the experimental design.

The effects of the manipulated variables are examined using analysis of variance (ANOVA). This study also includes variables that are not directly observed (e.g. user perceptions of interactive data visualization) but are otherwise inferred from several measured items. These perception measures provide a deeper understanding of the effects of different levels of interactivity and visualization by facilitating the examination of user reactions regarding their interaction with interactive data technology. Thus, structural equation modeling is used to test the overall research model and examine the relationships among the underlying theoretical constructs in the TPC and their effect on the measured variables.

Manipulation of Interactivity

Interactivity is manipulated by varying the quantity of interaction techniques available to users, based on the categories of interaction discussed in Yi et al. (2007) and the attributes of interactivity discussed in Clements et al. (2011). According to Yi et al. (2007), techniques for implementing interactivity can fall into one of four categories. The first, selection, allows a decision-maker to select or mark items of interest for further examination. Exploring allows a decision maker to show other relevant data by clicking on hyperlinks or using visual panning techniques. Abstracting or elaborating alters the information view and allows the viewing of more or less detailed information. Lastly, filtering uses query tools to allow the decision maker

to show data based on specific criteria. Clements et al. (2011) apply interactivity directly to the evaluation of XBRL-enabled tools and measure interactivity according to the following attributes – searching, exporting, comparing data, providing context, and taxonomy. A search attribute allows a decision maker to search for items. Exporting allows the decision maker to export information to different file formats without having to rekey data. Comparing is defined as the ability to compare information across time periods and between companies. Context is information provided to explain data elements, and taxonomy provides the definition of elements used within the XBRL documents and the relationships between those elements.

In order to manipulate interactivity, this study uses two interactive tools. In the low interactive condition, participants use the SEC's web-based interactive financial report viewer, EDGAR. Clements et al. (2011) evaluate EDGAR along their five attributes of interactivity and rate it as having very little interactivity. EDGAR allows a user to export filings to Excel and context is provided for each line item when a user hovers over the item. However, the viewer does not provide information on taxonomy, the ability to search for items, or the capability to compare information across multiple periods or multiple companies. Evaluating the SEC's viewer along the interaction techniques outlined in Yi et al. (2007) categorizes the viewer as including the exploring technique by allowing a user to view other relevant information about a particular line item. In addition, filtering is available on EDGAR by allowing a user to search for a company's information using the company CIK code or ticker symbol. A user can also filter a particular company's results by searching for types of filing documents (e.g. 10-K) and over a specific time period.

In the high interactivity condition, participants use Calcbench, an online XBRL analysis tool. Calcbench's web-based software includes a benchmarking tool that allows users to conduct financial statement analyses with multiple companies. Calcbench's benchmarking tool ranks highly on both Yi et al.'s (2007) and Clements et al.'s (2011) list of interactivity techniques. The benchmarking tool includes a filtering technique that allows a user to quickly analyze multiple companies at once. Filtering can be done based on industry classification, using a company's SIC code or by creating a custom-defined peer group with just the companies a user wishes to analyze and compare. If a peer group is created based on a company's sector, the user can filter the list by adding or removing companies or filtering based on certain criteria (e.g. Net Income > \$1,000,000). Once a custom group to analyze is created, the benchmark tool employs the selection technique, providing a predefined list of commonly used financial items and metrics by which the companies in the group can be compared. The selection technique is also incorporated within the benchmarking tool by allowing users to select additional relevant ratios or financial information to be included in the analysis from a drop-down list. The creation of other selfdefined metrics for comparing companies is also possible. Abstracting or elaborating is available via the benchmark tool by allowing a user to change time periods by which to view the selected metrics. The metrics can be viewed for quarterly and annual financial information and also by totaling the information for the last four quarters for each company. Abstracting/elaborating is also available within the benchmarking tool as a user can delve deeper to trace the underlying data points for each item by double-clicking on the item. Finally, the data being compared can be exported to a spreadsheet for additional analysis.

Manipulation of Visualization

The visualization manipulation is guided by the representation techniques outlined in Dilla et al. (2010). Encoding is a visualization technique that involves showing different representation of data such as converting tabular representations to graphs (Yi et al. 2007; Dilla et al. 2010). Similar to Tang et al. (2014), visualization is manipulated in this study using the encoding technique. In the visualization condition, participants are directed to use the visualization tool available within Calcbench. The visualization tool allows a user to depict and see the trend for a financial statement item using line charts. In the no visualization condition, participants are not instructed on how to use the visualization tool.

Dependent Variable Measurement

Three primary dependent variables (actual performance, task-technology fit, and cognitive load) are examined in this study. This study defines performance in terms of information acquisition. One of the proposed benefits of interactive technology (XBRL) is the effective automation of acquiring and analyzing financial information. Acquisition is measured by examining participant responses to the financial ratios used during the financial analysis task. An accuracy score for information acquisition is calculated based on the number of correctly entered financial ratios. Participants are asked to compute five financial ratios each for two companies for a maximum of ten points. A composite score for task-technology fit is calculated for the experimental analyses based on the sum of the mean scores for each of the five

dimensions of task-technology fit (DiStefano et al. 2009)⁷. A composite score is also calculated for cognitive load using the mean responses to four cognitive load questions⁸.

Participants

This study is primarily interested in how nonprofessional investors engage with interactive data visualization technology in their financial decision-making. Participants are graduate business students enrolled at four large state universities and one private university who served as surrogates for nonprofessional investors. Graduate business students are used as surrogates for online investors because they possess many of the same characteristics as online traders (Hodge 2001). Graduate business students typically have an understanding of basic accounting and finance, use the Web to retrieve information, are more open to new technologies, and are generally more self-motivated and highly educated than investors who do not engage in online trading (Hodge et al. 2004).

Participants were recruited by offering participation in this study as an alternative to completing a case or other assignment for a related course. A total of 234 email invitations were sent to participants, including the web link to participate in the study. Out of the 216 people who actively opened the attached link to the study, 42 people did not complete the study and are

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⁷ Another method of computing a composite score using regression-based factor scores from a principal components analysis was examined (DiStefano et al. 2009). Analyses results did not differ between using the task-technology fit factor score or the mean task-technology fit score. The mean task-technology fit score is used because it retains the original scale metrics and allows for easier interpretation.

⁸ Another method of computing a composite score using regression-based factor scores from a factor analysis was examined (DiStefano et al. 2009). Analyses results did not differ between using the cognitive load factor score or the mean of the cognitive load responses. The mean of the cognitive load responses is used because it retains the original scale metrics and allows for easier interpretation.

excluded from the analysis⁹. An additional four participants were removed from the analysis because their responses to the financial analysis questions suggested that they did not attend to the task¹⁰. All of the subsequent analyses pertain to the remaining 170 participants. Of the 170 participants, 150 were masters of accounting students, 16 were masters of business administration (MBA) students who had completed their core graduate accounting course, and 14 were professional MBA students.

Participant demographics are summarized in Table 1. The average participant is 26.79 years old, with an average of 5.47 years of full-time work experience. Fifty percent of the participants are male, 49.4 percent are female and one person chose not to answer the gender question. Participants had completed an average of 6.74 accounting courses and 2.05 finance courses. Overall, 23.53 percent of participants reported that they have invested in individual stocks in the past and 77.65 percent indicated they plan to invest in individual stocks in the future. Additionally, 55.88 percent of participants reported that they have evaluated a company's performance by analyzing financial statements at least once. Finally, 28.23 percent of participants reported prior experience with using either EDGAR or CALCBENCH¹¹. Participants are randomly assigned to each experimental condition and participant demographics did not have a significant effect on model results.

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⁹ Most participants complete the experimental task on their own at their own time. About 25 participants complete the task in a classroom setting.

¹⁰ Participant responses to the financial ratio calculations are examined. The answers from participants that are eliminated suggest that they did not view the financial statements for the companies in the analysis. For example, one participant entered 1000 for each financial ratio calculation.

¹¹ Forty participants reported prior experience with using the EDGAR interactive viewer, while seven participants reported prior experience with using Calcbench. In addition, one participant reported prior experience with using both the EDGAR interactive viewer and Calcbench.

Case Materials and Procedure

The case instructs participants to conduct two financial analysis tasks, one using the SEC EDGAR interactive viewer, and the other using the Calcbench benchmarking tool. Participants are instructed to assume the role of an investor evaluating companies for potential investment. The case information informs participants that they will evaluate four companies, equally divided into two groups – Group A and Group B. All participants complete the task for Group A first, followed by the task for Group B. For each group, participants are instructed to assume they have \$10,000 to potentially invest in the common stock of one company, and that they should evaluate the companies in each group relative to one another. The four companies included in the case are described as companies in the retail sector. The companies in Group A include DSW, Inc. and Genesco, Inc. DSW, Inc. is described as a specialty branded retailer of footwear and accessories for men and women with over 350 stores in the United States. Genesco, Inc. is described as a retailer of licensed/branded footwear, headwear, and sports apparel and accessories, operating in over 2000 retail stores in the United States, Puerto Rico, and Canada. The companies in Group B include Gap, Inc. and Nordstrom, Inc. Participants are informed that Gap is a specialty clothing and accessories retailer with over 3,000 stores in the United States and worldwide. Nordstrom is described as an American upscale fashion retailer of shoes, clothing, accessories, jewelry, cosmetics, and fragrances with over 200 stores throughout the United States.

The case instructs participants to evaluate the financial condition and earnings potential of the companies in each group using five financial metrics – return on assets, current ratio, inventory turnover, gross profit margin, and return on equity. Participants are informed that the

SEC has issued a mandate requiring public companies to report their financial statements using an interactive financial reporting technology and that the SEC is now encouraging software developers to build tools enabled with interactive technology in order to help investors in their financial analysis. Participants are then informed that the companies in each group report information about their financial operations using an interactive financial reporting technology located at a specific web site. In the low interactivity condition, the interactive reporting technology (the SEC's interactive viewer) is located at http://www.sec.gov/edgar/searchedgar/companysearch.html while in the high interactivity condition, the interactive technology (Calcbench) is located at http://www.calcbench.com. The SEC's interactive viewer and the Calcbench tool are embedded in the survey website while participants complete the task, allowing participants to interact with each interactive tool while viewing the case questions and entering the ratio calculations on the same screen. The case materials also provide participants with video and written instructions on how to access each

To conduct their analysis, participants complete a questionnaire which requires computing the five financial metrics, assessing each firm's performance, and deciding in which company they would invest their \$10,000. Participants are also asked to examine the trend in revenue and earnings per share for the most recent three years for each company they analyze. After completing the questionnaire, participants respond to post-experimental questions designed to elicit responses on perceived interactivity, perceived visualization, task-technology fit, perceived usefulness, task complexity, behavioral intent to use, cognitive load, and perceived performance. Following the survey questions, participants are asked to complete a separate

website and search for a company's financial information.

questionnaire to assess their level of financial reporting knowledge similar to Elliott et al. (2007). Finally, participants record their answers to demographic questions. Figure 3 presents a timeline of the experimental task.

Due to the incomplete factorial design used in this study, participants were randomly assigned into one of three experimental conditions (low interactivity/no visualization, high interactivity/no visualization, and high interactivity/visualization) to evaluate Group A and Group B. Participant responses following the task in Group B are used to calculate performance and examine the constructs in the research model. In order to obtain equal cell sizes during the Group B task, the survey flow was coded such that participants are first randomly assigned to the three experimental conditions for the Group B task and these assignments are stored. Then, the survey flow is coded to work backwards such that participants are randomly assigned to one of three experimental conditions for the Group A task, depending on their Group B assignment. For example, if a participant is assigned to the low interactivity/no visualization condition for Group B, the participants will be randomly assigned to the high interactivity/no visualization condition or high interactivity/visualization condition for Group A. On the other hand, if a participant is assigned to the high interactivity/no visualization or high interactivity/visualization condition in Group B, the only assignment choice in Group A is the low interactivity/no visualization condition.

Measurement of Variables and Scale Development

Scales are adapted from previous research to measure two exogenous variables (interactivity and visualization) and six endogenous variables (task-technology fit, perceived usefulness, behavioral intent to use, cognitive load, confidence, and perceived performance). All

scales, with the exception of the cognitive load and confidence scales, utilize a five-point Likert-type scale, anchored at strongly disagree and strongly agree. Table 2 details the constructs of interest and their corresponding measurement items.

Perceived Interactivity

The predicted effects of interactivity on decision processes and outcomes, and user attitudes require actual use of the tools included within interactive technology and the engagement between users and the interactive technology. This suggests that the effects of interactivity function via a behavioral dimension. Interactivity research suggests that a user's sense of perceived interactivity intervenes in the relationship between interactivity and behavior (e.g. Cho and Leckenby 1999; Wu 1999, 2005; Bucy and Tao 2007). Perceived interactivity is the "user's perception of the interactive experience" and an indicator of the "degree to which users process technological affordances and interactive media attributes" (Bucy and Tao 2007, p. 663-664). Interactivity is measured via a perceived interactivity scale designed to measure a user's perception of actual interactivity. The perceived interactivity scale is adapted from Song and Bucy (2008) and includes five items related to measuring active control.

Perceived Visualization

Visualization is measured by adapting the visualization manipulation check questions from Tang et al. (2014). Tang et al. (2014) include three visualization questions relating to the presence of visualization techniques. The visualization questions were deemed reliable with a Cronbach's alpha of 0.725 in Tang et al (2014). The visualization questions from Tang et al. (2014) elicited participant responses related to the graphical tools available within a technology, and the ability to visualize financial statement items. An additional item was added to the

adapted scale in order to maintain a four-item scale as consistent with each measured variable in this study. The fourth item asked participants if they are able to graphically view the trend in financial statement items while using a financial reporting technology.

Task-Technology Fit

Task-technology fit is a second-order formative construct with five dimensions. The TTF scale is adapted from Goodhue and Thompson (1995) and Goodhue (1998). Goodhue (1998) identifies and develops sixteen dimensions of TTF along which a system can be evaluated. The TTF constructs examined in this study are contextualized based on the requirements of a financial analysis task (i.e. information acquisition and information integration). Based on a review of Goodhue and Thompson (1995) and Goodhue et al. (1998), the current study utilizes five dimensions of TTF particularly relevant to using a technology in a financial analysis task. The five TTF dimensions examined in this study are accessibility, ease of use, flexibility, compatibility, and presentation.

Perceived Usefulness

The perceived usefulness scale is adapted from Davis et al. (1989) and Davis (1989) and includes four items included in the perceived usefulness scale in the technology acceptance model. The adapted scale is designed to capture the degree to which a user believes that using interactive data technology was useful while conducting financial statement analyses.

Behavioral Intent to Use

Behavioral intent to use is measured using a scale adapted from Davis et al. (1989) and Venkatesh et al. (2003). The adapted scale includes four items designed to capture the degree to which a user believes they would use an interactive data technology in the future.

Cognitive Load

Research on cognitive load has used several measurement techniques to assess cognitive load including objective performance measures, subjective ratings reported during or after a particular task, performance of subjects on a simple, secondary task, psycho-physiological techniques, and a combination of these. The use of subjective measurements of cognitive load has been shown to be highly reliable and valid (Paas et al. 1994; Paas et al 2003). This paper adapts the NASA-Task Load Index (NASA-TLX), a weighted and multi-dimensional subjective rating scale developed by Hart and Staveland (1988). The NASA-TLX was designed to assess dimensions of mental workload relative to overall cognitive load (Windell and Wiebe 2006; Wiebe et al. 2010). Cognitive load is assessed by asking participants two questions related to the extent to which they exerted mental effort and experienced mental load. The two items were measuring using a five-point Likert-type scale, anchored at very low and very high. In addition, the cognitive load scale included two items designed to elicit participant responses related to how hard they worked to complete the task. These two items were measured using a five-point Likert-type scale, anchored at not very hard and very hard.

Perceived Performance

Performance impact is measured via the perceived performance impact scale adapted from Goodhue and Thompson (1995). The original scale includes two items designed to measure individual perceptions of a technology's performance impact. The adapted scale is expanded to include four items in order to maintain a four-item scale. The additional items elicited participant responses about the extent to which using a financial reporting technology contributed to the improvement and efficiency of conducting financial statement analyses.

Control Variables

Although not explicitly tested in this study, Goodhue and Thompson's (1995) TPC model include task characteristics and decision-maker characteristics as antecedents to task-technology fit. Two control variables are thus measured in this study – task complexity and task knowledge. Goodhue and Thompson (1995, p. 216) define tasks as "the actions carried out by individuals in turning inputs into outputs". The bigger the gap between the requirements of a task and the functionality provided by a technology, the more task-technology fit is reduced (Goodhue and Thompson 1995).

Generally, decision-making during financial analysis involves the decision-maker attending to two interrelated tasks simultaneously – information acquisition and information integration. Dual-task interference, a phenomenon that occurs when problem-solvers perform two or more tasks simultaneously, usually occurs in this scenario (Shaft and Vessey 2006). When dual-task interference occurs, performance is diminished because the decision-maker cannot effectively attend to the subtasks. Elliott et al. (2007) differentiate accounting tasks based on their level of integrative complexity. Integrative complexity can be defined as the degree to which a task involves the recognition and integration of multiple pieces of information and their related dependencies. Integrative complexity impacts the ability of individuals to integrate information when making judgments and decisions (Elliott et al. 2007). Tang et al. (2014) consider the impact of task difficulty on decision accuracy in the context of interactive data visualization and conclude that it is important to consider the effect of interactive data visualization when task difficulty is relatively high due to the potential for miscalibration. A review of marketing JDM research suggests that by giving users active control over information

and enabling the ability to restructure the decision environment, interactive data visualization may create a better match between task requirements and the decision environment (e.g. Eick and Wills 1995). Goodhue (1998) advocates being explicit about task needs in developing a model of task-technology fit that is specific to a decision-making environment.

Task complexity is measured using a scale adapted from Hampton (2005). The scale consists of four items designed to capture perceptions of task complexity. The four items elicit perceptions related to user perceptions of how most nonprofessional investors would rate the financial analysis task. Item 1 assesses the degree to which the task is challenging. Item 2 assesses the degree of task difficulty. Item 3 assesses the degree of task complexity and item 4 asks the user if most nonprofessional investors would find the task requires a lot of thought and problem-solving.

Individual characteristics represent attributes of individual decision makers that could potentially affect how easily and how well they utilize the technology (Goodhue and Thompson 1995). Dilla et al. (2010) identify decision maker characteristics, including expertise, experience, cognitive style, and personality, that could potentially moderate the relationship between information representation and decision performance. Extant accounting research suggests that users with higher expertise, domain-specific knowledge, or higher cognitive abilities are more likely to choose appropriate information representations because of a more developed internal problem representation or schema (Vera-Munoz et al. 2001; Speier and Morris 2003; Cardinaels 2008). Vera-Munoz et al. (2001) found that when cash-flow data were presented in an inappropriate format, managers with a stronger knowledge base were better able to determine

relevant cash-flow items than managers with less domain-specific knowledge. This is consistent with the theoretical model of JDM in accounting posited by Libby and Luft (1993). Previous accounting research suggests that knowledge of accounting-related tasks is critical in determining performance, and that general-solving ability is critical in the acquisition of knowledge (Bonner and Walker 1994; Elliott et al. 2007). In addition, users with high expertise or high cognitive ability are more likely to choose appropriate information representations as a result of better-developed internal problem representations (Dilla et al. 2010). Drawing on this stream of research, this study considers the role of task knowledge, conceptualized as financial reporting knowledge on the relationship between interactive data visualization characteristics and TTF. Financial reporting knowledge is measured using a financial literacy quiz adapted from Elliott et al. (2007) and includes a subset of ten questions relating to different aspects of financial reporting.

Other Measured Variables

A confidence scale is used to capture decision-makers' perceptions of confidence in their success and performance in accurately completing the financial analysis task. Perceptions of confidence are captured to examine if assessments of confidence match actual accuracy while completing a financial analysis task. Tang et al. (2014) examine confidence and calibration as additional measures of performance and find that participants are generally overconfident in their decision-making accuracy and calibration is reduced, except when both interactivity and visualization are high. The confidence scale is adapted from the measures of process confidence in Hageman (2010) and consists of four items. Each question on the scale is measured using a five-point Likert-type scale, anchored at not at all confident and very confident.

Data Analysis and Results

This study uses analysis of variance (ANOVA) to first examine the relationships between interactive data visualization and performance by examining the effects of the manipulated experimental conditions on three dependent measures: task-technology fit, cognitive load, and actual performance. Thus, hypotheses H1a, H1b, H2a, H2b, H5a, and H5b are examined in the experimental analyses.

All of the hypothesized relationships and the entire research model are further examined in the structural model using structural equation modeling. The objective of the experimental analysis is to examine the cumulative effect of the treatment variables (interactivity and visualization) on actual performance (accuracy). On the other hand, the structural model is used to examine the relationships between characteristics of interactive data visualization and the constructs in the extended TPC model as outlined in Figure 2. Structural equation modeling is used to examine the structural model due to the inclusion of measured variables in the research model. The measured variables represent user perceptions of their experience while using interactive data technology and the corresponding effects on the underlying theoretical constructs in the TPC. Structural equation modeling facilitates the simultaneous testing of the validity of the items used to measure the constructs and the strength of the relationships between the constructs (Chin 1998; Elbashir et al. 2013). In addition, structural equation modeling is "particularly useful in testing theories that contain multiple equations involving dependence relationships" (Hair et al. 2010, 612), similar to the proposed research model.

Partial least squares (PLS) is used to validate and test the measurement and structural models represented in the research model. PLS is a components-based structural equation

modeling technique. PLS analysis is used to assess the reliability of the measurement model and test the structural model because this study includes constructs that are both exogenous and endogenous (mediating constructs) and one of the latent variables (task-technology fit) is formative in nature.

Results: ANOVA

Figure 4 presents the research model examined in the experimental analyses. Table 3 reports the means and standard deviations by experimental group/treatment for perceived interactivity, perceived visualization, task-technology fit, accuracy (actual performance), perceived performance, perceived usefulness, behavioral intent to use, and cognitive load.

Manipulation Check

Two one-way ANOVAs are conducted to assess the manipulation of interactivity and visualization. It is expected that individual perceptions of interactivity will increase between the low interactivity/no visualization condition and the two high interactivity conditions. In addition, perceptions of visualization should be higher in the high interactivity/visualization condition, compared to the low interactivity/no visualization condition and the high interactivity/no visualization condition. Table 3 shows that the mean perceived interactivity and mean perceived visualization is increasing across the three treatment conditions. Two one-way ANOVAs (IV = treatment group; DV = perceived interactivity, perceived visualization) with planned contrasts were conducted to assess the differences in perceived interactivity and perceived visualization between the three experimental groups. Perceived interactivity is higher in the high interactivity/no visualization condition ($t_{101.293} = 3.892$, p < 0.001) and the high interactivity/visualization condition ($t_{105.015} = 4.341$, p < 0.001) compared to the low

interactivity/no visualization condition. In addition, perceived visualization is higher in the high interactivity/visualization condition compared to the low interactivity/no visualization condition ($t_{96.382} = 6.065$, p < 0.001) and the high interactivity/no visualization condition ($t_{110.658} = 1.888$, p < 0.05). Thus, the interactivity and visualization manipulations were successful.

Effects of Interactive Data Visualization on Task-Technology Fit

H1a and H2a predict that interactivity and visualization will have a positive effect on task-technology fit, respectively. According to the expectations outlined in the hypotheses, a higher level of interactivity is superior to low interactivity, and high interactivity and high visualization are superior to high interactivity alone. Therefore, task-technology fit should follow an increasing trend across the three treatment conditions. Table 3 shows that task-technology fit is in the expected direction across the three treatment groups. The effect of interactivity and visualization on task-technology fit is examined by conducting a 3 X 1 ANOVA, with the three treatment groups/experimental conditions as the independent variable and task-technology fit as the dependent variable. The result of this analysis is displayed in Panel A of Table 4. Results indicate that differences in the three treatment groups have a positive and significant effect on task-technology fit (F = 13.528, p < 0.001)¹².

Planned contrasts were further used to examine the effects of interactivity and visualization on task-technology fit. In order to follow up on the significant results indicated in the ANOVA, planned contrasts are used to compare the differences in the effects of interactivity and visualization on task-technology fit across the treatment conditions. The results of the

 $^{^{12}}$ Controlling for the effects of financial reporting knowledge and task complexity yielded similar results for the effect of interactive data visualization on task-technology fit (F = 13.401, p < 0.001).

planned contrasts are displayed in Panel B of Table 4. Planned contrasts confirm that there is a significant difference in task-technology fit between the low interactivity/no visualization group and the other treatment groups (t = 4.758, p < 0.001). For the effect of interactivity, a planned contrast shows that there is a significant difference in task-technology fit between the low interactivity/no visualization group and the high interactivity/no visualization group (t = 3.833, p < 0.001). However, for the effects of visualization, the planned contrasts indicate that there is no significant difference in task-technology fit between the high interactivity/no visualization group and the high interactivity/visualization group (t = 0.695, p = 0.244). This suggests that interactivity is the key driver of task-technology fit. Specifically, interactivity alone has a positive effect on task-technology fit, while visualization does not have a significant effect. The results are consistent with the prediction in H1a. However, H2a is not supported.

Effects of Interactive Data Visualization on Actual Performance (Accuracy)

H1b and H2b predict that interactivity and visualization, respectively, will have a positive effect on performance. According to the expectations outlined in the hypotheses, accuracy should follow an increasing trend across the three treatment conditions. Table 3 shows that the mean accuracy score across the three treatment groups is in the expected direction. The effect of interactivity and visualization on actual performance is examined by conducting a 3 X 1 ANOVA, with the three treatment groups/experimental conditions as the independent variable and accuracy as the dependent variable. The result of this analysis is displayed in Table 5. Results indicate that the differences in the three treatment groups do not have a significant effect

on actual performance (F = 0.198, p = 0.411). Thus, H1b and H2b are not supported¹³. These results are inconsistent with prior research examining the effect of interactivity and visualization on accuracy (e.g. Tang et al. 2014). The results suggest that the accuracy measure may be a potential limitation in this study given that the mean accuracy score across the three treatment groups are all within one standard deviation of the possible maximum accuracy score.

Effects of Interactive Data Visualization on Cognitive Load

H5a and H5b predict that interactivity and visualization, respectively, will have a positive effect on cognitive load. It is expected that cognitive load will increase across the three experimental conditions because high interactivity and high visualization are both expected to increase the cognitive load experienced by a user. However, the mean cognitive load shown in Table 3 is only in the expected direction between the low interactivity/no visualization and the high interactivity/no visualization group. High interactivity and high visualization results in lower mean cognitive load. The effect of interactivity and visualization on cognitive load is examined by conducting a 3 X 1 ANOVA, with the three treatment groups/experimental conditions as the independent variable and cognitive load as the dependent variable. The result of this analysis is displayed in Table 6. Results indicate that the differences in the three treatment groups do not have a significant effect on cognitive load (F = 0.324, p = 0.362) Thus, H5a and H5b are not supported.

Results: Structural Model Analysis

SmartPLS 2.0 (Ringle et al. 2005) is used to validate and test the measurement and structural models represented in the research model. Bootstrapping resampling (1000 samples) is

¹³ Controlling for the effects of financial reporting knowledge and task complexity yielded similar results for the effect of interactive data visualization on accuracy (F = 0.152, p = 0.430).

used to generate t-statistics for conducting the statistical analysis. The measurement model and the structural model are discussed in the following sections.

Construct Reliability and Validity

Factor loadings, composite construct reliability, and average variance extracted (AVE) are employed to assess the convergent and discriminant validity of the reflective constructs¹⁴. Convergent validity identifies how well indicators of a specific latent construct capture the variance in the construct (Hair et al. 2010). Table 7 reports item loadings and cross loadings. All item loadings are 0.70 or higher, with the exception of two cognitive load items and one behavioral intent to use item. Eliminating these items improved the composite reliability and AVE for the cognitive load and behavioral intent to use constructs. These items are therefore eliminated from further analysis. Table 8 reports the related composite reliability and AVE for each reflective construct. The related composite reliability for each construct is greater than the recommended 0.70, and all AVE are greater than 0.50 supporting the convergent validity of the reflective constructs (Fornell and Larcker 1981; Hair et al. 2010). Discriminant validity identifies the extent to which a construct is truly distinct from other constructs (Hair et al. 2010). Table 8 reports the construct correlations and the square root of average variance extracted. The square root of all AVE is larger than the intercorrelations between the constructs, supporting discriminant validity (Chin 1998).

¹⁴ A construct can be reflective or formative in the way in its measurement. A reflectively measured construct is based on the assumption that the construct causes the indicators or measured variables (Hair et al. 2010). The direction of causality is from the construct to the measured variables. In a formatively measured construct, the direction of causality is reversed and the assumption is that the measured variables form the construct (Hair et al. 2010).

Task-technology fit is a second order formative construct comprised of five dimensions, measured reflectively – accessibility/locatability, ease of use, flexibility, compatibility, and presentation. Task-technology fit is estimated by first estimating factor scores for the reflective item measures representing the five dimensions using principal components analysis with promax rotation. Construct validity and reliability for the second order formative construct are evaluated according to the recommendations specified in Petter et al. (2007). First, to assess validity, principal components analysis with oblique rotation is used to examine item weightings for the five dimensions of task-technology fit using each construct's factor scores. As shown in Panel A of Table 9, all items load on the second order latent construct ranging from 0.826 to 0.875, with 72.11% of variance explained. Second, the presence of multicollinearity is determined in order to evaluate reliability. Variance inflation factors (VIF) are calculated using the factor scores from the five first order dimensions and a measure of performance (accuracy score). As shown in Panel B of Table 9, all VIFs range from 2.198 to 2.768, falling below the suggested cutoff of 3.3 (Diamantopoulos and Siguaw 2006; Petter et al. 2007).

Common Method Bias

As with all self-reported data, there is a potential for common method bias. Common method bias represents "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podaskoff et al. 2003, p. 879). The single unmeasured latent common factor method test was performed to rule out the presence of common method bias in this study (Podsakoff et al. 2003; Liang et al. 2007).

Following Podsakoff et al. (2003) and Liang et al. (2007), a common method construct was added to the measurement model. The first step in carrying out this test is to create a single

indicator construct for each indicator in the measurement model and link each single indicator to the substantive construct it is designed to measure. Therefore, a single item indicator was created for every item measure in this study and linked to their corresponding substantive construct (e.g. interactivity, visualization, etc.). Second, a common method construct that includes all of the indicators used in the research model is added to the model. Finally, a link is created between the common method construct and each single indicator construct. Common method bias is assessed by examining the path coefficients and significance of the links between the substantive constructs and single item indicator constructs as well as the path coefficients and significance of the links between the common method construct and the single item indicator constructs.

Common method bias is determined to have minimal effect "if the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances" (Liang et al. 2007, p. 87).

The results of this test are detailed in Table 10. The results indicate that the variance of the indicators to the substantive constructs is greater than the variance to the common method construct. In addition, all of the loadings on the common method construct are not statistically significant. Finally, the average variance extracted due to the substantive constructs is 75.1 percent compared to 2.8 percent for the common method construct. Thus, common method bias is deemed to be of no concern in this study.

Hypotheses Testing

Figure 5 presents the structural model with path loadings and significance levels relating to the hypothesized and controlled relationships. The model explains 69.2% of the variance in task-technology fit, 61.4% of the variance in perceived usefulness, 68.4% of the variance in

behavioral intent to use, and 62.6% of the variance in perceived performance. The effect of perceived interactivity on task-technology fit is examined in H1a. Hypothesis H1a predicts that interactivity will have a positive effect on user perceptions of task-technology fit. The model results indicate a significant, positive relationship (β = 0.520, p < .001) between perceived interactivity and task-technology fit. This suggests that financial statement users may perceive that interactivity (i.e. giving users increased or active control), a capability of interactive data visualization, provides support for conducting financial statement analysis.

H2a addresses the effect of visualization on task-technology fit. H2a predicts that visualization will have a positive effect on user perceptions of task-technology fit. As predicted, perceived visualization has a significant and positive effect on task-technology fit (β = 0.365, p < .001). Similar to the relationship between perceived interactivity and task-technology fit, this result suggests that financial statement users may perceive visualization (i.e. giving users increased or active control) as a capability of interactive data visualization that provides support for conducting financial statement analysis.

The effects of task-technology fit on the precursors to technology use are examined in hypotheses H3a, H3b, and H3c. H3a hypothesizes that task-technology fit will have a positive effect on perceived usefulness. Consistent with the hypothesized relationship, task-technology fit has a positive and significant effect on perceived usefulness (β = 0.784, p < .001). In addition, the results indicate that task-technology fit has a significant and positive effect on behavioral intention to use (β = 0.472, p < .001), supporting the prediction in H3b. Finally, H3c is also supported as model results show that perceived usefulness has a significant and positive effect on

the behavioral intention to use interactive data visualization technology (β = 0.403, p < .001). According to the technology-performance chain model, the impact of task-technology fit on technology use occurs via the relationship between task-technology fit and beliefs and attitudes about the consequences of using a technology. The results suggest that the fit between interactive financial reporting and task requirements has a positive impact on a user's belief that using interactive financial reporting technology would improve their performance during a financial analysis task. Likewise, the fit between interactive financial reporting and task requirements impacts the likelihood of whether financial statement users will adopt interactive financial reporting technology.

H4 predicts that task-technology fit will have a positive effect on perceptions of performance. Consistent with H4, the results indicate that task-technology fit has a significant and positive effect on perceived performance (β = 0.795, p < .001). High task-technology fit implies that interactive financial reporting technology closely meets the needs of a user while conducting a financial analysis task. Thus, assessments of fit between characteristics of interactive data visualization technology and task requirements have a positive impact on a user's perception of performance impact while conducting financial statement analyses.

H5a, H5b, and H6 examine the impact of interactivity and visualization on cognitive load and the subsequent effect of cognitive load on performance. H5a and H5b predict that interactivity and visualization will be positively related to cognitive load. However, the results do not indicate support for H5a as the relationship between perceived interactivity and cognitive load is negative ($\beta = -0.182$, p < 0.05). This suggests that high interactivity reduces rather than

increases cognitive load. In addition, the relationship between perceived visualization and cognitive load is not significant (β = 0.048, p = 0.312). Thus, H5b is not supported. H6 predicts that high cognitive load will have a negative effect on perceived performance. However, the results do not support this prediction. Results indicate that cognitive load does not significantly impact perceived performance (β = 0.029 p = 0.733, left-tailed). Thus, extending the TPC model by considering the effect of interactivity and visualization on cognitive load in this study suggests that the interactivity element of interactive data technology may mitigate cognitive load. However, the visualization element did not have an impact on cognitive load in this study. It is possible that the visualization manipulation is not sufficient enough to impact cognitive load, given that only one visualization technique (encoding) is used. The results also suggest that cognitive load does not affect perceptions of performance. Finally, extending the technology-performance chain model with insights from cognitive load theory does not appear to alter the predictions of the core technology-performance chain model since the cognitive load element does not exist in the technology-performance chain model.

Following the tests for direct effects in the structural model, the indirect and total effects of perceived interactivity, perceived visualization, and task-technology fit are examined. As noted in the theory section, characteristics of interactive data visualization will affect performance through the match between task requirements and technology characteristics (task-technology fit). In addition, task-technology fit affects the behavioral intention to use interactive data visualization technology through perceptions of usefulness. While the path coefficients and t-statistics of the total effects are generated in PLS, the path coefficients of the indirect effects are generated using the product term of the coefficients of the related direct paths. Bootstrap

procedures are used to construct 99 percent (p < 0.01) confidence intervals for testing the significance of the indirect effects (Hayes 2009; Elbashir et al. 2013).

The indirect and total effects of perceived interactivity on performance and behavioral intent to use are reported in Table 11. Panel A of Table 11 displays a summary of the indirect effects of interactivity. While the experimental analyses examined the effect of manipulating levels of interactivity on performance (accuracy) in hypothesis H1b, the structural model examines the total indirect effects of perceived interactivity on user perceptions of performance. The results show that perceived interactivity indirectly affects performance through task-technology fit (0.413, p < 0.01) and through cognitive load (-0.005, p < 0.01), leading to a total indirect effect of 0.408 on perceived performance. While not hypothesized, perceived interactivity is also significantly related to behavioral intent to use through task-technology fit (0.246, p < 0.01) and through task-technology fit and perceived usefulness (0.164, p < 0.01), leading to a total indirect effect of 0.410 on behavioral intent to use.

Given that the structural model does not test for the direct effect of perceived interactivity on performance or behavioral intent to use, the total effect of perceived interactivity is equal to the sum of the indirect effects. Panel B of Table 11 summarizes the total effect and t-statistic for the total effects of perceived interactivity on performance and the behavioral intent to use interactive data technology, and they are both significant at p < 0.001. Overall, the results support the expectation that perceived interactivity is an element of interactive data visualization that has a significant effect on the match between interactive financial reporting technology and

task requirements in a financial analysis task, and ultimately impacts user perceptions of performance and precursors to interactive data technology use.

The indirect and total effects of perceived visualization on performance and behavioral intent to use are reported in Table 12. Panel A of Table 12 displays a summary of the indirect effects of perceived visualization on performance. While the experimental analyses examined the effect of manipulating levels of perceived visualization on performance (accuracy) in hypothesis H2b, the structural model examines the total indirect effects of perceived visualization on user perceptions of performance. The results show that perceived visualization indirectly affects performance through task-technology fit (0.290, p < 0.001). However, the indirect effect of perceived visualization on performance through cognitive load is not statistically significant (0.001, p = 0.197, two-tailed). While not hypothesized, perceived visualization is also significantly related to behavioral intent to use through task-technology fit (0.172, p < 0.01) and through task-technology fit and perceived usefulness (0.115, p < 0.01), leading to a total indirect effect of 0.287 on behavioral intent to use.

Given that the structural model does not test for the direct effect of perceived visualization on performance or behavioral intent to use, the total effect of perceived visualization is equal to the sum of the indirect effects. Panel B of Table 12 summarizes the total effects and t-statistic for the total effects of perceived visualization on performance and the behavioral intention to use interactive data technology, and they are both significant at p < 0.001. Overall, the results support the prediction that perceived visualization is an element of interactive data visualization that has a significant effect on the match between interactive financial

reporting technology and task requirements while conducting a financial analysis task, and ultimately impacts user perceptions of performance and user attitudes towards interactive data technology use.

The results of H3a, H3b, and H3c indicate strong support for the effects of task-technology fit on user attitudes and beliefs about the consequences of using interactive data technology as outlined by the technology-performance chain model. To better understand the effects of task-technology fit on the precursors to interactive data technology utilization, the indirect and total effects of task-technology fit on the behavioral intent to use interactive data technology is examined. The indirect and total effects of task-technology fit on the behavioral intent to use interactive data technology are reported in Table 13. Panel A of Table 13 displays a summary of the indirect effects of task-technology fit on behavioral intention. The results show that task-technology fit indirectly affects behavioral intention through perceived usefulness, resulting in a total indirect effect of 0.316 (p < 0.01).

The structural model also tests for the direct effect of task-technology fit on behavioral intention. Thus, the total effect of task-technology fit on the behavioral intention to use interactive data technology is the sum of the direct and indirect effects of task-technology fit on behavioral intention. The total effect is 0.788. Panel B of Table 13 shows the total effect and t-statistic for the total effect and it is significant at p < 0.001. Overall, these results support the combination of both the utilization and task-technology fit models of performance as posited by the technology-performance chain model, and the expectation that the fit between interactive

data technology and task requirements while conducting financial statement analyses does affect a user's intention to utilize interactive data technology.

Summary and Conclusions

This research investigates the impact of characteristics of interactive data visualization (i.e. interactivity and visualization) on performance, precursors to interactive data technology utilization, and the fit between interactive financial reporting technology and task requirements in a financial decision-making context. Due to the prevalent use of the Internet as a disclosure and financial reporting venue, and the XBRL mandate by the SEC, interactive data visualization has become more salient in the financial accounting arena. However, there is very little research aimed at understanding the interaction between individual decision-makers and characteristics of interactive data visualization in a financial analysis context. The development of XBRL is expected to change the way financial information is rendered, acquired, and processed. In light of this, the SEC is encouraging the development of XBRL-enabled tools to facilitate efficient and effective financial analysis. This study examines the link between characteristics of interactive data visualization and task requirements in a financial decision-making context, and the subsequent impact of that relationship on performance and user attitudes towards interactive technology use. This research study particularly focuses on the impact of the user-interactive data technology interaction for nonprofessional investors.

A series of regression analyses are conducted in order to examine the effects of interactivity and visualization on task-technology fit, performance (accuracy), and cognitive load. The findings from the experimental results suggest that higher levels of interactivity

provide a better match between interactive data visualization tools and task requirements in a financial decision-making context. However, visualization does not appear to enhance tasktechnology fit. The experimental results also indicate that interactivity and visualization do not have an effect on accuracy on conducting the financial analysis task. These findings appear to be inconsistent with previous research investigating the impact of interactivity and visualization on financial decision-making (e.g. Tang et al. 2014). Tang et al. (2014) examine the effect of interactivity and visualization on accuracy, confidence, and calibration in financial decisionmaking and conclude that both high interactivity and high visualization were necessary in increasing accuracy and confidence and reducing calibration. It is possible that accuracy did not differ among the three conditions in this study due to the nature of the financial analysis task. The financial analysis scenarios used in this study involved simple acquisition tasks in order to correctly calculate each financial ratio. In addition, the mean accuracy scores are less than one standard deviation from the maximum accuracy score across all treatment conditions. On the other hand, completing the analysis task in Tang et al. (2014) required both information acquisition and information integration. Future research could replicate this study using an analysis task with high integrative complexity and investigate the effects of elements of interactivity data visualization on both information acquisition and information integration, similar to Hodge et al. (2004).

This study also explored the potential for characteristics of interactive data visualization to impose additional mental load on the decision-maker and extends the technology-performance chain model with insights from cognitive load theory. The experimental results indicate that neither interactivity nor visualization have a significant effect on cognitive load. However, the

results from examining user perceptions indicate that users reported less cognitive load when perceived interactivity is high. Future research could further explore the potential for interactive data visualization to increase cognitive load by using an experimental task involving the use of more features in the high interactivity condition. The analysis task in this study only required the use of a small subset of the available tools on the Calcbench website. It is possible that a burden is placed on working memory as a task increases in difficulty or complexity and more interactive features are used. Unfortunately, the results from the experimental analysis do not provide any information in this regard.

Following the experimental analysis, the relationships in the proposed research model are tested using structural equation modeling. Structural equation modeling is used in order to examine the effect of perceptions of interactivity and visualization in the research model, and to examine the simultaneous relationships between the constructs outlined in the research model. In addition, this study also includes variables that are not directly observed but are otherwise inferred from several measured items and designed to provide a deeper understanding of the impact of user perceptions of elements of interactive data visualization. Evidence from the structural model results indicate that both user perceptions of interactivity and visualization significantly improve task-technology fit. This finding suggests that individual perceptions of both interactivity and visualization contribute to perceptions of the fit between task requirements during a financial analysis task and characteristics of interactive data visualization. In comparison to the experimental results, both actual interactivity and user perceptions of interactivity had positive effects on task-technology fit. On the other hand, although actual visualization did not have a significant effect on task-technology fit according to the

experimental results, user perceptions of visualization has a positive impact on task-technology fit. In addition, examining the indirect effects of interactivity and visualization indicates that both elements of interactive data visualization have a positive impact on perceptions of performance and the behavioral intention to use interactive data technology. These results suggest that it may be important to consider the behavioral dimension of elements of interactive data visualization in conjunction with the actual provision of interactive or visualization features when considering the effects of interactive data visualization on financial decision-making and on user attitudes and beliefs about the consequences of interactive data technology use.

The structural results also indicate that task-technology is an important determinant of the precursors to interactive data technology utilization (perceived usefulness and behavioral intent to use). This finding is important to standard setters and regulators because it provides evidence that investors will experience an increase in the antecedents to the potential use of interactive technology if the technology closely meets the needs of the investor while performing financial statement analyses. The effects of task-technology fit on perceived usefulness and the behavioral intent to use interactive data technology also provides a direct examination of incorporating insights from utilization-focused models of IS use with insights from fit-focused models as outline in Goodhue and Thompson's (1995) technology-performance chain model.

As with all research, there are limitations to this study. First, this study utilized an incomplete factorial design and visualization was only manipulated in the high interactivity condition. This is due to the use of real-world interactive data visualization tools. The low interactivity condition was operationalized using the SEC's EGDAR interactive viewer and the

viewer does not provide visualization features. However, the use of actual existing interactive data reporting tools provides realism to the study and informs proponents of interactive data technology on the current state of XBRL-enabled tools. This research also has practical implications for standard setters and software developers. Debreceny and Gray (2001) assert that the provision of XBRL-enabled financial reports should fuel the development of interactive data viewers and research is needed on developing such tools and understanding their impact on decision-making in a financial context. This research study presents an initial analysis of this relationship.

Second, the visualization manipulation used in this study was a simple line chart that was included in the Calcbench benchmarking and analysis tool. Participants were specifically instructed to view the line chart and were provided with the steps to view the chart. However, the chart was available in both high interactivity conditions and it is possible that participants in the high interactivity/low condition discovered the charting tool and used it during their analysis. On the other hand, results from the manipulation check suggest that the manipulations were successful. Future research could examine the use of more advanced visualization tools or the use of different types of visualization tools to determine potential effects on performance and the task environment as visualization becomes increasingly salient.

The research reported in this study contributes to XBRL-related research examining the impact of interactive reporting on decision-making. There has been a paucity of such research due to the unavailability of interactive viewers that can harness the power of XBRL. XBRL-tools designed for investors are still relatively in their infancy (Clements et al. 2011). Results from this

study provide evidence on how interactivity and visualization contribute to performance, and potentially facilitate IS-based cognitions of the benefits of adopting and using interactive data visualization tools.

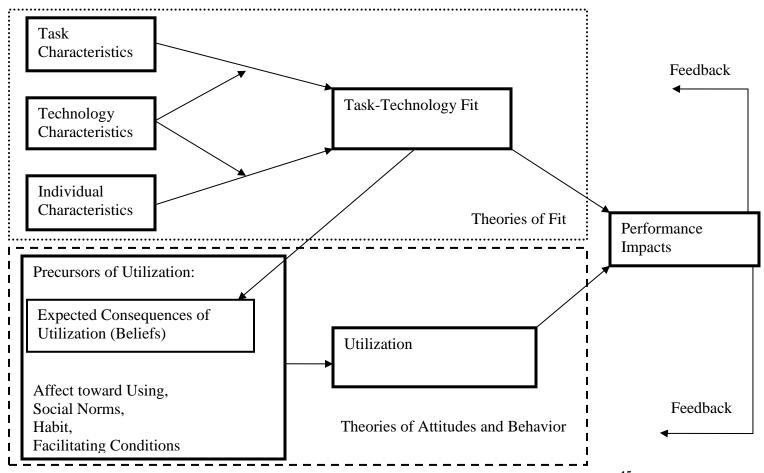


Figure 1: The Technology to Performance Chain Model¹⁵

¹⁵ Source: Adapted from Goodhue and Thompson (1995)

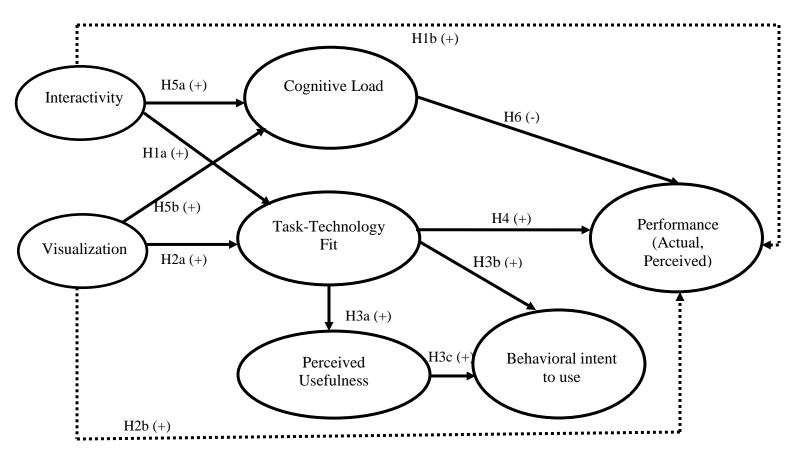


Figure 2: Theoretical Model of the Impact of Interactive Data Visualization on Individual Performance and User Attitudes and Beliefs

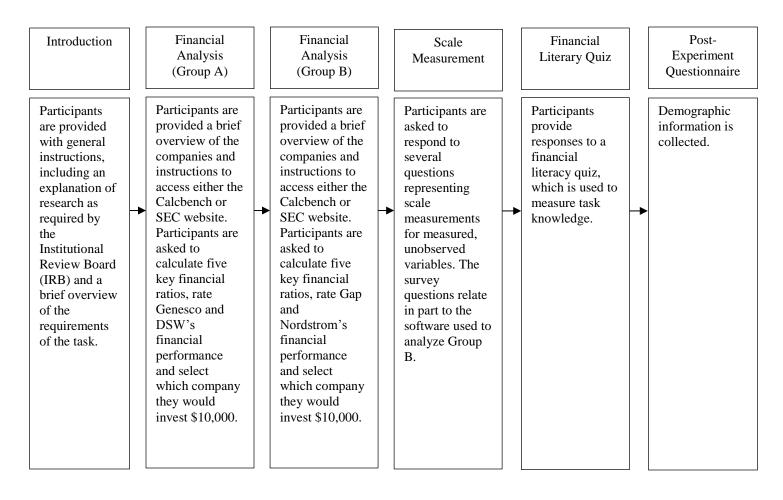


Figure 3: Sequencing of Experimental Task

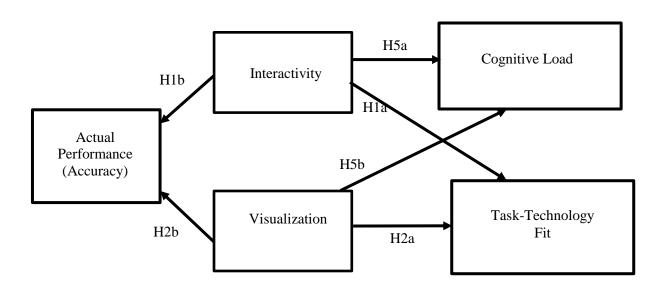


Figure 4: Experimental Research Model

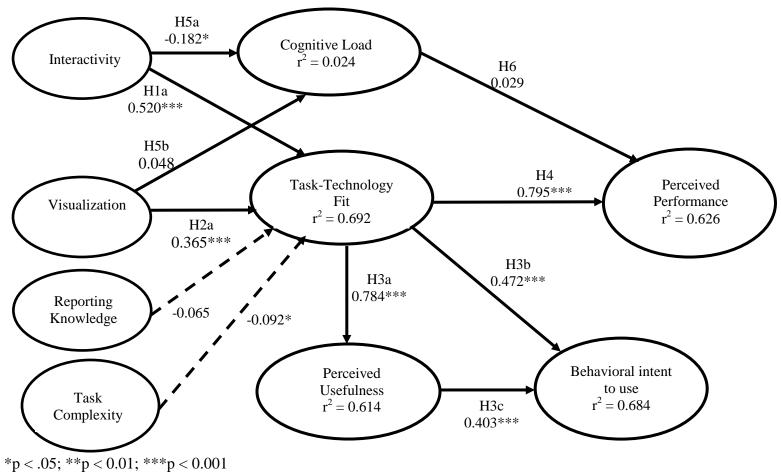


Figure 5: Results of Research Model Testing (Structural Model)¹⁶

¹⁶ Dotted lines represent relationships that are not hypothesized, but controlled for in the research model.

Table 1: Participant Demographics

Item	Item Frequency (n = 170)	
Panel A: Gender	(H = 170)	
Male	85	50.00
Female	84	49.41
Did not answer	1	0.59
Panel B: Age (in years)		
Under 25	90	52.94
25 to 40 years	66	38.82
40+ years	14	8.24
Panel C: Full-time Work Experie	ence (in years)	
< 1 year	45	26.47
1 to 2 years	27	15.88
3 to 6 years	50	29.41
7 to 10 years	27	15.88
10+ years	21	12.35
Panel D: Bought or sold common	stock or debt securities	
Yes	40	23.53
No	130	76.47
Panel E: Number of times evalua	ted a company's performand	ce by analyzing its
financial statements		
Never	75	44.12
1 to 5 times	56	32.94
6 to 10 times	24	14.12
10+ times	15	8.82
Panel F: Future Investment Plans		
Yes	132	77.65
No	38	22.35
Panel G: Courses Taken		
Accounting	Mean = $6.74 (5.09)$	N/A
Finance	Mean = $2.05 (2.72)$	N/A
Panel H: Experience using Intera		
Yes	48	28.24
No	122	71.76

Table 2: Descriptive Statistics for Item Measures¹⁷

Scale Item	Item Measure Name	Mean	Median	Standard Deviation
Task-Technology Fit (Goodhue and	Thompson 1995;	Goodhue	1998)	
Locatibility/Accessibility				
Please answer the following questions	regarding your ex	kperience w	hile using the	
EDGAR/CALCBENCH tool.				
This reporting technology makes it	LOC1	3.99	4.00	.955
easy to locate data				
It is easy to find out what data is	LOC2	3.91	4.00	.968
maintained on a given subject.				
The exact definition of the data	LOC3	3.71	4.00	1.057
fields relevant to this task are easy				
to find out.				
It is easy to locate the exact meaning	LOC4	3.59	4.00	1.006
of data elements.				
Ease of Use				
Please answer the following questions	regarding your ex	kperience w	hile using the	
EDGAR/CALCBENCH tool.			1	_
It is easy to learn how to use this	EOU1	4.06	4.00	.885
technology.				
I believe that this technology is easy	EOU2	4.08	4.00	.857
to use.				
I believe that it is easy to get the	EOU3	3.91	4.00	.931
technology to do what I want it to				
do.				
My interaction with the technology	EOU4	3.98	4.00	.910
is clear and understandable.				
Flexibility				
Please answer the following questions	regarding your ex	kperience w	hile using the	
EDGAR/CALCBENCH tool.	T		1	1
This technology is able to respond to	FLEX1	3.88	4.00	.996
my changing needs for data				
It is easy to change the selection of	FLEX2	3.94	4.00	1.064
data while using this technology.				

¹⁷ Locatability/accessibility, ease of use, flexibility, compatibility, presentation, perceived performance, perceived interactivity, perceived visualization, perceived usefulness, behavioral intent to use, and task complexity are all measured using a five-point Likert-type scale, anchored at strongly disagree and strongly agree. Confidence is measured using a five-point Likert-type scale, anchored at not at all confident and very confident. The first two cognitive load items (COG1 and COG2) are measured using a five-point Likert-type scale, anchored at very low and very high. COG3 and COG4are measured using a five-point Likert-type scale, anchored at not very hard and very hard.

Scale Item	Name		Median	Standard Deviation	
It is easy to change the presentation of data while using this technology.	FLEX3	3.59	4.00	1.149	
This technology responded very quickly to my changing needs for data.	FLEX4	3.86	4.00	1.068	
Compatibility Please answer the following questions EDGAR/CALCBENCH tool.	regarding your ex	perience wh	hile using the		
It is easy to compare or consolidate data from different sources.	COMP1	3.62	4.00	1.176	
There are no inconsistencies in definitions when comparing data from different sources.	COMP2	3.56	4.00	1.020	
Using this technology is compatible with most aspects of conducting financial statement analyses.	COMP3	4.01	4.00	.796	
This technology facilitates the analysis of data from different sources.	COMP4	3.78	4.00	1.025	
Presentation Please answer the following questions EDGAR/CALCBENCH tool.	regarding your ex	perience wl	hile using the		
The data that I need is displayed in a readable format.	PRES1	4.12	4.00	.837	
The data that I need is displayed in an understandable format.	PRES2	4.18	4.00	.838	
The data I need is presented in a useful format.	PRES3	4.10	4.00	.868	
The data that I need is organized efficiently to support the task.	PRES4	3.96	4.00	.987	
Perceived Interactivity (Song and B Please answer the following questions EDGAR/CALCBENCH tool.		perience wl	hile using the		
I had a lot of control over my experience while using the financial reporting technology.	PI1	3.92	4.00	.973	
I could choose freely what I wanted to see while using the financial reporting technology	PI2	4.11	4.00	.976	
There is a variety of content within the financial reporting technology.	PI3	4.26	4.00	.789	

Scale Item Item Measure Name		Mean	Median	Standard Deviation	
My actions decided the kind of	PI4	3.95	4.00	.905	
experience I got while using the					
financial reporting technology.					
I believe the financial reporting	PI5	4.07	4.00	.970	
technology is interactive.					
Perceived Visualization (Tang et al.	2014)				
Please answer the following questions	regarding your ex	perience wl	nile using the		
EDGAR/CALCBENCH tool.		-			
In addition to text, this financial	PVIS1	4.00	4.00	1.009	
reporting technology enabled the					
visualization of financial data.					
This financial reporting technology	PVIS2	3.79	4.00	1.116	
helps me to visually see the					
relationships among financial items.					
Using this financial reporting	PVIS3	3.60	4.00	1.158	
technology enabled me to					
graphically compare the financial					
results.					
Using this financial reporting	PVIS4	3.59	4.00	1.2044	
technology enabled me to					
graphically view the trend in					
financial statement items.					
Perceived Performance (Goodhue a					
Please answer the following questions	regarding your ex	perience wl	nile using the		
EDGAR/CALCBENCH tool.					
Using this technology had a large,	PERF1	3.91	4.00	1.010	
positive impact on my effectiveness					
and productivity in this financial					
analysis task.					
This technology is an important and	PERF2	3.98	4.00	.894	
valuable aid to me in the					
performance of financial analysis.					
This technology greatly contributed	PERF3	3.78	4.00	1.035	
to the improvement of my financial					
statement analysis.					
Using this technology helped me	PERF4	3.93	4.00	.977	
efficiently manage my financial					
statement analysis.					
Perceived Usefulness (Davis 1989; D	Davis et al. 1989)				

Perceived Usefulness (Davis 1989; Davis et al. 1989)

Please answer the following questions regarding your experience while using the EDGAR/CALCBENCH tool.

Scale Item	Scale Item Item Measure Name		Median	Standard Deviation	
Using this technology improved my performance on this financial analysis task.	PU1	4.03	4.00	.873	
Using this technology enhanced my effectiveness on this financial analysis task.	PU2	4.01	4.00	.939	
Using this technology made it easier to complete this financial analysis task.	PU3	4.17	4.00	.923	
I found this technology very useful while completing this financial analysis task.	PU4	4.12	4.00	.922	
Behavioral Intention to Use (Davis			DENGII. 1	1	
Please answer the following questions Assuming this technology was available, I would use it in future financial analysis tasks.	BIU1	4.05	4.00	1.031	
Assuming this technology was available, I predict I would use it in future financial analysis tasks.	BIU2	4.04	4.00	1.057	
Assuming this technology was available, I would not use alternative financial analysis technologies. (Dropped due to low loading).	BIU3	3.04	4.00	1.062	
Assuming this technology was available, I plan to use it again for future financial analysis tasks.	BIU4	3.85	4.00	.995	
Cognitive Load (Hart and Staveland		1 .	.•		
Please indicate your rating of the task How much mental effort was required to complete this task? (Dropped due to low loading).	COG1	2.86	3.00	.856	
How much perceptual activity was required to complete this task? (Dropped due to low loading).	COG2	3.02	3.00	.757	
How hard did you have to work to complete this task?	COG3	2.57	3.00	.834	
In general, how hard was this task for you?	COG4	2.38	2.00	.864	
Task Complexity (Hampton 2005) Please indicate your rating of the task	for each of the fol	lowing gues			
Please indicate your rating of the task	101 each of the 101	iowing ques	dolls.		

Scale Item	Item Measure Name	Mean	Median	Standard Deviation
Most nonprofessional investors would find the financial analysis task challenging.	TC1	3.16	3.00	1.097
Most nonprofessional investors would find the financial analysis task difficult.	TC2	2.96	3.00	1.045
Most nonprofessional investors would find the financial analysis task complex.	TC3	3.14	3.00	1.077
Most nonprofessional investors would say that this task requires a lot of thought and problem-solving.	TC4	3.11	3.00	1.061
Confidence in Performance (Hagem		.•		
Please indicate your rating for each of How confident are you that you accurately performed this task?	CONF1	3.71	4.00	.743
How confident are you in being successful at conducting financial analysis with the use of interactive technology?	CONF2	3.91	4.00	.752
How confident are you in being successful at conducting financial analysis manually?	CONF3	3.44	4.00	.967
How confident are you in the investment decision that you made?	CONF4	3.51	4.00	.844

Table 3: Descriptive Statistics by Treatment

Treatment Group	Perceived Interactivit y	Perceived Visualizatio n	Task- Technolog y Fit	Accuracy (Actual Performance	Perceived Performanc e	Perceived Usefulnes s	Behaviora l Intent to Use	Cognitiv e Load
(Low Interactivity/No	3.668	3.125	17.451	8.36	3.505	3.665	3.330	2.69
Visualization)	(0.852)	(1.090)	(4.124)	(1.65)	(1.019)	(0.877)	(1.020)	(0.72)
(n = 56)								
High Interactivity/No	4.218	3.912	20.233	8.51	4.118	4.237	3.921	2.77
Visualization	(0.631)	(0.823)	(3.565)	(2.87)	(0.752)	(0.786)	(0.775)	(0.75)
(n = 57)								
High	4.298	4.187	20.654	8.65	4.070	4.333	3.978	2.67
Interactivity/Visualizatio	(0.680)	(0.737)	(2.863)	(2.70)	(0.825)	(0.687)	(0.741)	(0.62)
n								
(n = 57)								

Notes:

Perceived Interactivity is calculated as the average of five questions that are measured using a five-point Likert-type scale, where 1 = strongly disagree and 5 = strongly agree.

Perceived Visualization is calculated as the average of four questions that are measured using a five-point Likert-type scale, where 1 =strongly disagree and 5 =strongly agree.

Task-Technology Fit is calculated as the sum of all the means of each task-technology fit dimension (i.e. locatability/accessibility, compatibility, ease of use, flexibility, and presentation. The mean for each dimension is computed as the average of four questions that are measured using a five-point Likert-type scale, where 1 = strongly disagree and 5 = strongly agree.

Accuracy is computed based on the number of correctly identified financial ratios. A total of ten ratios are calculated – five ratios each for two companies.

Perceived Performance is calculated as the average of four questions that are measured using a five-point Likert-type scale, where 1 =strongly disagree and 5 =strongly agree.

Perceived Usefulness is calculated as the average of four questions that are measured using a five-point Likert-type scale, where 1 =strongly disagree and 5 =strongly agree.

Behavioral Intent to Use is calculated as the average of four questions that are measured using a five-point Likert-type scale, where 1 = strongly disagree and 5 = strongly agree.

Cognitive load is calculated as the average of four questions that are measured using a five-point Likert-type scale. The first two items are anchored at 1 = very low and 5 = very high. The final two items are anchored at 1 = not very hard and 5 = very hard.

Table 4: Effects of Interactivity and Visualization on Task-Technology Fit

Panel A: ANOVA Results

Source	Type III Sum of Squares	df	Mean Square	F	p-value (one-tailed)
Intercept	64277.983	1	64277.983	5096.452	< 0.001
Low Interactivity/No Visualization vs.	341.249	2	170.625	13.528	< 0.001
High Interactivity/No Visualization vs.					
High Interactivity/Visualization					
Error	2106.254	167	12.612		
Total	66807.563	170			

Panel B: Planned Contrasts 18

	t-statistic	Df	p-value (one-tailed)
Low Interactivity/No Visualization < High Interactivity/No Visualization, High Interactivity/Visualization (-2, 1, 1)	4.758	89.054	< 0.001
High Interactivity/No Visualization > Low Interactivity/No Visualization (-1, 1, 0)	3.833	108.154	< 0.001
High Interactivity/Visualization > High Interactivity/No Visualization (0, -1, 1)	0.695	107.008	0.244

18 Degree of freedom is adjusted because the Levene's test for equality of variances is significant.

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 Table 5: Effects of Interactivity and Visualization on Accuracy

Panel A: ANOVA Results

Source	Type III Sum	df	Mean	F	p-value
	of Squares		Square		(one-tailed)
Intercept	12296.134	1	12296.134	2016.977	p < 0.001
Low Interactivity/No Visualization vs.	2.409	2	1.204	.198	0.411
High Interactivity/No Visualization vs.					
High Interactivity/Visualization					
Error	1018.085	167	6.096		
Total	13320.000	170			

Table 6: Effects of Interactivity and Visualization on Cognitive Load

Panel A: ANOVA Results

Source	Type III Sum of Squares	df	Mean Square	F	p-value (one-tailed)
T	•	1	1	0574.702	
Intercept	1247.236	1	1247.236	2574.703	p < 0.001
Low Interactivity/No Visualization vs.	.314	2	.157	.324	0.362
High Interactivity/No Visualization vs.					
High Interactivity/Visualization					
Error	80.898	167	.484		
Total	1328.625	170			

Table 7: Scale Item Loadings and Cross Loadings

Item Measure Name	1	2	3	4	5	6	7	8	9	10	11	12
BIU1	0.97	-0.09	0.67	0.67	0.65	0.66	0.70	0.76	0.80	0.72	-0.24	0.58
BIU2	0.97	-0.11	0.66	0.65	0.63	0.66	0.69	0.74	0.77	0.70	-0.23	0.55
BIU4	0.95	-0.03	0.67	0.66	0.64	0.65	0.69	0.73	0.78	0.67	-0.12	0.55
COG3	-0.11	0.96	-0.08	-0.11	-0.08	-0.15	-0.21	-0.04	-0.09	-0.19	0.34	-0.07
COG4	-0.03	0.94	-0.03	-0.05	-0.04	-0.13	-0.15	-0.04	-0.06	-0.17	0.24	-0.08
COMP1	0.61	-0.04	0.85	0.57	0.73	0.62	0.71	0.60	0.57	0.63	-0.15	0.71
COMP2	0.49	-0.13	0.82	0.55	0.59	0.54	0.61	0.52	0.52	0.53	-0.21	0.50
COMP3	0.63	-0.04	0.86	0.63	0.67	0.63	0.67	0.63	0.65	0.64	-0.11	0.55
COMP4	0.65	-0.01	0.90	0.58	0.73	0.67	0.70	0.63	0.67	0.63	-0.14	0.66
EOU1	0.57	-0.11	0.60	0.91	0.65	0.60	0.66	0.59	0.58	0.64	-0.20	0.49
EOU2	0.62	-0.02	0.56	0.92	0.61	0.56	0.65	0.61	0.59	0.64	-0.22	0.47
EOU3	0.65	-0.04	0.68	0.89	0.72	0.63	0.68	0.68	0.66	0.62	-0.13	0.58
EOU4	0.66	-0.15	0.61	0.92	0.67	0.62	0.66	0.64	0.62	0.68	-0.22	0.50
FLEX1	0.67	-0.16	0.76	0.73	0.88	0.73	0.73	0.71	0.70	0.69	-0.20	0.70
FLEX2	0.58	-0.06	0.62	0.66	0.88	0.58	0.60	0.56	0.59	0.63	-0.09	0.57
FLEX3	0.53	0.00	0.68	0.59	0.87	0.57	0.65	0.52	0.58	0.61	-0.09	0.65
FLEX4	0.54	-0.01	0.70	0.57	0.88	0.60	0.61	0.60	0.57	0.61	-0.14	0.65
PI1	0.59	-0.12	0.58	0.55	0.57	0.85	0.54	0.59	0.62	0.52	-0.07	0.54
PI2	0.61	-0.19	0.60	0.59	0.62	0.89	0.56	0.65	0.68	0.58	-0.11	0.56
PI3	0.54	-0.19	0.54	0.54	0.57	0.80	0.58	0.58	0.64	0.60	-0.11	0.53
PI4	0.52	-0.09	0.62	0.53	0.54	0.82	0.58	0.54	0.60	0.51	-0.05	0.56
PI5	0.59	-0.03	0.66	0.59	0.68	0.82	0.59	0.68	0.64	0.57	-0.14	0.64
LOC1	0.71	-0.18	0.69	0.73	0.65	0.67	0.89	0.67	0.67	0.74	-0.22	0.61
LOC2	0.68	-0.20	0.69	0.68	0.67	0.66	0.92	0.63	0.67	0.73	-0.17	0.59
LOC3	0.63	-0.18	0.76	0.62	0.69	0.59	0.92	0.61	0.62	0.65	-0.21	0.61
LOC4	0.58	-0.13	0.68	0.58	0.64	0.52	0.87	0.56	0.56	0.60	-0.19	0.56
PU1	0.69	-0.01	0.62	0.61	0.58	0.65	0.60	0.90	0.75	0.62	-0.11	0.52
PU2	0.68	-0.03	0.62	0.61	0.59	0.65	0.64	0.92	0.79	0.61	-0.22	0.60
PU3	0.70	-0.02	0.63	0.64	0.63	0.66	0.63	0.92	0.76	0.65	-0.17	0.57
PU4	0.75	-0.10	0.68	0.66	0.70	0.70	0.65	0.91	0.81	0.70	-0.16	0.60
PERF1	0.77	-0.05	0.66	0.61	0.64	0.74	0.67	0.82	0.92	0.68	-0.18	0.60
PERF2	0.78	-0.09	0.66	0.66	0.67	0.71	0.66	0.78	0.94	0.67	-0.10	0.54
PERF3	0.71	-0.02	0.62	0.59	0.63	0.69	0.64	0.79	0.93	0.65	-0.08	0.54
PERF4	0.77	-0.13	0.67	0.64	0.65	0.68	0.65	0.78	0.92	0.70	-0.12	0.57

Item Measure Name	1	2	3	4	5	6	7	8	9	10	11	12
PRES1	0.56	-0.18	0.53	0.58	0.57	0.48	0.56	0.48	0.56	0.84	-0.14	0.45
PRES2	0.64	-0.17	0.61	0.65	0.56	0.54	0.66	0.62	0.61	0.87	-0.15	0.44
PRES3	0.63	-0.14	0.63	0.61	0.70	0.63	0.69	0.67	0.67	0.91	-0.13	0.58
PRES4	0.70	-0.18	0.72	0.67	0.72	0.67	0.75	0.70	0.72	0.91	-0.21	0.61
TC1	-0.17	0.32	-0.17	-0.18	-0.10	-0.11	-0.20	-0.16	-0.10	-0.15	0.92	-0.14
TC2	-0.25	0.26	-0.19	-0.25	-0.18	-0.15	-0.24	-0.22	-0.18	-0.20	0.95	-0.15
TC3	-0.18	0.28	-0.16	-0.18	-0.13	-0.07	-0.21	-0.13	-0.11	-0.15	0.93	-0.10
TC4	-0.11	0.28	-0.10	-0.13	-0.12	-0.07	-0.14	-0.13	-0.04	-0.14	0.85	-0.10
PVIS1	0.53	-0.11	0.58	0.50	0.64	0.65	0.60	0.60	0.59	0.59	-0.10	0.86
PVIS2	0.51	-0.04	0.60	0.51	0.62	0.60	0.57	0.53	0.52	0.53	-0.10	0.88
PVIS3	0.50	-0.05	0.65	0.47	0.66	0.57	0.56	0.55	0.53	0.48	-0.18	0.90
PVIS4	0.52	-0.07	0.68	0.53	0.70	0.59	0.61	0.54	0.51	0.51	-0.13	0.91

1 = Behavioral Intent to Use; 2 = Cognitive Load; 3 = Compatibility; 4 = Ease of Use; 5 = Flexibility; 6 = Perceived Interactivity; 7 = Locatability/Accessibility; 8 = Perceived Usefulness; 9 = Performance; 10 = Presentation; 11 = Task Complexity; 12 = Perceived Visualization

Table 8: Convergent and Discriminant Validity ¹⁹

	AVE	Composite Reliability	1	2	3	4	5	6	7	8	9	10	11	12
LOC	0.81	0.94	0.90											
BIU	0.93	0.97	0.72	0.96										
COG	0.90	0.95	-0.19	-0.08	0.95									
COMP	0.74	0.92	0.79	0.70	-0.06	0.86								
TC	0.83	0.95	-0.22	-0.20	0.31	-0.17	0.91							
EOU	0.82	0.95	0.73	0.69	-0.09	0.68	-0.21	0.91						
FLEX	0.77	0.93	0.74	0.66	-0.07	0.79	-0.15	0.73	0.87					
PI	0.70	0.92	0.68	0.68	-0.15	0.72	-0.12	0.67	0.71	0.84				
PU	0.83	0.95	0.69	0.77	-0.04	0.70	-0.18	0.69	0.69	0.73	0.91			
PERF	0.86	0.96	0.70	0.81	-0.08	0.70	-0.13	0.68	0.70	0.76	0.85	0.93		
PRES	0.78	0.93	0.76	0.72	-0.19	0.71	-0.18	0.71	0.73	0.66	0.71	0.73	0.88	
PV	0.79	0.94	0.66	0.58	-0.08	0.71	-0.14	0.57	0.74	0.68	0.63	0.60	0.59	0.89

LOC = Locatability/Accessibility; BIU = Behavioral Intent to Use; COG = Cognitive Load; COMP = Compatibility; TC = Task Complexity; EOU = Ease of Use; FLEX = Flexibility; PI = Perceived Interactivity; PU = Perceived Usefulness; PERF = Performance; PRES = Presentation; PV = Perceived Visualization

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¹⁹ The square root of the AVE is shown on the diagonal in bold.

Table 9: Construct Validity and Reliability for Task-Technology Fit

Panel A: Test of Validity

Task-Technology Fit Dimensions	Item Loadings
1. Accessibility/Locatability	0.875
(Definition: Ease of determining	0.873
what data is available and where).	
2. Ease of Use (Definition: The degree	0.826
to which using a system for a task is	
perceived as being easy or difficult).	
3. Flexibility (Definition: Ease of	0.842
changing the content or format of	
the data to meet changing needs).	
4. Compatibility (Definition: Data	0.852
from different sources can be	
consolidated or compared without	
inconsistencies).	
5. Presentation (Definition: Data is	0.850
presented in a useful format).	

Panel B: Test of Multicollinearity

unci D.	1 est of Multiconnicality	
Γ	Sask-Technology Fit Dimensions	Variance Inflation Factor
		(Dependent variable = Accuracy
		Score)
1.	Accessibility/Locatability	2.198
	(Definition: Ease of determining	
	what data is available and where).	
2.	Ease of Use (Definition: The degree	2.460
	to which using a system for a task is	
	perceived as being easy or difficult).	
3.	Flexibility (Definition: Ease of	2.341
	changing the content or format of	
	the data to meet changing needs).	
4.	Compatibility (Definition: Data	2.768
	from different sources can be	
	consolidated or compared without	
	inconsistencies).	
5.	Presentation (Definition: Data is	2.542
	presented in a useful format).	

Table 10: Analysis for Common Method Bias

Construct	Indicator	Substantive Factor Loading	Variance Explained	Method Factor Loading	Variance Explained
Task-	COMP1	0.665**	0.443	0.122	0.015
Technology	COMP2	0.882*	0.778	-0.191	0.036
Fit	COMP3	0.348	0.121	0.459	0.210
	COMP4	0.641*	0.411	0.145	0.021
	EOU1	1.121***	1.256	-0.349	0.122
	EOU2	0.976***	0.953	-0.219	0.048
	EOU3	0.619*	0.383	0.195	0.038
	EOU4	0.891**	0.793	-0.096	0.009
	FLEX1	0.452	0.204	0.414	0.171
	FLEX2	0.919**	0.845	-0.165	0.027
	FLEX3	0.963**	0.928	-0.208	0.043
	FLEX4	0.725*	0.526	0.031	0.001
	LOC1	0.666*	0.443	0.176	0.031
	LOC2	0.813**	0.661	0.021	0.000
	LOC3	1.041***	1.084	-0.228	0.052
	LOC4	1.123***	1.260	-0.370	0.137
	PRES1	0.938**	0.879	-0.256	0.065
	PRES2	0.854**	0.729	-0.102	0.010
	PRES3	0.603	0.363	0.202	0.041
	PRES4	0.621*	0.386	0.237	0.056
Behavioral	BIU1	0.897***	0.805	0.062	0.004
Intent to Use	BIU2	0.960***	0.921	-0.011	0.000
	BIU3	0.707***	0.500	-0.102	0.010
	BIU4	0.927***	0.859	0.015	0.000
Cognitive	CL3	0.947***	0.897	-0.021	0.000
Load	CL4	0.952***	0.906	0.022	0.000
Interactivity	PI1	0.971***	0.942	-0.132	0.017
	PI2	0.934***	0.872	-0.050	0.003
	PI3	0.764***	0.584	0.042	0.002
	PI4	0.870***	0.756	-0.059	0.003
	PI5	0.643***	0.413	0.207	0.043

Construct	Indicator	Substantive Factor Loading	Variance Explained	Method Factor Loading	Variance Explained
Perceived	PU1	0.992***	0.984	-0.100	0.010
Usefulness	PU2	0.972***	0.944	-0.061	0.004
	PU3	0.957***	0.916	-0.038	0.001
	PU4	0.736***	0.542	0.196	0.038
Performance	PERF1	0.848***	0.720	0.086	0.007
	PERF2	0.943***	0.890	-0.005	0.000
	PERF3	1.046***	1.094	-0.127	0.016
	PERF4	0.881***	0.776	0.047	0.002
Task	TC1	0.921***	0.848	0.006	0.000
Complexity	TC2	0.920***	0.846	-0.060	0.004
	TC3	0.936***	0.876	0.014	0.000
	TC4	0.880***	0.774	0.043	0.002
Visualization	PVIS1	0.759***	0.576	0.120	0.014
	PVIS2	0.890***	0.792	-0.018	0.000
	PVIS3	0.967***	0.934	-0.077	0.006
	PVIS4	0.930***	0.865	-0.021	0.000
Average		0.851	0.751	-0.004	0.028

^{*} p < .05 ** p < .01 ***p < .001

Table 11: Indirect and Total Effects of Interactivity on Performance and on Behavioral Intention to Use Interactive Data Technology

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Interactivity	Path to:	_
Through:	Perceived Performance	Behavioral Intent to Use
	0.413**	0.246**
Task-Technology Fit	(0.415 - 0.425)	(0.248 - 0.257)
	-0.005**	
Cognitive Load	(-0.0050.003)	
Task-Technology Fit and		0.164**
Perceived Usefulness		(0.159 - 0.165)
Total Indirect Effects	0.408	0.410

Panel B: Total Effects of Interactivity

On	Coefficient	t-statistics	p-value
Performance	0.408	6.679	p < 0.001
Behavioral Intent to Use	0.410	7.491	p < 0.001

*
$$p < .05$$
; ** $p < 0.01$; *** $p < 0.001$

Table 12: Indirect and Total Effects of Visualization on Performance and on Behavioral Intention to Use Interactive Data Technology

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Visualization	Path to:	Path to:				
	Perceived Performance	Behavioral Intent to				
Through:		Use				
	0.290**	0.172**				
Task-Technology Fit	(0.285 - 0.293)	(0.170 - 0.177)				
	0.001					
Cognitive Load	(-0.0002 - 0.0007)					
Task-Technology Fit and Perceived		0.115**				
Usefulness		(0.109 - 0.115)				
Total Indirect Effects	0.291	0.287				

Panel B: Total Effects of Visualization

On	Coefficient	t-statistics	p-value
Performance	0.291	5.931	p < 0.001
Behavioral Intent to Use	0.287	5.934	p < 0.001

*p < .05; **p < 0.01; ***p < 0.001

Table 13: Indirect and Total Effect of Task-Technology Fit on Behavioral Intent to Use

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Task-Technology Fit	Path to:	
Through:	Behavioral Intent to Use	
	0.316**	
Perceived Usefulness	(0.303 - 0.315)	
Total Indirect Effects	0.316	

Panel B: Total Effects of Task-Technology Fit

On	Coefficient	t-statistics	p-value
Behavioral Intent to Use	0.788	22.087	p < 0.001

*p < .05; **p < 0.01; ***p < 0.001

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STUDY TWO: INTERACTIVE DATA TECHNOLOGY: FEEDBACK FROM THE TECHNOLOGY-PERFORMANCE CHAIN AND FUTURE TECHNOLOGY CHOICE

Introduction

Recently, the Securities and Exchange Commission (SEC) has been concerned with the issue of providing better access, and more accurate and reliable financial information to users via new technological capabilities such as the interactive reporting of financial data using eXtensible Business Reporting Language (XBRL). In 2006, Chairman Cox referred to interactive data as "a marriage made in heaven for investing and high tech" (Cox 2006, 2). Proponents of XBRL note that the technology provides several benefits to nonprofessional investors, financial analysts, and others consumers of financial information. It is expected that interactive financial reporting via XBRL will improve communications with consumers of financial information, reduce costs of financial data gathering and evaluation, increase financial reporting transparency, and facilitate the comparison of financial information across multiple periods and companies.

Interactive data reporting is expected to revolutionize the accessibility of financial information, especially to retail investors, promote more efficient markets by reducing the information gap, and facilitate a more complete analysis of financial information (Gunn 2007; SEC 2009). However, despite the proposed benefits of interactive financial reporting, prior research suggests that investors may choose not to use it (e.g. Hodge et al. 2004). This suggests that the SEC's mandate for interactive financial reporting may not provide benefits to investors as anticipated. Anecdotal evidence suggests that investors generally make a choice between reporting technologies based on how well the technology supports their information needs

(Hodge and Pronk 2006). Janvrin et al. (2013) find that most users in their experimental study preferred an XBRL reporting format to Excel and PDF after going through a tutorial using the three financial reporting formats. The evidence from prior research thus suggests that a precursor to utilization is whether investors perceived the value of interactive data technology. The evidence from Janvrin et al. (2013) also suggests that the choice to use interactive financial reporting technology might be dependent on prior exposure or experience with the technology.

The purpose of this study is to examine the role of feedback from prior exposure to interactive financial reporting technology on future choice to use the technology. Particularly, this study focuses on examining the role of experiential feedback on future technology choice following initial, direct exposure to interactive financial reporting technology. Information systems (IS) research has long recognized that in order for new technologies to enhance performance, a critical element is that users must accept and use the technology. A large body of IS research (e.g. Mathieson 1991; Taylor and Todd 1995a; Taylor and Todd 1996b; Venkatesh and Davis 2000) has been aimed towards empirically testing models that explain the acceptance and adoption of technological innovations (e.g. Technology Acceptance Model [Davis 1989], and The Unified Theory of Acceptance and Use of Technology [Venkatesh et al. 2003]). However, this research stream has primarily focused on the initial adoption of technology. "Before an IS implementation can truly be considered as a success, a significant number of users should have moved beyond the initial adoption stage, using the IS on a continued basis" (Limayem et al. 2007, p. 706). The latter point is even more important in voluntary use environments where users might have a choice of technologies to use. Recently, IS research has begun to investigate the factors that contribute to continued IS use (e.g. Bhattercherjee 2001b;

Hsu and Chiu 2004; Chiu et al. 2005; Limayem et al. 2008). Specifically, this research stream has considered the impact of past behavior on attitudes, beliefs, and intentions and the findings suggest that prior behavior is important in determining continued use of technology. The current study seeks to examine the factors that influence future beliefs and future technology choice within the context of interactive financial reporting technology.

This study is informed by Goodhue and Thompson's (1995) technology-performance chain model (TPC) and Bhattacherjee's (2001a) IS continuance theory. Goodhue and Thompson's (1995) TPC model considers the impact of past behavior or feedback from past experience with technology on current attitudes and beliefs towards using the technology. According to TPC, the interaction between an individual, a task, and a technology influences individual judgments of the fit between a task and the technology, which affect utilization via user attitudes and beliefs towards technology use. As a consequence, experience with the technology provides important feedback that could affect future utilization and future performance as a result of learning. The concept of IS continuance is important in determining the success of technology adoption because it seeks to explain the continued choice to use a technology, where the choice to continue usage follows initial acceptance or adoption (Bhattacherjee 2001a; Limayem et al. 2007). The IS continuance model posits that a user's IS continuance intention is determined primarily by two mechanisms - prior experience with a technology and the expectations of future benefits from continued use of the technology (Bhattacherjee 2001a; Bhattacherjee 2001b). This study incorporates insights from the TPC model and IS continuance theory by examining how experiential feedback in terms of

assessments of task-technology fit and performance following initial use of interactive financial reporting technology act as antecedents in the choice to use the technology.

Participants are asked to conduct a financial analysis task using their choice of two interactive financial reporting technologies - the SEC's Electronic Data Gathering Analysis and Retrieval (EDGAR) interactive viewer (low interactivity software) and Calcbench's benchmarking and analysis tool (high interactivity software). Participants were exposed to both interactive data technologies in a prior study and used both technologies to complete a financial analysis task. Prior to beginning the financial analysis task, participants are instructed to refer to their experience with prior use of the two interactive data technologies and to choose between the SEC's EDGAR interactive viewer or Calcbench's benchmarking and analysis tool to conduct their financial analysis task. The task also required participants to respond to several questions designed to measure task-technology fit, performance, perceived usefulness, satisfaction, IS continuance intention, and utilization. Following their choice of interactive data technology, participants complete the financial analysis task using the technology they chose. The collected data is evaluated using partial least squares (PLS) analysis.

The results of this study provide support for all of the hypothesized relationships developed in the research model. Higher assessments of task-technology fit lead to increased satisfaction with interactive data technology and increased perceived usefulness. In addition, the results indicate that user assessments of the performance impact of interactive data technology lead to increased perceived usefulness and satisfaction with interactive data technology use. Finally, perceived usefulness and satisfaction have positive effects on IS continuance intention, which subsequently leads to an increase in the extent of utilization.

This study has important theoretical and practical implications. The primary motivation for interactive data (e.g. XBRL) is to facilitate the creation, exchange, and analysis of financial reporting information. Although extant accounting research (e.g. Hodge et al. 2004; Pinsker and Wheeler 2009) suggests that interactive financial reporting may improve the effectiveness and efficiency of financial statement analysis, research evidence also suggests that investors may choose not to use the technology (e.g. Hodge et al. 2004). In addition, prior research suggests that investors generally make a choice between reporting technologies based on how well the technology supports their information needs (Janvrin et al. 2013). This suggests that the choice to use interactivity data technology may be dependent on prior experience with the technology. This study contributes to the literature by developing and testing a research model which considers the effects of the feedback dimension of the TPC model on the IS continuance model. The results indicate that assessments of task-technology fit and performance from prior use of interactive data technology are an important antecedent to the belief that interactive data technology improves performance, and the extent to which expectations about interactive data technology are confirmed or disconfirmed. In addition, the results in this study extend the IS continuance model by confirming that IS continuance intention has a positive impact on the degree of interactive data technology utilization.

Previous research (e.g. Janvrin et al. 2013) that has examined the choice to use interactive data technology has only compared the choice to use an XBRL versus an Excel or PDF reporting format. This study contributes to the literature by examining the choice to use one of two interactive reporting technologies. In this scenario, it is more likely that a user's choice is based on the extent to which interactive features are present and beneficial to the decision process,

rather than the discrepancy between the capabilities of interactive data technology and more static financial reporting formats. Approximately 76 percent of participants chose to use the highly interactive viewer (i.e. Calcbench's benchmarking and analysis tool). Participants were asked to state the reasons for their choice of technology. Participant responses suggest that interactive data technology choice is primarily driven by repeated prior experience and presentation format for participants who chose the lower interactive technology. On the other hand, participants who chose the high interactive data technology are primarily driven by comparability, ease of use, and the ability to quickly find and select the information needed. This research provides practical guidance to software developers and standard setters on factors that may be important to nonprofessional investors in using interactive data technology.

The remainder of this paper is organized as follows. The next section discusses the background research, theoretical foundation, and develops the hypotheses. Section III discusses the research design and methodology. Section IV and V will include the results and a summary discussion of the study, respectively.

Theory and Hypotheses Development

Interactive Data and User Adoption of Technology

Due to the vast amount of information being produced by accounting information systems, many companies now utilize interactive technologies on their investment relations websites, enterprise system dashboards, and other user interfaces in order to aid in the organization and analysis of data (Kelton and Yang 2008; Dilla et al. 2010). Effective in 2009, the SEC introduced a new standard for financial statement reporting intended to improve the

usefulness of financial information to investors. The SEC's mandate requires public companies to provide their financial information to the SEC and on their corporate Web sites in an interactive data format using XBRL (SEC 2009). XBRL uses a set of tags to consistently identify data so that software applications will automatically recognize the information, making it easier to acquire and analyze financial information in a variety of formats, and thereby reducing the costs and efforts associated with current financial data analysis (SEC 2009).

A fundamental goal of interactive financial data reporting is its proposed benefits to investors, particularly nonprofessional investors. Evidence from previous research suggests that nonprofessional investors are more likely to benefit from interactive financial data reporting because in comparison to professional analysts, nonprofessional investors do not possess the relevant knowledge about the relationship between different financial statement items and typically follow a sequential search strategy while looking for information (Hunton and McEwen 1997; Maines and McDaniel 2000; Arnold et al. 2012). The tagging of related financial information in XBRL should thus be more beneficial to nonprofessional investors rather than professional investors.

Evidence from prior studies suggests that interactive data is beneficial to nonprofessional investors during a financial analysis task because it facilitates information acquisition and information evaluation/integration (e.g. Hodge et al. 2004; Arnold et al. 2012; Janvrin et al. 2013). However, we have limited knowledge on whether and why a decision maker will choose to use interactive data technology. Previous studies have typically assigned participants to a reporting technology, rather than allowing participants to make a choice (Janvrin et al. 2013). In

addition, since the use of interactive data technology is voluntary, prior evidence suggests that decision makers may choose not to use the technology even when it is available (e.g. Hodge et al. 2004). Janvrin et al. (2013) provides an initial examination of factors that may affect the choice to use interactive data technology by comparing user choice between using XBRL, Excel, or PDF to complete a financial analysis task. The results of Janvrin et al. (2013) indicate that participants chose to use XBRL primarily due to the expected time savings, while the choice to use Excel was primarily driven by prior experience, and no participants chose PDF.

Understanding information technology (IT) acceptance has been a major reoccurring theme in IS research. This is primarily because the proposed benefits of IT use cannot be fully realized if users do not accept and use these systems. Several perspectives exist in the literature on IS acceptance (e.g. Technology Acceptance Model [Davis et al. 1989]); The Unified Theory of Acceptance and Use of Technology [Venkatesh et al. 2003]). These models propose factors that contribute to the initial acceptance of an IS. However, the success of an IS is heavily dependent on its continued use rather than its first-time use (Bhattacherjee 2001a). Evidence from IS research acknowledges the existence of a post-acceptance stage where a user evaluates their initial acceptance or adoption during a final confirmation stage and determines if he/she will continue or discontinue using a technology (Bhattacherjee 2001a). Extant IS studies have called for research examining the boundary conditions in existing technology adoption and usage research, which typically use the same set of antecedents to explain technology use for both initial adopters and experienced adopters (Venkatesh et al. 2002; Bhattacherjee and Sanford 2009). According to Bajaj and Nidumolu (1998), although existing models of technology

adoption and usage have been successful in predicting IS usage in specific situations, these models generally ignore the effect of feedback from prior behavior.

Research on IS continuance can typically be divided into three primary groups (Larsen et al. 2009). One research stream only considers IS adoption as a predictor of IS continuance (e.g. Chiu et al. 2005; Lin et al. 2005). A second group focuses on the factors that explain continued use of IS over time (e.g. Kim and Malhotra 2005; Bhattacherjee and Sanford 2009). These studies incorporate insights from several IS-based studies that examine usage behavior primarily based on the influence of past behavior while excluding the typical intention-behavior link.

These studies involve the gathering of data over intervals of time (i.e. longitudinal studies) with the underlying premise that a model of use which considers a direct path from past behavior to future behavior provides a better fit than a model in which the effect of past behavior on future behavior is mediated by behavioral intention (Bagozzi 1981; Fredricks and Dossett 1983; Bajaj and Nidumolu 1998). Finally, the third group of IS continuance research incorporates insights from Bhattacherjee's (2001a) IS continuance model with complementary theoretical perspectives of IS use (e.g. Larsen et al. 2009; Lin 2012; Lin and Wang 2012).

The model presented in this study is situated in the third group because this facilitates the investigation of factors affecting continued use of interactive data technology while considering use in the context of the requirements of the task environment in which interactive data technology is being used. Specifically, this study informs the IS continuance model with the tenets from Goodhue and Thompson's (1995) technology-performance chain (TPC) model, which enables the consideration of the relevance of interactive data technology to a decision

environment while investigating future or continued use. Larsen et al. (2009) suggest that this approach facilitates theory development by allowing the consideration of work-related issues in understanding technology use.

The IS Continuance Model and the TPC

The IS continuance model (Bhattacherjee 2001a) provides a theoretical lens for investigating the factors that influence a user's choice to use interactive data technology. The IS continuance model posits that a user's IS continuance intention is determined primarily by two mechanisms - prior experience with a technology and the expectations of future benefits from continued use of the technology (Bhattacherjee 2001a; Bhattacherjee 2001b). In the IS continuance model, prior experience with technology is captured by the satisfaction construct, which is defined as the post-acceptance or post-use affect as a result of prior IS use. On the other hand, expectations of the future benefits of continued IS use is captured by the perceived usefulness construct, and perceived usefulness is defined as the degree to which the use of an IS facilitates improved task performance (Davis et al. 1989; Bhattacherjee 2001a). According to the IS continuance model, satisfaction and perceived usefulness are both determined by the extent to which a user's expectation about a technology is confirmed or disconfirmed following initial use (Bhattacherjee 2001a). The IS continuance model as proposed by Bhattacherjee (2001a) is depicted in Figure 6.

To investigate the factors influencing a user's choice of interactive data technology, this study extends the IS continuance model with insights from Goodhue and Thompson's (1995) technology-performance chain (TPC) model. The TPC model (Goodhue and Thompson 1995; Goodhue 2006) is a theoretical model of technology and performance that incorporates insights

from both utilization-focused and task-technology fit focused models of IS and individual performance. According to TPC, the interaction between a task, technology, and a decision maker influences user perceptions of how well a task is supported by a technology (i.e. the tasktechnology fit). Subsequently, task-technology fit directly impacts the precursors to technology use (i.e. user attitudes and beliefs towards use such as expected consequences of use, affect towards use, etc.) and performance. The precursors to utilization have a direct effect on actual usage, which also influences performance. In the TPC model, performance is defined as "how well an individual accomplishes a portfolio of tasks" (Goodhue 2006, 191). Figure 7 shows the TPC model as discussed in Goodhue and Thompson (1995) and Goodhue (2006). Feedback from past technology use is an important dimension in the TPC model (Goodhue 2006). Two primary forms of feedback may occur once a technology has been used and performance impacts have been experienced. First, actual technology use may cause individuals to revise their expected consequences of utilization and future technology use depending on whether they experienced a better or worse effect on performance than expected. Second, learning may occur from using the technology, which may lead to improvements in the fit between an individual and the technology, thereby improving overall task-technology fit (Goodhue 2006).

This study considers the first form of feedback by examining how user assessments of performance after initial use of interactive data technology influences a user's future choice of interactivity data technology during a financial analysis task. Specifically, this study defines feedback as experiential feedback, which is an individual's post-use reflection of their actual experience with using interactive data technology. In the IS continuance model, confirmation is defined as the "realization of the expected benefits of IS use" (Bhattacherjee 2001a, p. 355-356).

Confirmation in the IS continuance model is determined by the extent to which perceptions of performance is in congruence with pre-use expectations, similar to the feedback dimension in the TPC model. In the context of interactive data technology, previous accounting research suggest that interactive financial reporting in XBRL may improve performance in financial analysis tasks by facilitating information acquisition and information integration (e.g. Hodge et al. 2004; Arnold et al. 2012; Tang et al. 2014). However, if the purported benefits of interactive data technology are not realized, the extent of confirmation will be reduced, which would subsequently affect future interactive data technology use.

Venkatesh et al. (2011) advocate the extension of the IS continuance model with considerations of different aspects of an IS, similar to expectations of performance, which may be subject to revision following prior IS use. Particularly, Venkatesh et al. (2011) assert that consideration of an IS usage context is important in extending the IS continuance model because there may be different IS contexts where performance effects are not the only concern. For example, Bhattacherjee (2001b) examines the antecedents to electronic commerce service continuance and contextualizes confirmation along a customer's expectation of three dimensions - marketing, sales, and service. According to TPC, task-technology fit is defined as "the correspondence between task requirements, individual abilities, and the functionality and features of the technology" (Goodhue 2006, 190). Task-technology fit represents the match between task requirements and technology functionalities and is considered an antecedent to precursor attitudes and beliefs toward technology use in the TPC model. Thus, this study also considers the role of task-technology fit from the TPC model as a dimension of confirmation in the IS continuance model.

Figure 8 presents the proposed research model. The proposed research model contextualizes confirmation in the IS continuance model with two constructs from the TPC model – performance and task-technology fit. Evidence from social psychology and IS studies support the notion that past behavior influences future attitudes, beliefs, and behavior (e.g. Chaiken and Stangor 1987; Taylor and Todd 1995a; Bajaj and Nidumolu 1998; Venkatesh et al. 2002). Bajaj and Nidumolu (1998) suggest that past usage can create a positive feedback loop that can explain continued IS usage. In addition, a few IS studies have considered the impact of task-technology fit as an antecedent to satisfaction and perceived usefulness following previous use of a technology (e.g. Larsen et al. 2009; Lin 2012; Lin and Wang 2012). Within the context of interactive data technology, satisfaction is defined in the research model as the extent to which prior use of interactive data technology during a financial analysis task induces positive moods or attitudes about future interactive data technology use. In addition, perceived usefulness is defined as a user's expectation of the probability that using interactive data technology will increase performance while conducting financial statement analysis. The following hypotheses are proposed:

H1: Higher levels of task-technology fit will have a positive effect on user assessments of satisfaction.

H2: Higher assessments of performance will have a positive effect on user assessments of satisfaction.

H3: Higher levels of task-technology fit will have a positive effect on perceived usefulness.

H4: Higher assessments of performance will have a positive effect on perceived usefulness.

According to the IS continuance model, perceived usefulness has a positive impact on satisfaction. The relationship between perceived usefulness and satisfaction is examined in the proposed research model. In the context of interactive data technology, if a user experiences an expected or better effect of interactive data technology use on performance, the experiential feedback from initial use of interactive data technology is positive, which should subsequently induce positive attitudes and affect towards future interactive data technology use. This leads to the following hypothesis:

H5: Perceived usefulness will have a positive effect on user satisfaction.

According to the IS continuance model, IS continuance intention is determined by both user satisfaction and perceived usefulness. The relationships between perceived usefulness, satisfaction, and IS continuance intention is also examined within the proposed research model. User satisfaction following initial IS use is similar to the attitude construct in IS models of technology use (Bhattacherjee 2001b). Satisfaction facilitates the repeated occurrence or discontinuation of an action. Similar to a customer's repurchase decision, if a user is satisfied (dissatisfied) with prior use of interactive technology, a positive (negative) feeling is attributed to future use (Bhattacherjee 2001a; Limayem et al. 2007). Perceived usefulness has been shown to be a stable determinant of user intentions in both the pre-adoption and post-adoption stages of using a technology (e.g. Bhattacherjee 2001a; Bhattacherjee 2001b; Limayem et al. 2007).

Perceived usefulness and satisfaction both represent the rational and affective elements of behavioral intention, respectively (Bhattacherjee 2001b). This leads to the following hypotheses:

H6: Perceived usefulness will have a positive effect on IS continuance intention.

H7: User satisfaction will have a positive effect on IS continuance intention.

Although not explicitly stated, the IS continuance model implies that the intention to continue IS use is a determinant of the choice to continue usage or actual utilization (Limayem et al. 2007). In addition, this implication is consistent with theories in IS and psychology that examine the determinants of actual behavior and present behavioral intention as an important predictor of behavior (e.g. The Technology Acceptance Model [Davis 1989], Theory of Planned Behavior [Azjen 1991]). Research that has examined the IS continuance model has examined both IS continuance intention (e.g. Larsen et al. 2009; Lin and Wang 2012) and utilization (e.g. Limayem and Cheung 2008) as the dependent variables of interest. In addition, Bhattacherjee and Barfar (2011) advocate considering continuance behavior or use in testing the IS continuance model because it is possible for a discrepancy to exist between reported user intentions and actual behavior. This study is concerned with examining the effects of the experiential feedback following interactive data technology use on future choice to use the technology. Therefore, a link between IS continuance intention and utilization is hypothesized as follows:

H8: IS continuance intention will have a positive effect on utilization.

Research Design and Methodology

This study represents the second phase of a two-phase broader study designed to improve our understanding of the performance impacts of interactive data technology and the factors that influence the initial adoption and continued use of interactive data technology. Participants were exposed to two interactive financial reporting technologies in the first phase of this study (see Chapter 2 for more detail), which occurs prior to the task for the current study. In phase one, participants conducted two financial analysis tasks, each with a different interactive reporting technology – the SEC's Electronic Data Gathering Analysis and Retrieval (EDGAR) interactive viewer, and Calcbench's online analysis tool. The two interactive technologies differ in the degree of interactivity and the availability of visualization tools (i.e. graphical interface) present²⁰.

This study examines the relationship between previous technology use (e.g. phase one) on future technology choice (e.g. phase two). The dependent variable of interest in this study is utilization which is defined as the degree of reliance on the interactive data technology that the respondent chooses to use during a financial analysis task. Structural equation modeling is used to examine the research and structural models due to the inclusion of measured variables in the research model. Structural equation modeling facilitates the simultaneous testing of the validity of the items used to measure the constructs and the strength of the relationships between the constructs (Chin 1998; Elbashir et al. 2013). In addition, structural equation modeling is "particularly useful in testing theories that contain multiple equations involving dependence relationships" (Hair et al. 2010, 612), similar to the proposed research model.

Participants

This study is primarily interested in the factors that contribute to a nonprofessional investor's choice of financial reporting technology while conducting a financial analysis task.

²⁰ In phase one, all participants are exposed to the interactive and financial analysis features in both the SEC's EDGAR interactive viewer and the Calcbench analysis tool. However, the visualization tools are only available in the Calcbench analysis tool and only half of the participants are exposed to the visualization tools.

Participants are graduate business students enrolled at four large state universities and one private university who served as surrogates for nonprofessional investors. Graduate business students are used as surrogates for online investors because they possess many of the same characteristics as online traders (Hodge 2001). Graduate business students typically have an understanding of basic accounting and finance, use the Web to retrieve information, are more open to new technologies, and are generally more self-motivated and highly educated than investors who do not engage in online trading (Hodge et al. 2004).

Participants were recruited by offering participation in this study as an alternative to completing a case or assignment for course credit. Data collection for this study commenced upon completion of phase one. A total of 234 email invitations were sent to participants, including the web link to participate in phase one. 170 participants were retained for the analysis in phase one. From those 170 participants, three chose not to proceed to phase two and one participant did not complete the task in phase two. All of the subsequent analyses pertain to the remaining 166 participants. Of the 166 participants, 136 were masters of accounting students, 16 were masters of business administration (MBA) students who had completed their core graduate accounting course, and 14 were professional MBA students. Participant demographics are summarized in Table 14.

Case Materials and Procedure

In this study, participants are instructed to assume the role of an investor evaluating companies for potential investment. The case instructs participants to conduct a financial analysis task using their choice of two interactive financial reporting technologies. The case informs participants that they will evaluate two companies – Gordmans Stores, Inc and Zumiez,

Inc. Participants are instructed to assume they have \$10,000 to potentially invest in the common stock of Gordmans or Zumiez, and that they should evaluate Gordmans and Zumiez relative to one another. Both companies in the case are described as companies in the retail sector. Participants are informed that Gordmans is a value retailer of name brand apparel and home fashions with over 90 stores in 19 states nationwide. Zumiez is described as a specialty apparel store that sells action-sports related clothing for sports like skateboarding, snowboarding, and surfing. Zumiez currently operates over 500 stores in the United States and Canada. The case instructs participants to evaluate the financial condition and earnings potential of Gordmans and Zumiez using five financial metrics – return on assets, current ratio, inventory turnover, gross profit margin, and return on equity. Participants are informed that these metrics represent a select number of financial ratios that are used to evaluate the performance of companies in the retail sector.

Prior to beginning the financial analysis task, participants are instructed to refer to their experience with their previous use of the two interactive reporting technology tools and to choose between using the SEC's EDGAR interactive viewer or Calcbench's analysis tool to conduct their financial analysis. Participants are instructed that once they make a choice, they can no longer go back and switch reporting technologies. Following their choice, participants are asked to briefly state why they selected the technology they chose. In addition, participants are asked to respond to scale measurement items designed to elicit responses measuring task-technology fit, performance impact, perceived usefulness, satisfaction, and continuance intention. Responses to these items are elicited at this point in the exercise in order to obtain user perceptions before their repeated use of the interactive technology of their choice. This provides

insights on the theorized effects of prior perceptions on future behavior. After recording their responses to the measurement items, participants proceed to completing the financial analysis task. To conduct the analysis, participants complete a questionnaire which requires computing the five financial metrics, assessing each firm's performance, and deciding in which company they would invest \$10,000. After completing the questionnaire, participants respond to questions designed to elicit responses on their extent of utilization of the technology chosen. Figure 9 presents a timeline of the experimental task.

Exogenous Variables

Scales are adapted from previous research to measure task-technology fit and performance. Both scales utilize five-point Likert-type scales anchored at strongly disagree and strongly agree²¹.

Task-Technology Fit

Task-technology fit is measured via a multi-dimensional scale. The TTF scale is adapted from Goodhue and Thompson (1995) and Goodhue (1998). Goodhue (1998) identifies and develops sixteen dimensions of TTF related to information needs during a decision-making task. The TTF dimensions examined in this study are contextualized based on the requirements of a financial analysis task (i.e. information acquisition and information integration). Based on a review of this research, the current study identifies five dimensions of TTF relevant to using a technology in a financial analysis task. The five TTF dimensions examined in this study are accessibility, ease of use, flexibility, compatibility, and presentation. Table 15 details the constructs that form TTF, their meaning, and the measurement items.

²¹ Both the task-technology fit scale and the performance scale were also used in phase one.

Performance

Performance is measured via the perceived performance impact scale adapted from Goodhue and Thompson (1995). The original scale includes two items designed to measure individual perceptions of technology's performance impact. The adapted scale is expanded to include four items. Table 15 details the performance construct and its corresponding measurement items.

Endogenous Variables

Scales are adapted from previous research to measure perceived usefulness, satisfaction, IS continuance intention, and the extent of utilization. All scales utilize five-point Likert-type scales, anchored at strongly disagree and strongly agree. Table 15 details these constructs and their corresponding measurement items²².

Perceived Usefulness

The perceived usefulness scale is adapted from Davis et al. (1989) and Davis (1989) and includes four items included in the perceived usefulness scale in the technology acceptance model (TAM). The adapted scale is designed to capture the degree to which a user believes that using interactive data technology was useful while conducting financial statement analyses.

Satisfaction

The satisfaction scale is adapted from Bhattacherjee (2001a; 2001b) and includes six items from the original scale. The satisfaction scale was designed to measure a user's satisfaction with their use of interactive financial reporting technology. In addition, the reverse coded items from the original scale were reworded in this study in order to eliminate the reverse coding.

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²² The perceived usefulness scale was also used in phase one.

IS Continuance Intention

The continuance intention scale is adapted from Bhattacherjee (2001a; 2001b). The original scale includes three items. The adapted scale is contextualized for the continued use of interactive reporting technology and includes the original three items, with an additional item added to maintain a four-item scale. The additional item asks if the user would continue the use of the interactive data technology for financial analysis tasks.

Utilization

In this study, utilization is defined as the degree of reliance on the interactive data technology that a user chooses to use during a financial analysis task. Utilization is operationalized using Hampton's (2005) scale originally designed to measure an individual's degree of reliance on a decision aid. The adapted scale includes four items designed to evaluate an individual's reliance on their choice of interactive data reporting technology during their decision making.

Data Analysis and Results

The measurement and structural models represented in the proposed research model are tested using partial least squares (PLS), a components-based structural equation modeling technique. PLS allows the modeling of both reflective and formative constructs in the same model (Hair et al. 2010)²³. In the research model, the task-technology fit construct is multi-dimensional in nature and measured using a formative approach. All other constructs in the

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²³ A construct can be reflective or formative in the way in its measurement. A reflectively measured construct is based on the assumption that the construct causes the indicators or measured variables (Hair et al. 2010). The direction of causality is from the construct to the measured variables. In a formatively measured construct, the direction of causality is reversed and the assumption is that the measured variables form the construct (Hair et al. 2010).

research model are reflective in nature. SmartPLS 2.0 (Ringle et al. 2005) is used to validate and test the measurement and structural models represented in the research model. Bootstrapping (1000 samples) resampling is used to generate t-statistics for conducting the statistical analysis. The measurement model and the structural model are discussed in the following sections.

Measurement Model Reliability and Validity

Factor loadings, composite construct reliability, and average variance extracted (AVE) are employed to assess the convergent and discriminant validity of the reflective constructs. Convergent validity identifies how well indicators of a specific latent construct capture the variance in the construct (Hair et al. 2010). Table 16 reports item loadings and cross loadings. All item loadings are greater than 0.70. Table 17 reports the related composite reliability and AVE for each reflective construct. The related composite reliability for each construct is greater than the recommended 0.70, and all AVE are greater than 0.50 supporting the convergent validity of the reflective constructs (Fornell and Larcker 1981; Hair et al. 2010). Discriminant validity identifies the extent to which a construct is truly distinct from other constructs (Hair et al. 2010). Table 17 also reports the construct correlations and the square root of AVE. The square root of all AVE is larger than the correlations between the constructs, supporting discriminant validity (Chin 1998).

Task-technology fit is a second order formative construct comprised of five dimensions, measured reflectively – accessibility/locatability, ease of use, flexibility, compatibility, and presentation. Task-technology fit is estimated by first estimating factor scores for the reflective item measures representing the five dimensions using principal components analysis with promax rotation. Construct validity and reliability for the second order formative construct are

evaluated according to the recommendations specified in Petter et al. (2007). First, to assess validity, principal components analysis with oblique rotation is used to examine item weightings for the five dimensions of task-technology fit using each construct's factor scores. As shown in Panel A of Table 18, all items load on the second order latent construct ranging from 0.743 to 0.833, with 63.09% of variance explained. Second, the presence of multicollinearity is determined in order to evaluate reliability. Variance inflation factors (VIF) are calculated using the factor scores from the five first order dimensions and dependent measures for perceived usefulness and satisfaction²⁴. As shown in Panel B of Table 18, all VIFs range from 1.597 to 2.078, falling below the suggested cutoff of 3.3 (Diamantopoulos and Siguaw 2006; Petter et al. 2007), suggesting that the task-technology fit construct is reliable.

Common Method Bias

As with all self-reported data, there is a potential for common method bias. Common method bias represents "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podaskoff et al. 2003, p. 879). The single unmeasured latent common factor method test was performed to rule out the presence of common method bias in this study (Podsakoff et al. 2003; Liang et al. 2007).

Following Podsakoff et al. (2003) and Liang et al. (2007), a common method construct was added to the measurement model. The first step in carrying out this test is to create a single indicator construct for each indicator in the measurement model and link each single indicator to the substantive construct it is designed to measure. Therefore, a single item indicator was created

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²⁴ Composite scores were calculated for perceived usefulness and satisfaction based on the mean participant responses on the perceived usefulness and satisfaction scales.

for every item measure in this study and linked to their corresponding substantive construct (e.g. Performance, Continuance Intention, etc). Second, a common method factor is added to the model and includes all of the indicators used in the model. Finally, a link is created between the common method construct and each single indicator construct. Common method bias is assessed by examining the path coefficients and significance of the links between the substantive constructs and single item indicator constructs as well as the path coefficients and significance of the links between the common method construct and the single item indicator constructs. Common method bias is determined to have minimal effect "if the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances" (Liang et al. 2007, p. 87). The results of this test are detailed in Table 19. The results indicate that the variance of the indicators to the substantive constructs is greater than the variance to the common method construct. In addition, all of the loadings on the common method construct are not statistically significant. Finally, the average variance extracted due to the substantive constructs is 80% compared to 2% for the common method construct. Thus, common method bias is deemed to be of no concern in this study.

Hypotheses Tests

Participants were asked to state the reasons behind their choice of technology. Three recurring reasons reported for the participants who chose to use the low interactivity software were repeated prior experience with the software, the similarity between the viewer's display format and the format of financial statements, and ease of use. For participants who chose to use the higher interactivity software, the reasons cited include the ability to compare companies side by side, the ability to quickly find and select the specific data needed, and ease of use. Forty

participants chose to use the SEC's EDGAR interactive viewer, while one hundred and twenty-six participants chose to use the Calcbench analysis tool²⁵.

The hypothesized relationships and the entire research model are examined using PLS analysis. Figure 10 presents the structural model with path loadings and significance levels related to the hypothesized relationships. The model explains 58.7% of the variance in perceived usefulness, 46.9% of the variance in satisfaction, 54.4% of the variance in IS continuance intention, and 36.3% of the variance in utilization.

H1 and H2 examine the impact of task-technology fit and performance on satisfaction with using interactive data technology. H1 predicts that task-technology fit will have a positive effect on user assessments of satisfaction. Consistent with H1, task-technology fit has a significant and positive effect on satisfaction (β = 0.339, p < 0.001). This suggests that higher task-technology fit leads to higher satisfaction with interactive data technology use. H2 predicts that performance will have a positive effect on user assessments of satisfaction. Consistent with H2, performance has a significant and positive effect on satisfaction (β = 0.171, p < 0.05). Thus, financial statement users will experience higher satisfaction with interactive data technology use when their perceptions of performance are high. Taken together, these results suggest that both task-technology fit and performance impact post-use affect following interactive data technology use.

²⁵ Out of the 126 who chose to use Calcbench's analysis tool, 67 participants had also used the visualization tool in phase one. Thirty-seven (55.22 percent) of those participants used the visualization tool again in this study while completing the task. In addition to the reasons cited for choosing Calcbench, another reason cited among these participants was the provision of a graphical tool to view trends.

H3 and H4 examine the effects of task-technology fit and performance on the perceived usefulness of interactive data technology. H3 posits that higher levels of task-technology fit will have a positive effect on perceived usefulness. Consistent with this prediction, task-technology fit has a significant and positive effect on perceived usefulness (β = 0.292, p < 0.01). H4 predicts that the performance will have a positive effect on perceived usefulness. The results indicate that performance has a significant and positive effect on perceived usefulness (β = 0.526, p < 0.001). Taken together, these results suggest that both task-technology fit and performance impact the belief that using interactive data technology is beneficial.

H5 examines the effect of perceived usefulness on satisfaction. H5 predicts that, perceived usefulness will have a positive effect on satisfaction following initial use of a technology. The results indicate that perceived usefulness has a marginally significant effect on satisfaction ($\beta = 0.250$, p = 0.057).

H6 and H7 examine the impact of perceived usefulness and satisfaction on IS continuance intention. H6 predicts that perceived usefulness will have a positive effect on IS continuance intention. Consistent with this prediction, the results indicate that perceived usefulness has a positive and significant effect on IS continuance intention (β = 0.316, p < 0.05). H7 predicts that satisfaction will have a positive effect on IS continuance intention. As indicated in the results, this hypothesis is supported and satisfaction has a positive and significant effect on IS continuance intention (β = 0.502, p < 0.001).

Finally, H8 examines the link between IS continuance intention and the extent of utilization. The research model developed in this study extends the IS continuance model and

proposes that IS continuance intention should affect actual utilization. Previous IS research (e.g. Bhattacherjee and Sanford 2009) has suggested that there exists an intention-behavior gap in intention-based research models, which is defined as a low correlation between individual intentions and actual behavior. Bhattacherjee and Barfar (2011) advocate considering continuance behavior or actual use in testing the IS continuance model because it is possible for a discrepancy to exist between reported user intentions and actual behavior. Thus, H8 predicts that IS continuance intention will have a positive effect on utilization. The results are consistent with H8 (β = 0.603, p < .001), supporting the extension of the IS continuance model to include actual behavior (utilization). Taken together, the results of hypotheses testing suggest that variables from TPC model are important in explaining a user's continued use of interactive data technology. Specifically, the results indicate that for nonprofessional investors to continue using interactive data technology past the initial use/adoption stage, the interactive data technology must be perceived as supporting task requirements while conducting financial analyses, and providing performance impacts.

The results of hypotheses testing indicate strong support for the effects of task-technology fit and performance on the constructs in the IS continuance model. Following the tests for direct effects in the structural model, the indirect and total effects of task-technology fit and performance are examined. While the path coefficients and t-statistics of the total effects are generated in PLS, the path coefficients of the indirect effects are generated using the product term of the coefficients of the related direct paths and bootstrap procedures are used to construct 99 percent (p < 0.01) confidence intervals for testing the significance of the indirect effects (Hayes 2009; Elbashir et al. 2013).

The indirect and total effects of task-technology fit on satisfaction, IS continuance intention, and utilization are reported in Table 20. Panel A of Table 20 displays a summary of the indirect effects of task-technology fit. The results show that task-technology fit indirectly affects satisfaction through perceived usefulness (0.073, p < 0.01). The results also indicate that task-technology fit indirectly affects IS continuance intention through perceived usefulness (0.092, p < 0.01), through satisfaction (0.170, p < 0.01), and through perceived usefulness and satisfaction (0.037, p < 0.01), resulting in a total indirect effect of 0.299 on IS continuance intention. Finally, the results show that task-technology fit indirectly affects utilization through perceived usefulness and IS continuance intention (0.056, p < 0.01), through satisfaction and IS continuance intention (0.102, p < 0.01), and through perceived usefulness, satisfaction, and IS continuance intention (0.022, p < 0.01), resulting in a total indirect effect of 0.180 on utilization.

Given that the structural model tests for the direct effect of task-technology fit on satisfaction, the total effect of task-technology fit on satisfaction is the sum of the direct and indirect effects of task-technology fit on satisfaction. On the other hand, the structural model does not test for the direct effect of task-technology fit on IS continuance intention or utilization, and the total effects of task-technology fit on IS continuance intention and on utilization are equal to the total indirect effects. Panel B of Table 20 shows the t-statistics for the total effects of task-technology fit on satisfaction, IS continuance intention, and utilization, and they are all statistically significant. Overall, these results suggest that it is important to consider different aspects of an IS, similar to performance expectations that may be subject to revision following prior IS use, as advocated by Venkatesh et al. (2011). In particular, this study examines the impact of task-technology fit as a dimension of confirmation in its consideration of IS

continuance. The results indicate that task-technology fit has significant effects on user beliefs that using interactive data technology will improve performance and on the post-use affect following interactive data technology use. In addition, task-technology fit has significant effects on a user's intention to continue interactive data technology use through its effect on perceived usefulness and satisfaction, with subsequent effects on actual utilization.

The indirect and total effects of performance on satisfaction, IS continuance intention, and utilization are reported in Table 21. Panel A of Table 21 displays a summary of the indirect effects of performance. The results show that performance indirectly affects satisfaction through perceived usefulness (0.131, p < 0.01). The results also indicate that performance indirectly affects IS continuance intention through perceived usefulness (0.166, p < 0.01), through satisfaction (0.086, p < 0.01), and through perceived usefulness and satisfaction (0.066, p < 0.01), resulting in a total indirect effect of 0.318 on IS continuance intention. Finally, the results show that performance indirectly affects utilization through perceived usefulness and IS continuance intention (0.100, p < 0.01), through satisfaction and IS continuance intention (0.052, p < 0.01), and through perceived usefulness, satisfaction, and IS continuance intention (0.040, p < 0.01), resulting in a total indirect effect of 0.192 on utilization.

Given that the structural model tests for the direct effect of performance on satisfaction, the total effect of performance on satisfaction is the sum of the direct and indirect effects of performance on satisfaction. On the other hand, the structural model does not test for the direct effect of performance on IS continuance intention or utilization, and the total effects of performance on IS continuance intention and on utilization are equal to the total indirect effects.

Panel B of Table 21 shows the t-statistics for the total effects of performance on satisfaction, IS continuance intention, and utilization and they are all statistically significant. Overall, these results suggest that it is important to consider how user assessments of performance after initial use of technology influences future technology use as advocated in the TPC model. In particular, this study examines the impact of prior assessments of performance as a dimension of confirmation in its consideration of IS continuance. The results indicate that perceptions of performance have significant effects on perceived usefulness and on the post-use affect following interactive data technology use. In addition, performance has significant effects on a user's intention to continue interactive data technology use through its effect on perceived usefulness and satisfaction, with subsequent effects on actual utilization.

Supplemental Analyses

The results of model estimation and testing indicate strong support for the research model developed in this study. Out of the 166 participants in this study, 75.9 percent (126 participants) chose to use the Calcbench analysis tool to conduct their financial analysis task, while the remainder of participants chose to use the SEC's EDGAR interactive viewer²⁶. Janvrin et al. (2013) investigated user choice in the context of interactive data technology and found that for participants who chose to use an XBRL-enabled technology, their choice was primarily driven by perceptions of efficiency gains. However, technology choice was primarily driven by greater experience with the technology for participants who chose to use Excel (Janvrin et al. 2013). In

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²⁶ The two interactive technologies differ in the availability of interactive and visualization features. For example, EDGAR employs two interactivity techniques – exploring and filtering in its interactive viewer. On the other hand, Calcbench employs four interactivity techniques – exploring, filtering, selection, and abstraction/elaboration. In addition, the Calcbench interactive tool employs the encoding technique in making visualization available to users, while EDGAR does not have a visualization feature.

order to better understand the factors pertinent to interactive data technology choice and utilization, additional analyses are conducted to explore potential group differences between participants who chose to use the SEC's EDGAR interactive viewer and participants who chose to use the Calcbench analysis tool. The study sample is subdivided into two groups, Calcbench and EDGAR based on technology choice. The Calcbench group contains 126 responses from participants who chose to use Calcbench, while the EDGAR group contains the remaining 40 responses from participants who chose to use the SEC's EDGAR interactive viewer. Model estimation is then conducted independently for the Calcbench sample and the EDGAR sample.

Model configuration and results for the EDGAR group are presented in Figure 11. This model is identical in structure to the original research model presented in Figure 10. A closer examination of the results from the EDGAR group shows that the relationship between task-technology fit and satisfaction, and the relationship between performance and satisfaction are no longer significant. In addition, the relationship between perceived usefulness and satisfaction now shows increased statistical significance, while the relationship between perceived usefulness and continuance intention is no longer significant. This suggests that for the group who chose to use Edgar, continuance intention is primarily determined by satisfaction with initial or previous use of interactive data technology and not perceived usefulness. Perceived usefulness and satisfaction both represent the rational and affective elements of behavioral intention, respectively (Bhattacherjee 2001b). This finding thus suggests that for participants who chose to use the SEC's EDGAR interactive viewer, the confirmation of perceptions of instrumentality (satisfaction) supersedes and is more important in determining their continuance intention and utilization relative to the instrumentality of interactive data technology (perceived usefulness).

Model configuration and results for the Calcbench group are presented in Figure 12. This model is identical in structure to the original research model presented in Figure 10. However, the results show that the relationship between perceived usefulness and satisfaction is no longer significant. This finding suggests that for the Calcbench group, IS continuance intention and subsequently, utilization, is primarily driven by both the rational assessments of the usefulness of interactive data technology and the post-use affective reactions to the confirmation of perceptions of interactive data technology instrumentality.

Table 22 details the results of chi-square difference tests for each of the hypothesized paths between the EDGAR group and the Calcbench group. The results indicate that there are significant group differences between the EDGAR and Calcbench group for the relationship between performance and satisfaction, and the relationship between perceived usefulness and IS continuance intention. This suggests that for the Calcbench group, performance is a more important determinant of satisfaction, and perceived usefulness is a more important determinant of IS continuance intentions.

Prior IS research (Bhattacherjee and Barfar 2011) suggests that satisfaction or affective processing may assume a dominant role in determining IS continuance relative to perceived usefulness or reasoned processing, depending on the stage of use. In particular, rational processing is more likely to determine use when the relationship between a technology and use is not fully developed, such as with new technology (Bhattacherjee and Barfar 2011). On the other hand, increased experience with a technology will facilitate the development of the technology to use relationship, such that users rely less on rational processing and more on affective processing

in determining use because affective processing is more efficient and utilizes less cognitive resources (Bhattacherjee and Barfar 2011). The results of supplemental analyses support this assertion. Participants who chose to use the EDGAR interactive viewer cited prior experience with the technology and familiarity with EDGAR's presentation format as reasons for their choice, while participants who chose to use Calcbench primarily cited efficiency gains, including the ability to compare companies side by side, and the ability to quickly find and select the specific data needed.

Summary and Conclusions

This study investigates the role of experiential feedback following the use of interactive financial reporting technology on future choice to use the technology. In an effort to improve financial reporting and analysis, the SEC issued a mandate requiring that all public companies provide their financial information to the SEC and on their corporate website in an interactive format using XBRL. Interactive financial reporting is expected to provide many benefits to investors, including the efficient gathering and evaluating of financial information, increase in financial reporting transparency, and facilitating the comparison of financial information from multiple companies and over multiple periods. However, the benefits of interactive data technology cannot be realized if investors choose not to use it. This study incorporates insights from the technology-performance chain model and the IS continuance theory to examine the antecedents to IS continuance in the context of interactive data visualization technology.

Anecdotal evidence suggests that investors generally make a choice between reporting technologies based on how well the technology supports their information needs (e.g. Hodge and

Pronk 2006; Janvrin et al. 2013). Janvrin et al. (2013) found that most users preferred an XBRL reporting format to Excel or PDF after going through a tutorial on how to use the three reporting formats. However, in Hodge et al. (2004), participants chose not to use an XBRL-enabled tool even when it was made available. This suggests that the choice to use interactive financial reporting technology might be dependent on prior exposure or experience with the technology. The current study therefore contributes to this research stream by exploring the antecedents that affect the choice to use an interactive data technology.

The findings in this study suggest that prior assessments of the fit between interactive data technology and task requirements in a financial decision-making task serve as an antecedent to the belief that interactive data technology improves performance and to the extent a user's expectation about interactive data technology is confirmed or disconfirmed following initial use. Thus, higher assessments of task-technology fit leads to increased assessments of the usefulness of interactive data technology and increased satisfaction with interactive data technology use. In addition, the results also indicate that perceptions of performance lead to increased assessments of the usefulness of interactive technology and increased satisfaction with interactive data technology use. As expected, perceptions of usefulness as well as satisfaction increase the intention to continue interactive data use, which in turn leads to an increase in the extent of utilization.

The results were further examined by separately grouping participant responses based on the interactive data technology chosen. The results reveal that for participants who chose to use the lower interactive software, task-technology fit and performance have positive effects on perceived usefulness, which in turn has significant positive effects on satisfaction. However, task-technology fit and performance do not impact satisfaction directly. In addition, satisfaction is the primary determinant of IS continuance intention and perceived usefulness no longer has a significant effect on IS continuance intention. On the other hand, task-technology fit and performance have significant effects on satisfaction and perceived usefulness for participants who chose the high interactivity software. However, perceived usefulness does not have an impact on satisfaction. Bhattacherjee (2001a) defines perceived usefulness as the degree to which the use of an IS facilitates improved task performance, while satisfaction is the post-use affect as a result of using a technology. Bhattacherjee (2001b) asserts that perceived usefulness represents the rational dimension of behavioral intentions, while satisfaction represents attitudes or the affective dimension. In the IS continuance model, user satisfaction is affected by the perceptions of the instrumentality of a technology. Overall, the results from the low interactivity group are consistent with this expectation. However, the results also suggest that the affective dimension of behavioral intention supersedes the rational dimension in determining continuance intentions and ultimately, utilization for participants who chose the low interactivity software.

As discussed in Clements et al. (2011), XBRL-enabled interactive financial reporting technologies differ in the levels of interactivity and other features made available to users. Therefore, the results of the supplementary analyses provide an initial interesting exploration into the factors that motivate the intention to reuse, and the choice to utilize interactive financial reporting technology. The results suggest that for users who select lower interactive software (e.g. the SEC's EDGAR interactive viewer), their continuance intention and choice is not driven by high perceptions of usefulness, but primarily by their satisfaction with interactive data

technology use. On the other hand, for users who select a higher interactive software (e.g. Calcbench), satisfaction from prior use and perceptions of usefulness represent complementary processes that motivate the intention to reuse and the choice to utilize interactive financial reporting technology.

Participants were asked to state the reasons behind their choice of technology. Two recurring reasons reported for the participants who chose to use the low interactivity software was repeated prior experience with the software, and the similarity between the viewer's display format and the format of financial statements. For participants who chose to use the higher interactivity software, the reasons cited include the ability to compare companies side by side, the ability to quickly find and select the specific data needed, and ease of use. These findings are similar to prior user choice research in the context of interactive data technology (e.g. Janvrin et al. 2013), which report efficiency gains as the primary determinant for the choice to use XBRLenabled technology. In addition, prior experience supersedes the perception of usefulness when users are more familiar with a technology (e.g. Janvrin et al. 2013). However, a limitation of the comparison between the low interactivity group and the high interactivity group is the small sample size in the former group due to the limited number of users who chose to use the low interactive software. It is likely that the analyses for the low interactivity group lack enough power for good testing given the small sample size. Future studies on the topic would be needed in order to explicate the persistence of the theoretical effects explored in the supplementary analyses. Future research in this area can also examine changes in the antecedents to continued use as interactive data technology becomes more widely available and investors are exposed to repeated use. Another limitation of this study is that it required a significant amount of time to

complete both phases. It is possible that the choice to use the high interactivity software in this phase is primarily driven by efficiency concerns because the software provided calculated financial ratios and was quicker to use.

This research also has practical implications for standard setters and software developers. Debreceny and Gray (2001) assert that the provision of XBRL-enabled financial reports should fuel the development of interactive data viewers and research is needed on developing such tools and understanding their impact on decision-making in a financial context. This research study presents an initial analysis of this relationship. The research reported in this study contributes to XBRL-related research examining the impact of interactive reporting on decision-making. Although the evidence from extant research support the claim that interactive data technology improves financial decision-making performance, getting users to adopt and continue using interactive data technology remained an unexplored question. In order for technology advancements to be successful, users must adopt and continue using the technology. Results from this study provide evidence on factors that facilitate the choice to continue using interactive technology following initial use or exposure.

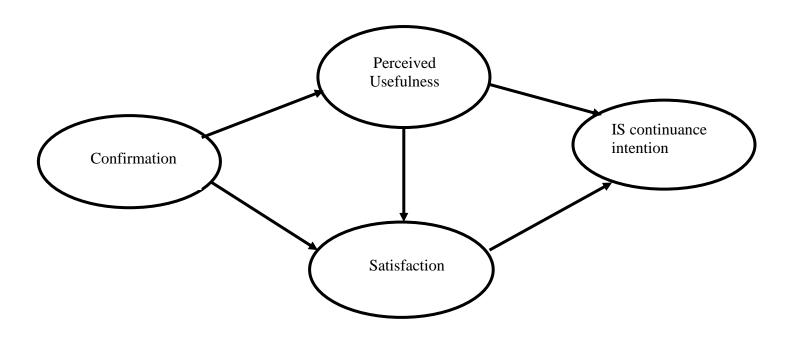


Figure 6: Model of Information Systems (IS) Continuance

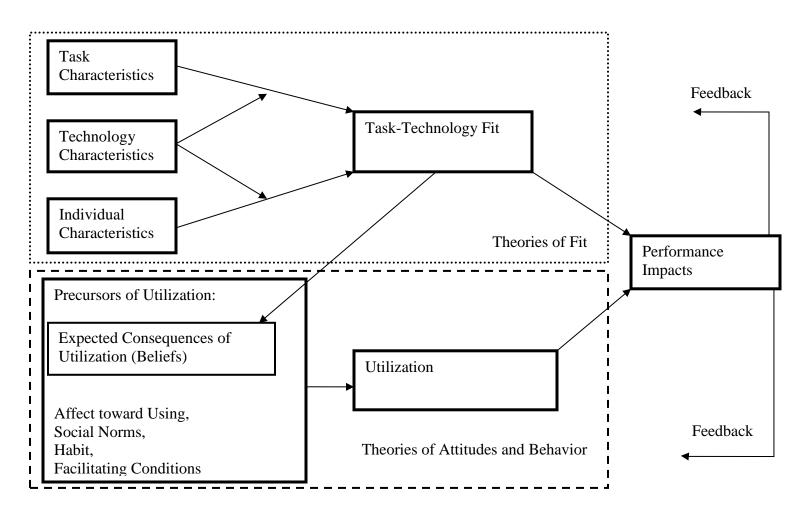


Figure 7: The Technology to Performance Chain Model

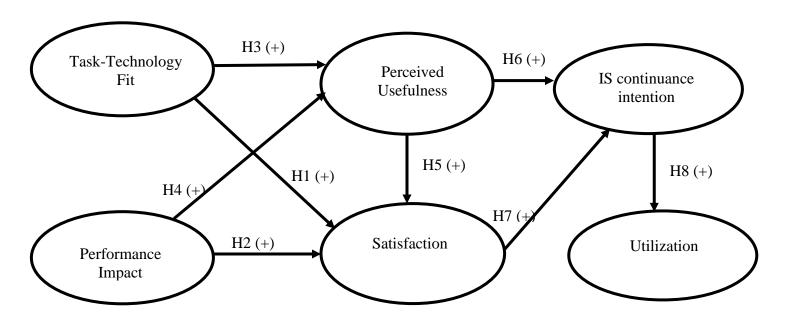


Figure 8: Theoretical Model of the Impact of Experiential Feedback on Future Technology Choice

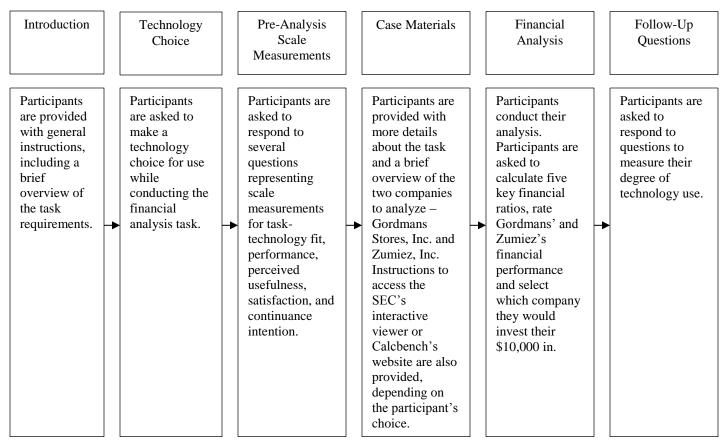


Figure 9: Timeline of Experimental Task

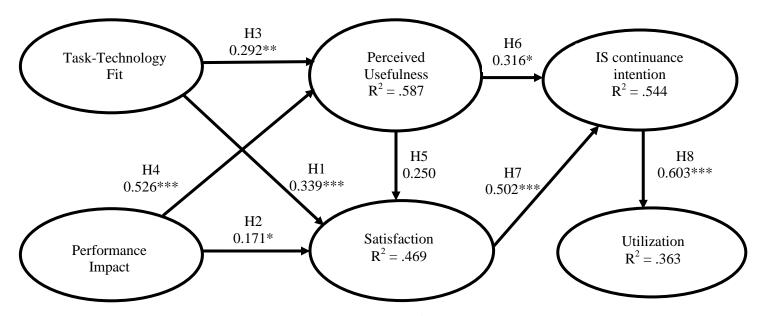


Figure 10: Results of Research Model Testing

^{*} p < 0.05

^{**} p < 0.01 *** p < 0.001

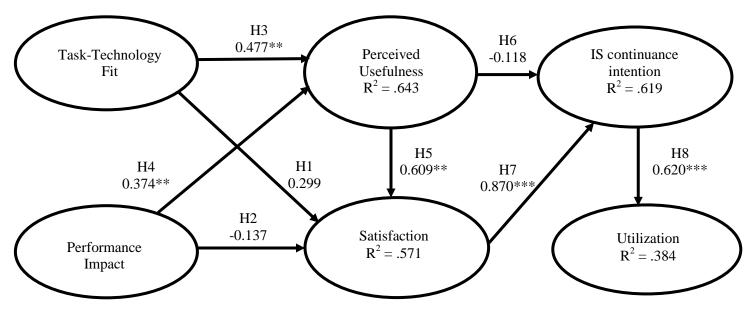


Figure 11: Impact of Experiential Feedback on Future Technology Choice – EDGAR Model Results

 $[\]begin{array}{ll} * & p < 0.05 \\ ** & p < 0.01 \\ *** & p < 0.001 \end{array}$

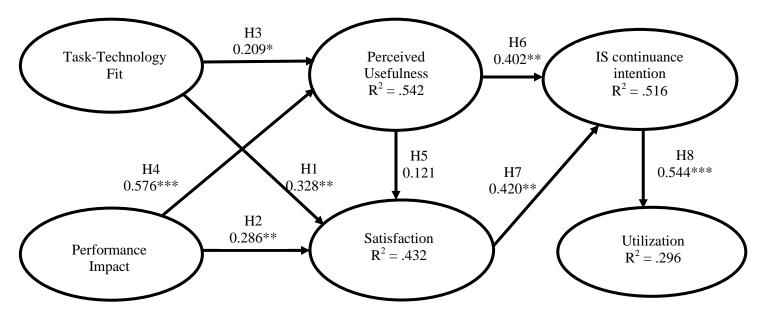


Figure 12: Impact of Experiential Feedback on Future Technology Choice - Calcbench Model Results

^{*} p < 0.05

^{**} p < 0.01

^{***} p < 0.001

Table 14: Participant Demographics

Item	Frequency (n = 166)	Percent
Panel A: Gender		
Male	82	49.40
Female	83	50.00
Did not answer	1	0.60
Panel B: Age (in years)		
Under 25	90	54.22
25 to 40 years	62	37.35
40+ years	14	8.43
Panel C: Full-time Work Exp	perience (in years)	
< 1 year	43	25.90
1 to 2 years	26	15.66
3 to 6 years	49	29.52
7 to 10 years	27	16.27
10+ years	21	12.65
Panel D: Bought or sold com	mon stock or debt securities	
Yes	40	24.10
No	126	75.90
Panel E: Number of times eva	aluated a company's performance b	y analyzing its
Never	71	42.77
1 to 5 times	56	33.73
6 to 10 times	24	14.46
10+ times	15	9.04
Panel F: Future Investment F	Plans	
Yes	130	78.31
No	36	21.69
Panel G: Courses Taken	· · · · · · · · · · · · · · · · · · ·	
Accounting	Mean = $6.63 (5.11)$	N/A
Finance	Mean = $2.06(2.75)$	N/A

Table 15: Descriptive Statistics for Item Measures

Scale Item	Item Measure Name	Mean	Median (Panga)	Standard Deviation
Task-Technology Fit (Goodhue and		Goodhu	(Range)	Deviation
Locatibility/Accessibility	Thompson 1775,	Goodila	<i>(</i> 1770)	
Please answer the following questions	regarding the fina	ancial repo	orting technology	v vou chose
(i.e. the EDGAR/CALCBENCH tool)			51 viii. g)) 0 0 0 0
This reporting technology makes it	LOC1	4.33	4.00	.625
easy to locate data.			(2.00 - 5.00)	
It is easy to find out what data is	LOC2	4.22	4.00	.695
maintained on a given subject.			(2.00 - 5.00)	
The exact definition of the data	LOC3	4.02	4.00	.814
fields relevant to this task are easy			(2.00 - 5.00)	
to find out.				
It is easy to locate the exact meaning	LOC4	3.92	4.00	.807
of data elements.			(2.00 - 5.00)	
Ease of Use				
Please answer the following questions		ancial repo	orting technology	y you chose
(i.e. the EDGAR/CALCBENCH tool)				
It is easy to learn how to use this	EOU1	4.29	4.00	.747
technology.			(1.00 - 5.00)	
I believe that this technology is easy	EOU2	4.29	4.00	.712
to use.			(2.00 - 5.00)	
I believe that it is easy to get the	EOU3	4.19	4.00	.667
technology to do what I want it to			(2.00 - 5.00)	
do.				
My interaction with the technology	EOU4	4.23	4.00	.694
is clear and understandable.			(2.00 - 5.00)	
Flexibility				
Please answer the following questions		ancial repo	orting technology	y you chose
(i.e. the EDGAR/CALCBENCH tool)		4.20	1.00	712
This technology is able to respond to	FLEX1	4.20	4.00	.713
my changing needs for data.	EL EMO	4.21	(2.00 - 5.00)	077
It is easy to change the selection of	FLEX2	4.21	4.00	.877
data while using this technology.	ELEX2	2.07	(1.00 - 5.00)	001
It is easy to change the presentation	FLEX3	3.87	4.00	.991
of data while using this technology.	ELEX/	110	(1.00 - 5.00)	920
This technology responded very	FLEX4	4.16	4.00	.829
quickly to my changing needs for			(1.00 - 5.00)	
data.				

Item Measure Name	Mean	Median (Range)	Standard Deviation					
155		(8-7						
s regarding the fina	ancial repo	orting technolog	y you chose					
	1	ε.						
t is easy to compare or consolidate COMP1 4.00 4.00								
		(1.00 - 5.00)						
COMP2	3.86	4.00	.873					
		(2.00 - 5.00)						
COMP3	4.20	4.00	.673					
		(2.00 - 5.00)						
COMP4	4.04	4.00	.853					
		(2.00 - 5.00)						
•			l					
s regarding the fina	ancial repo	orting technolog	y you chose					
	1	ε ε.	, ,					
	4.35	4.00	.694					
		(2.00 - 5.00)						
PRES2	4.36	4.00	.661					
		(2.00 - 5.00)						
PRES3	4.32	4.00	.714					
		(2.00 - 5.00)						
PRES4	4.28	4.00	.700					
		(2.00 - 5.00)						
Davis et al. 1989)			·					
	ancial repo	orting technolog	y you chose					
	•	0						
PU1	4.26	4.00	.642					
		(2.00 - 5.00)						
PU2	4.30	4.00	.663					
PU3	4.41	5.00	.652					
PU4	4.35	4.00	.650					
	-							
1		\/	1					
	Name regarding the final COMP1 COMP2 COMP3 COMP4 regarding the final PRES1 PRES2 PRES3 PRES4 Pavis et al. 1989) regarding the final PU1 PU2 PU3	Name Stregarding the financial reports COMP1	Name (Range)					

Scale Item	Item Measure Name	Mean	Median (Range)	Standard Deviation					
Continuance Intention (Bhattacherjee 2001a; 2001b)									
Please answer the following questions regarding the financial reporting technology you chose									
(i.e. the EDGAR/CALCBENCH tool).									
If I could, I intend to continue using	CI1	4.22	4.00	.700					
this financial reporting technology			(2.00 - 5.00)						
rather than discontinue its use.									
If possible, my intentions are to	CI2	3.98	4.00	.863					
continue using this financial			(1.00 - 5.00)						
reporting technology rather than any									
alternative financial reporting tools.									
I would like to continue the use of	CI3	4.18	4.00	.707					
this financial reporting technology.			(2.00 - 5.00)						
If I could, I will continue using this	CI4	4.19	4.00	.687					
financial reporting technology for			(2.00 - 5.00)						
financial analysis tasks.									
Performance Impact (Goodhue and	Thompson 1995))							
Please answer the following questions	regarding the fina	ncial repo	orting technology	y you chose					
(i.e. the EDGAR/CALCBENCH tool)									
Using this technology had a large,	PERF1	4.22	4.00	.723					
positive impact on my effectiveness			(2.00 - 5.00)						
and productivity in this financial									
analysis task.									
This technology is an important and	PERF2	4.23	4.00	.667					
valuable aid to me in the			(2.00 - 5.00)						
performance of financial analysis.									
This technology greatly contributed	PERF3	4.08	4.00	.802					
to the improvement of my financial			(2.00 - 5.00)						
statement analysis.									
Using this technology helped me	PERF4	4.19	4.00	.717					
efficiently manage my financial			(2.00 - 5.00)						
statement analysis.									
Satisfaction (Bhattacherjee (2001; 2									
Please answer the following questions		incial repo	orting technology	y you chose					
(i.e. the EDGAR/CALCBENCH tool)									
I was satisfied with my use of this	SATIS1	4.27	4.00	.682					
financial reporting technology.	(1.00 - 5.00)								
My choice to use this financial	SATIS2	4.25	4.00	.709					
reporting technology is a wise one.			(1.00 - 5.00)						
My experience with using this	SATIS3	4.23	4.00	.721					
technology was very satisfactory.			(1.00 - 5.00)						

Scale Item	Item Measure Name	Mean	Median (Range)	Standard Deviation
I think I did the right thing by	SATIS4	4.27	4.00	.671
deciding to use this financial			(1.00 - 5.00)	
reporting technology.				
If I were to do it again, I would feel	SATIS5	4.32	4.00	.679
the same way about using this			(1.00 - 5.00)	
financial reporting technology.				
I was pleased with my use of this	SATIS6	4.29	4.00	.652
financial reporting technology.			(1.00 - 5.00)	
Utilization/Usage (Hampton 2005)				
Please indicate your rating of the EDC	GAR/CALCBENC	H tool in	the following qu	estions.
I would prefer to always conduct	UTIL1	4.25	4.00	.740
this task using this technology.			(2.00 - 5.00)	
I heavily relied on this technology	UTIL2	4.36	4.00	.642
while completing the financial			(2.00 - 5.00)	
analysis task.				
I extensively used this technology	UTIL3	4.22	4.00	.761
while completing the financial			(1.00 - 5.00)	
analysis task.				
I am confident in the conclusion of	UTIL4	4.01	4.00	.772
my analysis as a result of using this			(1.00 - 5.00)	
technology.				

Table 16: Scale Item Loadings and Cross Loadings

Item Measure Name	1	2	3	4	5	6	7	8	9	10
LOC1	0.85	0.54	0.43	0.75	0.65	0.50	0.54	0.62	0.42	0.43
LOC2	0.81	0.51	0.37	0.62	0.61	0.43	0.53	0.53	0.38	0.40
LOC3	0.87	0.58	0.49	0.55	0.61	0.37	0.49	0.49	0.46	0.42
LOC4	0.84	0.56	0.47	0.50	0.58	0.37	0.47	0.48	0.45	0.39
COMP1	0.59	0.83	0.50	0.51	0.65	0.46	0.50	0.51	0.39	0.45
COMP2	0.53	0.79	0.40	0.47	0.45	0.42	0.46	0.41	0.33	0.31
COMP3	0.51	0.81	0.51	0.51	0.59	0.49	0.52	0.43	0.48	0.49
COMP4	0.51	0.87	0.53	0.43	0.61	0.47	0.53	0.42	0.47	0.51
CI1	0.47	0.52	0.91	0.51	0.56	0.59	0.67	0.42	0.67	0.57
CI2	0.49	0.54	0.88	0.44	0.51	0.51	0.56	0.39	0.60	0.54
CI3	0.51	0.58	0.94	0.47	0.59	0.58	0.67	0.42	0.63	0.56
CI4	0.46	0.53	0.95	0.48	0.56	0.60	0.64	0.43	0.64	0.54
EOU1	0.64	0.51	0.42	0.90	0.59	0.50	0.56	0.54	0.39	0.42
EOU2	0.64	0.52	0.45	0.91	0.59	0.55	0.57	0.53	0.40	0.44
EOU3	0.69	0.55	0.51	0.88	0.62	0.53	0.60	0.44	0.45	0.50
EOU4	0.63	0.50	0.47	0.90	0.59	0.54	0.56	0.54	0.42	0.45
FLEX1	0.65	0.58	0.48	0.63	0.84	0.52	0.57	0.57	0.47	0.45
FLEX2	0.64	0.60	0.56	0.60	0.88	0.50	0.61	0.59	0.58	0.52
FLEX3	0.67	0.60	0.51	0.52	0.86	0.43	0.56	0.57	0.52	0.43
FLEX4	0.56	0.64	0.54	0.54	0.86	0.52	0.55	0.57	0.53	0.48
PU1	0.46	0.52	0.54	0.51	0.51	0.86	0.64	0.52	0.52	0.55
PU2	0.44	0.46	0.55	0.50	0.45	0.87	0.66	0.46	0.53	0.49
PU3	0.44	0.44	0.47	0.52	0.47	0.88	0.62	0.50	0.50	0.49
PU4	0.43	0.53	0.60	0.55	0.57	0.90	0.67	0.50	0.58	0.56
PERF1	0.57	0.54	0.63	0.61	0.60	0.71	0.88	0.56	0.57	0.61
PERF2	0.54	0.57	0.67	0.61	0.63	0.67	0.93	0.49	0.58	0.53
PERF3	0.52	0.52	0.58	0.51	0.55	0.63	0.88	0.51	0.49	0.43
PERF4	0.52	0.54	0.57	0.53	0.59	0.61	0.87	0.49	0.50	0.44
PRES1	0.52	0.48	0.31	0.47	0.56	0.41	0.45	0.82	0.46	0.31
PRES2	0.56	0.53	0.40	0.52	0.53	0.54	0.48	0.85	0.49	0.46
PRES3	0.54	0.39	0.37	0.47	0.60	0.49	0.50	0.89	0.49	0.37
PRES4	0.56	0.46	0.48	0.52	0.61	0.51	0.55	0.88	0.44	0.39
SATIS1	0.51	0.48	0.59	0.51	0.62	0.60	0.54	0.57	0.87	0.51

Item Measure Name	1	2	3	4	5	6	7	8	9	10
SATIS2	0.45	0.50	0.67	0.44	0.54	0.52	0.54	0.43	0.89	0.58
SATIS3	0.48	0.48	0.64	0.45	0.62	0.56	0.58	0.49	0.90	0.56
SATIS4	0.43	0.42	0.61	0.36	0.49	0.55	0.54	0.45	0.91	0.51
SATIS5	0.43	0.43	0.61	0.37	0.49	0.51	0.52	0.47	0.91	0.53
SATIS6	0.46	0.43	0.63	0.39	0.54	0.54	0.54	0.53	0.92	0.53
UTIL1	0.41	0.52	0.57	0.40	0.48	0.52	0.52	0.42	0.56	0.86
UTIL2	0.32	0.31	0.34	0.43	0.41	0.49	0.46	0.39	0.40	0.74
UTIL3	0.36	0.45	0.49	0.41	0.45	0.46	0.43	0.32	0.45	0.85
UTIL4	0.46	0.41	0.49	0.41	0.41	0.46	0.42	0.31	0.47	0.76

Table 17: Tests of Convergent and Discriminant Validity²⁷

	Average Variance Extracted	Composite Reliability	1	2	3	4	5	6	7	8	9	10
Locatability/	0.71	0.91	0.84									
Accessibility												
Compatibility	0.68	0.90	0.65	0.83								
Continuance	0.85	0.96	0.52	0.59	0.92							
Intent												
Ease of Use	0.80	0.94	0.73	0.58	0.52	0.90						
Flexibility	0.74	0.92	0.73	0.70	0.60	0.67	0.86					
Perceived	0.77	0.93	0.50	0.56	0.62	0.59	0.57	0.88				
Usefulness												
Performance	0.79	0.94	0.61	0.61	0.69	0.64	0.67	0.74	0.89			
Presentation	0.74	0.92	0.63	0.54	0.45	0.57	0.67	0.57	0.58	0.86		
Satisfaction	0.81	0.96	0.51	0.51	0.69	0.46	0.61	0.61	0.60	0.54	0.90	
Utilization	0.65	0.88	0.49	0.54	0.60	0.51	0.55	0.60	0.57	0.44	0.60	0.80

The square root of the AVE is shown on the diagonal in bold.

Table 18: Construct Validity and Reliability for Task-Technology Fit

Panel A: Test of Validity

Т	ask-Technology Fit Dimensions	Item Loadings
1.	Accessibility/Locatability	0.791
	(Definition: Ease of determining what data is available and where).	
2.	Ease of Use (Definition: The degree	0.824
	to which using a system for a task is perceived as being easy or difficult).	
3.	Flexibility (Definition: Ease of	0.833
	changing the content or format of the data to meet changing needs).	
4.	Compatibility (Definition: Data	0.743
	from different sources can be	
	consolidated or compared without	
	inconsistencies).	
5.	Presentation (Definition: Data is	0.777
	presented in a useful format).	

Panel B: Test of Multicollinearity

Task-Technology Fit Dimensions	Variance Inflation Factor (Dependent variable = Perceived Usefulness)	Variance InflationFactor (Dependent variable = Satisfaction)
1. Accessibility/Locatability	1.782	1.783
(Definition: Ease of determining		
what data is available and where).		
2. Ease of Use (Definition: The	2.003	2.004
degree to which using a system		
for a task is perceived as being		
easy or difficult).		
3. Flexibility (Definition: Ease of	2.063	2.078
changing the content or format of		
the data to meet changing needs).		
4. Compatibility (Definition: Data	1.600	1.597
from different sources can be		
consolidated or compared without		
inconsistencies).		
5. Presentation (Definition: Data is	1.753	1.780
presented in a useful format).		

Table 19: Common Method Bias Analysis

Construct	Indicator	Substantive Factor Loading	Variance Explained	Method Factor Loading	Variance Explained
Task-	COMP1	0.783**	0.614	-0.067	0.004
Technology Fit	COMP2	0.692**	0.479	-0.082	0.007
	COMP3	0.302	0.091	0.384	0.147
	COMP4	0.361	0.130	0.330	0.109
	EOU1	0.937***	0.878	-0.191	0.037
	EOU2	0.838***	0.702	-0.082	0.007
	EOU3	0.677**	0.458	0.087	0.008
	EOU4	0.799***	0.638	-0.043	0.002
	FLEX1	0.802***	0.643	-0.028	0.001
	FLEX2	0.535*	0.286	0.266	0.071
	FLEX3	0.752***	0.565	0.011	0.000
	FLEX4	0.538*	0.289	0.227	0.052
	LOC1	1.114***	1.241	-0.328	0.107
	LOC2	0.990***	0.979	-0.279	0.078
	LOC3	0.828***	0.685	-0.106	0.011
	LOC4	0.771***	0.594	-0.080	0.006
	PRES1	0.850***	0.723	-0.194	0.037
	PRES2	0.612**	0.375	0.095	0.009
	PRES3	0.616**	0.379	0.067	0.005
	PRES4	0.655**	0.429	0.059	0.003
Continuance	CI1	0.838***	0.702	0.080	0.006
Intention	CI2	0.908***	0.824	-0.033	0.001
	CI3	0.947***	0.896	-0.002	0.000
	CI4	0.984***	0.968	-0.045	0.002
Perceived	PU1	0.822***	0.675	0.049	0.002
Usefulness	PU2	0.890***	0.791	-0.029	0.001
	PU3	0.955***	0.911	-0.093	0.009
	PU4	0.843***	0.710	0.069	0.005
Performance	PERF1	0.720***	0.518	0.184	0.034
	PERF2	0.908***	0.825	0.020	0.000
	PERF3	0.977***	0.993	-0.130	0.017
	PERF4	0.940***	0.883	-0.080	0.006
Satisfaction	SATIS1	0.749***	0.561	0.153	0.023

Construct	Indicator	Substantive	Variance	Method	Variance
		Factor	Explained	Factor	Explained
		Loading		Loading	
	SATIS2	0.869***	0.755	0.028	0.001
	SATIS3	0.821***	0.674	0.093	0.009
	SATIS4	1.003***	1.005	-0.109	0.012
	SATIS5	0.999***	0.998	-0.107	0.011
	SATIS6	0.966***	0.933	-0.051	0.003
Utilization	UTIL1	0.781***	0.609	0.087	0.008
	UTIL2	0.837***	0.700	-0.074	0.005
	UTIL3	0.922***	0.850	-0.092	0.009
	UTIL4	0.673***	0.453	0.081	0.007
Average		0.805	0.677	0.001	0.021

 $[\]begin{array}{l} * & p < 0.05 \\ ** & p < 0.01 \\ *** & p < 0.001 \end{array}$

Table 20: Indirect and Total Effects of Task-Technology Fit on Satisfaction, IS **Continuance Intention, and Utilization**

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Task-Technology	Path to:		·
Fit	Satisfaction	IS Continuance Intention	Utilization
Through:		Intention	
	0.073**	0.092**	
Perceived Usefulness	(0.074 - 0.083)	(0.080 - 0.088)	
		0.170**	
Satisfaction		(0.185 - 0.197)	
Perceived Usefulness and		0.037**	
Satisfaction		(0.045 - 0.052)	
Perceived Usefulness and IS			0.056**
Continuance Intention			(0.048 - 0.054)
Satisfaction and IS Continuance			0.102**
Intention			(0.113 - 0.121)
Perceived Usefulness, Satisfaction,			0.022**
and IS Continuance Intention			(0.027 - 0.032)
Total Indirect Effects	0.073	0.299	0.180

Panel B: Total Effects of Task-Technology Fit

On	Coefficient	t-statistics	p-value
Satisfaction	0.412	4.448	p < 0.001
IS Continuance Intention	0.299	4.060	p < 0.001
Utilization	0.180	3.264	p < 0.001

p < 0.05** p < 0.01

^{****}p < 0.001

Table 21: Indirect and Total Effects of Performance on Satisfaction, IS Continuance Intention, and Utilization

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Performance	Path to:		
Through:	Satisfaction	IS Continuance Intention	Utilization
	0.131**	0.166**	
Perceived Usefulness	(0.119 - 0.133)	(0.135 - 0.148)	
		0.086**	
Satisfaction		(0.080 - 0.090)	
Perceived Usefulness and		0.066**	
Satisfaction		(0.072 - 0.082)	
Perceived Usefulness and IS			0.100**
Continuance Intention			(0.081 - 0.089)
Satisfaction and IS Continuance			0.052**
Intention			(0.049 - 0.054)
Perceived Usefulness,			0.040**
Satisfaction, and IS Continuance			(0.044 - 0.050)
Intention			
Total Indirect Effects	0.131	0.318	0.192

Panel B: Total Effects of Performance

On	Coefficient	t-statistics	p-value
Satisfaction	0.303	2.988	p < 0.01
IS Continuance Intention	0.318	4.497	p < 0.001
Utilization	0.192	4.202	p < 0.001

 $[\]begin{array}{l} * & p < 0.05 \\ ** & p < 0.01 \\ *** & p < 0.001 \end{array}$

Table 22: Chi-Square difference test of paths for Calcbench and Edgar Users

Hypothesis	Path	t-statistic	p-value (two-tailed)
H1	TTF -> Satisfaction	0.108	0.914
H2	Performance -> Satisfaction	1.889	0.061*
Н3	TTF -> Perceived Usefulness	1.215	0.226
H4	Performance -> Perceived Usefulness	1.005	0.316
H5	Perceived Usefulness -> Satisfaction	1.423	0.157
Н6	Perceived Usefulness -> Continuance Intention	1.860	0.065*
H7	Satisfaction -> Continuance Intention	1.564	0.120
Н8	Continuance Intention -> Utilization	0.516	0.606

 $[\]begin{array}{ll} * & p < 0.10 \\ ** & p < 0.05 \\ *** & p < 0.01 \\ **** & p < 0.001 \end{array}$

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STUDY THREE: THE EFFECTS OF INTERACTIVITY ON USER PERCEPTIONS OF CREDIBILITY AND INVESTMENT CHOICE

Introduction

Mercer (2004, p.186) defines disclosure credibility as "investors' perceptions of the believability of a particular disclosure." The existing literature on disclosure credibility suggests that investor credibility assessments of management disclosures are influenced by situational incentives present at the time of disclosure, the credibility of management, the degree of assurance on the disclosure, and characteristics of the disclosure itself, including disclosure venue, timing, and precision (Hodge 2001; Mercer 2004; Elliott et al. 2012). Due to the development of new technologies and the continued increase in internet usage, the Web has become a prevalent disclosure and financial reporting venue in recent years (Lymer et al. 1999; Ettredge et al. 2001; Ettredge et al. 2002; Cho and Roberts 2010). Investors rely heavily on corporate websites for financial statements, press releases, speeches, and links to further information (Lymer and Debreceny 2003). Internet financial reporting (IFR), the use of companies' web sites to report and provide information about financial performance, continues to grow in importance as the Securities and Exchange Commission (SEC) continues to pursue its initiative to make internet delivery of financial information the norm.

Despite the increase in IFR, there is very little understanding of how users utilize or interact with internet financial reporting web sites and the subsequent effects on decision making. According to a Financial Accounting Standards Board (FASB) Business Reporting Research Project, the two basic dimensions of financial and business reporting include its content and its presentation (FASB 2000). In terms of presentation, reporting on a Web site could be

comparable to paper and include text and static graphics. On the other hand, Web reporting can involve the use of dynamic forms of presentations such as audio, video, dynamic graphic images, and hyperlinked texts (FASB 2000; Debreceny et al. 2002; Kelton and Yang 2008). The latter form of Web reporting is thus interactive in nature.

Yi et al. (2007) defines interactivity as "the dialog between the user and the system as the user explores the data set to uncover insights" (Yi et al. 2007, 1224). The interactivity concept is increasingly salient in financial reporting contexts. Recently, the SEC issued a mandate requiring public companies to provide financial information to the SEC and on their corporate Web sites in an interactive format using the eXtensible Business Reporting Language (XBRL; SEC 2009). According to the SEC, the new standard for interactive financial statement reporting is intended to improve the usefulness of financial information to investors. It is expected that interactive reporting will benefit users because interactive financial information is easier to acquire and analyze in a variety of forms including the use of spreadsheets and commercially available software, thereby reducing the costs and efforts associated with analysis (SEC 2009). However, there is a lack of understanding of the impact of interactive reporting on users as a result of the dearth of research investigating the impact of interactive financial reporting or interactivity on decision making. Prior research has shown that interactive financial reporting could potentially lead to improved decision making by facilitating information acquisition and information integration (e.g. Hodge et al. 2004; Arnold et al. 2012; Tang et al. 2014). On the other hand, extant research evidence suggests interactivity may introduce biases by inducing affective responses to presented information (e.g. Hodge et al. 2001; Rose et al. 2004; Elliott et al. 2012).

The purpose of this research study is to examine the effects of increasing interactivity in IFR on investor perceptions of forecast credibility and on a firm's attractiveness as a potential investment choice. This study broadens our understanding of the interactivity concept by investigating information processing in an interactive disclosure environment via the lens of the elaboration likelihood model (ELM). ELM (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b) is a model of information processing and persuasion or influence that seeks to explicate the process through which attitudes are formed or changed as a result of communicated information. ELM is a dual-process theory of persuasion that posits that there are two routes to information processing. The central route is where critical thinking about issue- relevant information occurs. On the other hand, the peripheral route is primarily governed by non-content elements or cues associated with presented information (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). ELM has been utilized in extant advertising and political communication research to examine the effects of interactivity on attitude formation (e.g. Macias 2003; Sicilia et al. 2005; Sundar and Kim 2005; Song and Bucy 2008).

This study examines the effects of increasing interactivity on forecast credibility and the investment decision within the context of management earnings forecasts. Hirst et al. (2008, p. 315) defines management earnings forecasts as "voluntary disclosures that provide information about expected earnings for a particular firm". Management earnings forecasts represent voluntary disclosures which are primarily designed to influence by establishing or changing investor expectations (Hirst et al. 2008; Davis et al. 2012). However, in order for management earnings forecasts to influence or be used, investors must judge its credibility or believability (Mercer 2004). Forecast characteristics (e.g. forecast news, form, the use of accompanying

attributions, horizon, and disaggregation) represent forecast attributes, over which management has great discretion (see Hirst et al. 2008 for a review). Other forecast characteristics that have emerged in recent years include the readability of a forecast (e.g. Rennekamp 2012), and the language used in a forecast (e.g. Davis et al. 2012; Davis and Tama-Sweet 2012; Riley 2014). Previous disclosure research has shown the characteristics of a forecast can act as an influence mechanism in predicting investor behavior (e.g. Hirst et al. 2007; Lansford et al. 2007; Davis et al. 2012). For instance, managers can use attribution to boost the credibility of good-news forecasts by accompanying them with verifiable statements (Hirst et al. 2007). According to ELM, information processing in the central route occurs as a result of careful consideration of communicated information. This suggests that in order for disclosure communication to be used, central route processing must occur, and characteristics of a forecast can be used to strengthen the disclosure communication.

In comparison to static presentation formats, research in disclosure contexts also suggests that interactivity affects investor judgments by positively influencing perceptions of credibility (e.g. Hodge 2001). In addition, multimedia has been shown to affect perceptions of reliability and induce affective responses that alter the future recall of financial information and decision-making (e.g. Kida et al. 1998; Rose 2001; Rose et al. 2004; Elliott et al. 2012). This suggests that interactivity can function as a peripheral cue and affect attitudes and perceptions since interactivity is only an element that may be associated with a disclosure setting.

The research in this study employs both an experimental design and a survey of perceptual measures based on the experimental manipulations. The experimental design enables the examination of the manipulated independent variables on the primary dependent variables of

interest. On the other hand, individual perceptions of the manipulated independent variables and the dependent variables are collected to facilitate the examination of the user's experience while completing the experimental task and the simultaneous examination of the relationships among all of the variables in the research model. A 2 x 2 experiment is conducted where the level of interactivity and the argument quality of disclosure communication are manipulated between-subjects. Participants are asked to analyze a fictional company for a potential investment and decide if they would invest \$10,000. The information presented to participants included financial statements, accompanying notes for the company, and a press release of management's earnings forecast for the year. The level of interactivity represents an operationalization of the peripheral route in ELM, while the argument quality of disclosure communication represents an operationalization of the central route. The effects of varying interactivity and argument quality on perceptions of credibility and on the investment decision are examined.

The results from the experimental analysis suggest that actual argument quality and interactivity do not significantly impact forecast credibility. However, the results from the structural model suggest that nonprofessional investors are influenced by both the perceptions of argument quality and perceptions of interactivity. Both perceived argument quality and perceived interactivity had a significant and positive effect on forecast credibility. This suggests that the effects of interactivity and argument quality are determined by user perceptions, and these perceptions may be formed independent of both actual interactivity and actual argument quality. However, the results also indicate that perceived argument quality has a stronger impact on actual investment behavior than perceived interactivity. While perceived argument quality and perceived interactivity both have positive effects on the investment decision, the total effect of

perceived argument quality on the investment decision is higher, indicating that perceived argument quality has a greater impact on actual behavior.

This research contributes to both theory and practice. Despite the increase in interactivity in accounting contexts and the current stage of financial reporting on the Web, the interactivity concept has not been sufficiently examined in extant accounting research (Dilla et al. 2010). In addition, although prior interactivity research in marketing and political science (e.g. Song 2008; Jiang et al. 2010) has shown that interactivity can function as an influence mechanism, this aspect of interactivity has not been considered in prior accounting research. Dilla et al. (2010) call for such research that examines the impact of interactivity on accounting decision processes, such as the effects of increasing interactivity on perceived reliability and a firm's attractiveness as a potential investment.

This research is important to our understanding of interactivity in financial reporting contexts. Although not directly examined, extant research in disclosure contexts suggests that interactivity may positively influence investor perceptions of credibility and reliability, which in turn affects future investment judgments and decisions (Hodge 2001; Elliott et al. 2012). Management disclosures serve as an important source of information to investors; however, its use depends heavily on investor perceptions of reliability or credibility (Mercer 2004). This study makes a contribution to the disclosure literature by examining an increasing use of interactive Web sites as a disclosure venue and the subsequent impact on investor perceptions of credibility. Specifically, the results indicate that perceptions of interactivity may potentially affect investor perceptions of credibility, which in turn affects investment behavior. However, the results also show that the influence of disclosure communication on forecast credibility and

the investment decision is stronger than the effects of perceived interactivity, suggesting that in the context of increasing interactivity, disclosure communication is more important in affecting investor beliefs and subsequent behavior.

In order to explicate the information processing that occurs, this study uses ELM to shed light on the influence processes that are antecedents to perceptions of credibility and investment choice. This study contributes to ELM research by simultaneously examining the effects of both central route and peripheral route processing. Given that the actual route to persuasion occurs along a continuum and attitude change can occur as a result of both central and peripheral route processing, the results from this study suggest that although prior research in accounting show that the presence of interactive features (e.g. multimedia) induces affective responses and may influence attitudes and perceptions, interactivity may not be a huge concern if communicated information is otherwise sound.

Lastly, the research reported in this study makes a contribution to our understanding of interactivity in financial reporting contexts. Prior research (Tang et al. 2014) examines the impact of interactivity on financial decision making. However, the Tang et al. (2014) study only considers the effects of objective interactivity. The research conducted in this study examines both the effects of objective or actual interactivity and perceptions of interactivity. Liu and Shrum (2002) based on their review of conceptualizations of interactivity note that regardless of how objective interactivity is manipulated, perceptions of interactivity or the way users experience interactivity has positive impacts on attitudes and behavior. The results of this study supports the perceptual view of interactivity, which acknowledges that actual interactivity and

perceptions of interactivity are different (Lee et al. 2004; Wu 2005; Song and Zinkhan 2008; Voorveld et al. 2011).

The remainder of this paper is organized as follows. The next section discusses the background research, theoretical foundation, and develops the hypotheses. Section three discusses the methodology and experimental design. Sections four and five will include the results and a summary discussion of the study, respectively.

Theory and Hypotheses Development

The Interactivity Concept

A primary advantage of providing information on the Internet has been its potential to enable active and selective user participation. Generally, interactivity refers to the user's ability to manipulate information views or restructure information during decision making (Lurie and Mason 2007; Yi et al. 2007). In a broader context, interactivity is a characteristic or element of interactive data visualization. Dilla et al. (2010, 1) define interactive data visualization as "computer-supported visual representation of data that allows users to select the information they wish to view and its format." Interactivity is an important element in interactive data visualization because it is the primary ingredient that separates interactive data visualization from static presentation formats.

With the increase in financial reporting on the Web and the SEC's support for online financial disclosures, the concept of interactivity has become increasingly important in the financial reporting arena. Conceptualizations of interactivity have been defined and discussed in several ways within the political science, computer science, and marketing and advertising

domains (e.g. Ariely 2000; Liu and Shrum 2002; Yi et al. 2007; Song and Bucy 2008). Within this research stream, the effects of interactivity are mixed. Some studies have found that interactivity on Web sites led to more information processing, comprehension, website involvement, purchase intention, and positive attitudes towards the Web site, product, or a political candidate (Macias 2003; Sicilia et al. 2005; Sundar and Kim 2005; Song and Bucy 2008; Jiang et al. 2010), while other studies report mixed or negative effects of interactivity (e.g. Sundar 2000; Sundar et al. 2003). This is likely because interactivity is a complex concept and multiple definitions, measurements, and operationalizations exist in the interactivity literature.

In defining interactivity, previous marketing and advertising research have differentiated between the loci of interactivity or where interactivity actually resides. There are three predominant definitions of interactivity – the functional or mechanic view, the contingency view, and the perceptual view (Liu and Shrum 2002; Song 2008; Voorveld et al. 2011). The functional view is objective in nature and refers to the actual provided opportunity for interaction via technological features or dimensions of control. In the functional view, interactivity is defined based on the number of features or interfaces available to users (Liu and Shrum 2002; Sundar and Kim 2005). Although previous accounting research does not directly discuss applied conceptualizations of interactivity, the authors' view of interactivity is consistent with the functional/mechanic view. Hodge (2001) utilized a hyperlink display versus static hard copy displays to operationalize interactivity; while other studies integrate the presence of multimedia (e.g. Wheeler and Arunachalam 2008; Elliott et al. 2012). An exception is Tang et al. (2014) who directly examine the effect of interactivity in financial decision making and adopt the functional

view of interactivity²⁸. The contingency view defines interactivity as the "degree of responsiveness of messages exchanged between two users or between a user and a media system in a mediated communication situation" (Song 2008). According to the contingency view, interactivity is measured as "a process involving users, media, and messages, with an emphasis on how messages relate to one another" (Sundar et al. 2003, 34-35). The perceptual view of interactivity is based on a user's perception of their interaction during a communication process and their perception of control over information and communication flow (Liu and Shrum 2002, Chung and Zao 2004; Wu 2005; Voorveld et al. 2011).

Jiang et al. (2010) advocate conceptualizing interactivity to match the context of a study. Of the three existing views, only the perceptual view is robust enough to take into account the actual use of interactive features (functional view), reciprocal communication (contingency view) and the subjective states of the individuals using the interactive medium in one model. Similar to Bucy and Tao (2007) and Song and Bucy (2008), this study adopts the perceptual view of interactivity, which proposes that the locus of interactivity is in the relationship between an interactive technology and user perceptions while engaging with interactive features. The perceptual view posits that interactive features may influence perceptions of interactivity which in turn impact an individual's judgments and decisions. In addition, while interactive features may remain constant, individual differences may cause user perceptions of interactivity to vary. The premise here is that even if interactive features are offered, decision makers might choose not to engage with or access them. For example, results from Hodge et al. (2004) show that while

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²⁸ In their study, Tang et al. (2014) use the term 'mechanic' view.

the use of XBRL improves the transparency of financial reporting, over half of their participants choose not to use the XBRL-enabled technology.

The perceptual view defines interactivity as perceived interactivity, which is "the degree to which users actually experience a sense of reciprocal involvement (regardless of the number of technological features) during engagement with information and communication technologies" (Song 2008, 17-18). Several marketing research studies (e.g. Cho and Leckenby 1999; Chung and Zhao 2004; Wu 1999, 2005; Song and Bucy 2008; Yoo et al. 2010; Noort et al. 2012) have found a positive relationship between perceived interactivity and outcomes such as attitude toward the site and/or the brand, intent to purchase, online flow experience, and satisfaction.

Interactivity and the Elaboration Likelihood Model

The Elaboration Likelihood Model (ELM) is a general theory of persuasion and attitude formation and change developed in Petty and Cacioppo (1986a). ELM provides a framework for organizing and understanding the information processing underlying the persistence of communication-induced attitude change. ELM postulates that attitude change occurs along two different routes of influence, the "central route" and the "peripheral route". The primary difference between the two routes lies in the level of thoughtful consideration or "elaboration" of message arguments. In the central route, attitude change occurs as a result of cognitive activity and careful scrutiny of the merits of issue-relevant information in presented communication. The peripheral route involves less cognitive effort or "elaboration," and attitude change occurs as a result of non-content elements or cues associated with presented information such as affect,

number of arguments, source credibility, and source likability (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). Figure 13 depicts the basic tenets of the elaboration likelihood model.

According to ELM, consequences of the central and peripheral routes to information processing differ in three distinct ways. First, attitudes formed or changed via the central route are generally more stable than attitudes formed or changed via the peripheral route. Second, attitudes formed or changed via the central route are relatively resistant to counter-persuasion compared to attitudes formed via the peripheral route. Lastly, attitudes formed via the central route versus the peripheral route, are more predictive of long-term behaviors. (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). The rationale is that enhanced or critical thinking on issue-relevant information increases temporal persistence. It is important to note that based on ELM's arguments, it is possible for individuals to process information along the central or the peripheral routes and still experience the same outcomes. ELM asserts that attitude formation or change can occur by varying the quality of the arguments in a persuasive message (argument quality), via the presence of simple cues within the persuasion context (peripheral cues), and/or by affecting the extent of the likelihood of message elaboration (elaboration likelihood) (Petty and Cacioppo 1986b). Bhattacherjee and Sanford (2006, 811) define argument quality as "the persuasive strength of arguments embedded in an informational message, while peripheral cues are defined as "meta-information about the message (e.g. message source) but not its embedded arguments."

ELM provides a lens for examining the effects of increasing interactivity in a disclosure setting because it facilitates the simultaneous examination of the effects of interactivity and the

influence of disclosure communication on perceptions of credibility and investment decisions. Although well-accepted theoretical models of persuasion do exist (e.g. Elaboration Likelihood Model [Petty and Caccioppo 1986a, 1986b; Heuristic-Systematic Model [Eagly and Chaiken 1993]), extant accounting disclosure research has generally not integrated such theories while investigating the effects of different disclosures on user perceptions and decision making. An exception is Clements and Wolfe (1997, 113) who discuss that "increasing the quantity and quality of peripheral cues in an annual report through the use of multimedia could enhance its persuasive capability." Clements and Wolfe (1997) examine the impact of paper and multimedia report forms on satisfaction, persuasion, and recall. With respect to persuasion, participants were equally persuaded by both report formats. However, their study does not investigate how persuasion occurred. Using ELM as a theoretical lens allows the investigation of how message arguments are processed.

Previous disclosure research has almost exclusively investigated the power of multimedia (typically video and images) to influence (e.g. Huang and Windsor 1998; Clements and Wolfe 2000; Elliott et al. 2012), while interactivity in a broader context has not been considered. Although in more recent accounting research, Tang et al. (2014) investigate the effects of interactivity and visualization on financial decision-making, their research does not focus on interactivity as an influence mechanism. The evidence from research that has examined multimedia in disclosure settings can be extended to interactivity. The results from these studies suggest that interactivity potentially induces positive moods which may override critical scrutiny of presented information and influence users of financial information. For example, (Elliott et al. 2012) examined the effects of text versus video restatement announcements online and found

that participants who viewed the online video restatement announcements made larger investments in the firm and were more confident in the firm's ability to meet analysts' expectations in comparison to participants who viewed the online text restatement announcements. In addition, there is evidence of heightened emotional processing or affective responses to financial data in the presence of multimedia (e.g. Kida et al. 1998; Clements and Wolfe 2000; Rose 2001; Rose et al. 2004).

Song and Bucy (2008) and Song (2008) propose an elaboration likelihood model of interactive media based on the premise that interactivity can function as a peripheral cue in influencing attitudes. Interactivity is a non-issue relevant aspect of communication and has nothing to do with message arguments. Prior research in various domains (e.g. marketing, public relations, and political science) has shown that Web site interactivity influences attitudes and impressions. For instance, interactivity influences perceptions of an organization reputation's (Guillory and Sundar 2014), increases Web site involvement and purchase intention (Jiang et al. 2010), increases online shoppers' satisfaction and behavioral intentions (Dholakia and Zhao 2008), influences perceptions of political candidates and their policy positions (Sundar et al. 2003), and is an antecedent to positive and repeat customer relations (Cyr et al. 2009). This study proposes that increased interactivity in IFR may have positive effects on investor perceptions of forecast credibility by acting as a peripheral cue due to the presence of interactive design features that are independent of the content of information on corporate Web sites. This study also acknowledges that the concept of interactivity as an influence mechanism on perceptions of forecast credibility goes beyond the mere provision of interactive design features, and requires that investors engage with provided interactive features. This conceptualization aligns with the

perceptual view of interactivity (Liu and Shrum 2002; Wu 2005; Voorveld et al. 2011). The following hypothesis is proposed:

H1: Interactivity will have a positive effect on user perceptions of forecast credibility.

ELM defines a strong argument as a message that elicits predominantly favorable thoughts when it is scrutinized, whereas a weak argument elicits predominantly unfavorable thoughts about the message (Petty and Cacioppo 1986b). This study examines disclosure credibility within the context of management earnings forecasts. Voluntary disclosures such as management's earnings forecast have been documented as an influencing tool in management's communication with investors (e.g. Hutton et al. 2003; Mercer 2005; Hirst et al. 2007; Davis et al. 2012; Riley et al. 2014). Prior research has examined antecedents, characteristics, and consequences of management's earnings forecast and acknowledged that managers possess great discretion over forecast characteristics in comparison to antecedents and consequences (Hirst et al. 2008; Han 2013). The research examining forecast characteristics has typically investigated the effects of quantitative information contained in earnings forecasts such as forecast form (e.g. Hirst et al. 1999; Libby et al. 2006), forecast disaggregation (e.g. Hirst et al. 2007), and forecast timing (e.g. Libby et al. 2008) on investor reactions. However, in recent years, another stream of research on forecast characteristics has focused on examining the narrative used in earnings forecasts. For example, Rennekamp (2012) examines the readability of a press release and finds that investors overreact to more readable disclosures. In addition, Riley et al. (2014) examine the effect of concrete versus abstract language and find that investors reading a concretely written press release are more (less) likely to invest when the information contained in the press release is positive (negative).

The research on forecast narratives can be extended to another forecast characteristic – forecast attributions (e.g. Hutton et al. 2003; Elliott et al. 2012). Forecast attributions represent qualitative information that accompany management's earnings forecasts and provide explanations or causes for the earnings forecast (Hirst et al. 2008; Han 2013). For example, Hutton et al. (2003) found that managers can increase the credibility of their good news earnings forecast by supplementing them with verifiable forward-looking statements versus qualitative, "soft talk" statements²⁹. Verifiable forward-looking statements increase the credibility of good news forecast because they are specific in nature and can be compared with actual earnings realizations. On the other hand, soft-talk statements include vague and general information about the positivity of management's forecast and did not affect security prices (Hutton et al. 2003). Along similar lines, Barton and Mercer (2005) found that analysts reacted positively (negatively) to provided explanations for poor performance when analysts perceived the explanation to be plausible (implausible). Consistent with ELM postulates, the plausibility or persuasive strength of management's earnings forecasts (i.e. its argument quality) will be directly related to perceptions of forecast credibility. This leads to the following hypothesis:

H2: The argument quality of management's earnings forecasts will have a positive effect on user perceptions of forecast credibility.

²⁹ Hutton et al. (2003) define verifiable forward-looking statements as statements that are specific enough to be compared with subsequent realizations. Verifiable forward-looking information can increase credibility because they are specific in nature and can be compared with actual earnings realizations. On the other hand, soft-talk statements include vague and general information about the positivity of management's forecasts. Hutton et al. (2003) identify soft-talk statements as more qualitative explanatory discussions that include discussions of internal and external factors affecting the firm's performance.

Although ELM makes a distinction between the central route and peripheral routes to persuasion, the actual route to persuasion lies on a continuum where at different levels of elaboration, persuasion or attitude change can occur as a result of a combination of central and peripheral route processing. However, according to ELM, the impact of peripheral cues on persuasion is less significant when elaboration likelihood is high. As elaboration likelihood increases, the effect of peripheral cues on attitude change is less significant, and the effect of argument quality on attitude change increases. In the case of forecast credibility, this suggests that argument quality might mitigate or reduce the effect of interactivity on forecast credibility. This leads to the following hypothesis:

H3: Argument quality will weaken the relationship between interactivity and user perceptions of forecast credibility.

According to ELM, the route to persuasion is dependent on both personality and situational factors that impact the likelihood of elaboration and moderate the effects of argument quality and peripheral cues on attitude change. ELM postulates that motivational factors are important in determining the extent or likelihood of elaboration. ELM studies typically examine motivational factors such as an issue's personal relevance to the message recipient, personal responsibility or accountability, and an individual's need for cognition. According to ELM, an individual can vary in their motivation to elaborate on presented information, which in turn affects their attitude formation or change. When motivation is high, the likelihood of elaboration is also high and information processing is more likely to occur via the central route. However, when the motivation to elaborate is low, information processing is more likely to occur via the peripheral route (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). Consistent with ELM,

this study uses an individual's need for cognition as a potential moderator of the degree of elaboration likelihood. Need for cognition is defined as the "tendency to engage in and enjoy effortful cognitive endeavors (Petty and Cacioppo 1986a).

Applying the tenets of ELM to information technology acceptance, Bhattacherjee and Sanford (2006) operationalize motivation as job relevance and find that potential users who viewed a new information technology system as being highly relevant to their work performance were more motivated to engage in effortful cognitive processing and thereby made more informed decisions about the new system's use. Prior accounting research has shown that people with a propensity towards effortful processing strategies are generally less affected by mood (e.g. Rose 2001). Rose (2001) examined the effects of multimedia designed to create affective responses on recall and investment decisions following the analysis of financial data. The results showed that multimedia presented in conjunction with financial data can cause users to construct memories that match affective states and subsequent investment decisions. However, the recall and decision-making of individual investors with a high need for cognition were less affected by the presence of multimedia. ELM asserts that when motivation is high, attitude formation or change is more likely to occur via the central route. On the other hand, if an individual lacks the motivation to effectively scrutinize a message's arguments, attitude formation or change will be predominantly based on positive or negative cues associated with the message (Petty and Cacioppo et al. 1986b) This leads to the following hypotheses:

H4a: The relationship between interactivity and user perceptions of forecast credibility will be weaker when an individual's need for cognition is high.

H4b: The relationship between argument quality and user perceptions of forecast credibility will be stronger when an individual's need for cognition is high.

ELM postulates that the ability to critically scrutinize presented information is another determinant of the likelihood of elaboration. Factors that determine ability to elaborate include the presence of distractions, relevant knowledge of the topic, and the complexity of the message (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). A fundamental goal of interactive financial data reporting is its proposed benefits to investors, particularly nonprofessional investors. Although previous accounting research has established that there are differences in how professional and nonprofessional investors acquire and analyze financial information (e.g. Bouwman et al. 1987; Hodge and Pronk 2006), prior literature generally treats nonprofessional investors as a homogenous group (e.g. Maines and McDaniel 2000; Hodge et al. 2004) and ignores individual differences that could possibly account for differences in information processing or decision outcomes (Elliott et al. 2008). Previous research suggests that knowledge of accounting-related tasks is critical in determining performance, and that general problemsolving ability is critical in the acquisition of knowledge (Bonner and Walker 1994; Elliott et al. 2007). Drawing on this stream of research, this study examines the role of financial reporting knowledge on the likelihood of elaboration. Decision makers with high financial reporting knowledge will be more inclined to critically scrutinize financial disclosures and form informed judgments about disclosure credibility. Consistent with ELM, decision makers with a low ability or low financial reporting knowledge are more likely to process the message in financial disclosures along the peripheral route. This leads to the following hypotheses:

H5a: The relationship between interactivity and user perceptions of forecast credibility will be weaker when an individual's financial reporting knowledge is high.

H5b: The relationship between argument quality and user perceptions of forecast credibility will be stronger when an individual's financial reporting knowledge is high.

Prior research examining management's earnings forecasts has investigated several consequences to management's earnings forecast, including stock market reactions, analyst and investor behavior, and a reputation for accuracy and transparency (for a review, see Hirst et al. 2008 and Han 2013). Jennings (1987) asserts that investor reactions to management disclosures are a function of both the new information in the disclosure and the credibility of the disclosure itself. Mercer (2004, p. 186) defines disclosure credibility as "investors' perceptions of the believability of a particular disclosure." Prior disclosure research on management's earnings forecast has not typically focused on forecast credibility as an antecedent to investor judgments or behavior, but rather focused on the link between forecast characteristics and investor reactions (e.g. Hales et al. 2011; Rennekamp 2012) or the link between forecast characteristics and perceptions of credibility (e.g. Rennekamp 2012) independently. Hirst et al. (2007) assert that differences in investor perceptions of credibility should influence subsequent investor judgments, and find that forecast credibility influenced price-earnings multiple valuations. Barton and Mercer (2005) also find support for the link between the plausibility of earnings explanations and earnings forecasts. Along similar lines, disclosure research in other contexts (e.g. restatement announcements) suggests that the effects of restatements on investor decisions are dependent on investor trust (Hodge et al. 2012). In the context of this study, good news forecast should generate positive investor reactions if the forecast is deemed credible or believable. This leads to the following hypothesis:

H6: Perceptions of forecast credibility will have a positive effect on the investment decision.

ELM suggests that an individual may reach the same attitude via either the central or the peripheral route. However, ELM postulates three differences based on the route taken. These differences are reflected in the strength of attitude changes as a result of each route to persuasion. According to ELM, attitude changes formed along the central route tend to be more stable, more predictive of behavior, and less susceptible to counter-persuasion (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). In a disclosure setting, this suggests that users who form their perceptions of forecast credibility via the central route will show greater supporting behavioral intention (e.g. investment decision, judgment of earnings potential) than users who form their perceptions via the peripheral route. This leads to the following hypothesis:

H7: Individuals who form their perceptions of forecast credibility via the central route will exhibit stronger behavioral supporting intentions than individuals who form their perceptions via the peripheral route.

Figure 14 depicts the proposed research model as outlined by the preceding hypotheses.

Research Design and Methodology

This study adopts a 2 x 2 between-subjects factorial design with interactivity (low vs. high) and argument quality (weak vs. strong) as independent variables.

Participants

Participants are 117 individuals recruited from Amazon's Mechanical Turk (MTurk) in exchange for \$2.00. Amazon's MTurk is a crowdsourcing Internet marketplace that allows 'Requesters' to post Human Intelligence Tasks (HITs) that 'Workers' can complete for pay.

MTurk is becoming an increasingly popular source of experimental data for judgment and decision-making research and has been shown to have similar validity as other methods of

recruiting participants while increasing the efficiency of data gathering (Paolucci et al. 2010; Horton et al. 2011; Rennekamp 2012). In order to participate in this study, MTurk workers were required to be over 18 years old, be located in the United States, have a 90 percent or higher HIT approval rate, and have at least 100 approved HITs.

A total of 254 participants responded to the MTurk HIT and completed the study. Fifty responses were removed from the analysis due to incorrect calculation of the financial ratios required to evaluate the company used in the study. An additional 37 participants failed the manipulation check questions and were eliminated from the analysis. Participant responses are further screened to eliminate participants with no investing experience and who had never taken an accounting or finance course. This screening was used to eliminate participants who may not possess the relevant knowledge to complete the task. Forty more participants were eliminated based on the additional screening. All of the subsequent analyses pertain to the remaining 117 participants.

Table 23 summarizes the participant demographics. The average participant is 32.85 years old, with an average of 12.24 years of full-time work experience. Participants have completed an average of 2.63 accounting courses and 2.21 finance courses. Overall, 41.03 percent of participants indicated they had invested in individual stocks in the past and 77.78 percent indicated they planned to invest in individual stocks in the future. Additionally, 75.21 percent of participants indicated that they have evaluated a company's performance by analyzing

its financial statements at least once. Accordingly, this sample of participants should have sufficient knowledge to act as nonprofessional investors (Rennekamp 2012)³⁰.

Case Materials and Procedure

The case instructs participants to assume the role of an investor evaluating the common stock of a company named Alpha. Alpha, a fictitious firm, is a provider of printing and related services to the merchandising, publishing, and financial markets. Participants are informed that they will be viewing both financial and non-financial information about Alpha and then will be asked to make several judgments about the company. The information provided in the case is constructed from press releases, forms 8-K and 10-K, and Internet websites for companies operating in the publishing and commercial printing industries. The case provides the participants with definitions of four key financial ratios and described them as critical to the financial performance and earnings potential of firms in the publishing and commercial printing industry. In addition, participants are informed that they have \$10,000 to potentially invest in Alpha.

Participants were given instructions to the case and provided with a web address for Alpha, Inc. The case informed participants that Alpha's website includes general information about Alpha as well as Alpha's most recent annual report, which are available on their Investor

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³⁰ Elliott et al. (2007) examine whether and when MBA students are good proxies for nonprofessional investors and conclude that when tasks are relatively low in integrative complexity, early MBA students are good proxies for nonprofessional investors. The task used in this study is similar to the low integrative complexity task used in Elliott et al. (2007) where participants analyze a firm's financial information and view an analyst report discussing the firm's performance and future potential. The participants in this study have similar characteristics as the early MBA students in Elliott et al. (2007). For study1 (study 2) conducted in Elliott et al. (2007), the early MBA students had an average of 5.2 (5.8) years of work experience, had taken an average of 1.8 (1.6) accounting courses and 1.0 (0.6) finance courses, and 83% (84%) had evaluated a company's performance by evaluating its financial statements at least once.

Relations page. Participants were then asked to use the information on Alpha's website to complete the task. The website provided contains a profile of Alpha, Alpha's financial statements and accompanying notes, and an auditor's report. Alpha's website also included a landing or home page, an about us page, and an investor relations page. The profile information on Alpha's website states that Alpha was founded in 1990, works with more than 20,000 customers in North America, is traded on the New York Stock Exchange, and has three business segments – Print, Logistics, and Financial. A brief description of each business segment is provided. After viewing this information, participants complete the financial analysis questionnaire. The questionnaire asks participants to calculate four key ratios (return on assets, current ratio, inventory turnover, and return on sales) for Alpha based on the information contained in the financial statements. Following this analysis, participants provide a preliminary estimate of Alpha's stock price and are asked if they would invest their \$10,000 in Alpha's stock. In addition, participants are asked how much of their \$10,000 they would invest in Alpha versus a fixed yield savings account. The preliminary estimate and investment question provide premanipulation responses used as control variables in subsequent statistical testing.

Following the initial investment exercise, participants view a press release stating that Alpha has provided a forecast for the current year. Next, participants view the earnings announcement. With the exception of the experimental manipulations, the content of the announcement is identical across all experimental conditions. After viewing the press release, participants report their reaction to Alpha's forecast and assess its credibility. Participants also provide a post-manipulation estimate of Alpha's stock price and are asked if they would invest their \$10,000 in Alpha's stock. Participants are also asked how much of their \$10,000 they

would invest in Alpha versus a fixed yield savings account. The next phase of the study includes questions designed to obtain perceptions of forecast credibility, interactivity, argument quality, need for cognition, and measure of financial reporting knowledge. Finally, participants respond to manipulation check and demographic questions. Figure 15 presents a timeline of the experimental task.

Manipulation of Interactivity

Interactivity is manipulated by varying the ability of users to interact with the information presented on Alpha's Web site as guided by the seven categories of interaction discussed in Yi et al. (2007). In the high interactivity condition, participants can use an interactive viewer to view Alpha's financial statements and notes information. The interactive viewer uses a drop-down list box to select available sections of the annual report and specific note information related to a financial statement item. The drop-down list box corresponds to both the filter and connect interactivity techniques discussed in Yi et al. (2007). In the high interactivity condition, participants can hover over financial statement items within the interactive viewer and view the definition on each item, corresponding to the abstract/elaborate interactivity technique described in Yi et al. (2007). Finally, participants in the high interactivity condition were also given the option to view Alpha's annual reports using Excel or PDF. Participants in the low interactivity condition have the same information available to them on Alpha's Web site. However, the annual report is only available in PDF. Appendix C displays screenshots of Alpha's website in the high interactivity and low interactivity conditions.

Manipulation of Argument Quality

The argument quality manipulation is adapted from the experimental materials used in Hirst et al. (2007)³¹. Argument quality is manipulated by varying the use of "soft talk" and verifiable forward-looking statements. Across all experimental conditions, a press release is issued. In the strong argument quality condition, the press release includes the use of verifiable-forward looking statements regarding the Company's future financial outlook by providing forecasts of net income, revenue from operations, gross margin, and selling, general, and administrative expenses. In the weak argument quality condition, "soft talk," vague positive statements regarding the Company's future financial outlook is used and the press release only includes a forecast of net income. Appendix C details the experimental manipulations in the weak and strong argument quality conditions.

Measurement of Latent Variables and Scale Development

Scales are adapted from previous research to measure perceived interactivity, perceived argument quality, need for cognition, perceived forecast quality, perceived forecast clarity, and forecast credibility. All scales, with the exception of the forecast credibility scale, utilize seven-point Likert-type scales, anchored at strongly disagree and strongly agree. Table 24 details these constructs and their corresponding measurement items.

Perceived Interactivity

A perceived interactivity scale was administered in order to measure participants' perceptions of actual interactivity. The perceived interactivity scale was adapted from Song and

³¹ Hirst et al. (2007) examine the influence of aggregated (forecast with no precise information on how the forecast will be achieved) and disaggregated (verifiable forecast supplemented with forecasts of line items) forecasts on forecast credibility.

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Bucy (2008). The original scale includes 15 items designed to measure three aspects of interactivity – two-way communication, active control, and synchronicity. The original scale was adapted for the current study and includes five items related to the active control dimension. The two-way communication and synchronicity dimensions are not applicable to the available interactive features in this study.

Argument Quality

A perceived argument strength scale is adapted from Zhao et al. (2011). The original scale included ten items designed to measure the perceived argument strength of the message in persuasive communication. The adapted scale used in this study includes seven items as applicable to the current study.

Moderating Variables

Participants are asked to complete both a need for cognition scale and a financial literacy quiz. The need for cognition scale includes 18 items from Cacioppo et al. (1984) designed to measure an individual's tendency to engage in and enjoy effortful cognitive endeavors. The scale was deemed reliable in the Cacioppo et al. (1984) study with a Cronbach's alpha of .90.

The financial literacy quiz was adapted from Elliott et al. (2007) and includes 15 questions designed to measure financial reporting knowledge. The number of correct responses on the financial literacy quiz is used to assess participants' level of financial reporting knowledge.

Dependent Variables

Perceptions of forecast credibility are adapted from Hirst et al. (2007). Hirst et al. (2007) sought to explain the mechanisms through which forecast disaggregation influenced forecast credibility and developed a model where the effect of forecast disaggregation on forecast credibility is determined by three components – perceived forecast clarity, perceived financial reporting quality, and perceived precision of management's beliefs. However, the results from Hirst et al. (2007) reveal that the perceived precision of management's beliefs scale is not reliable. In addition, forecast disaggregation did not have an effect on the perceived precision of management's beliefs. In this study, participants respond to questions designed to measure perceptions of Alpha's forecast quality, forecast clarity, and forecast credibility. Forecast credibility is measured with two questions, the first question is anchored at extremely discreditable and extremely credible, while the second question is anchored at extremely unbelievable and extremely believable.

In order to capture supporting behavioral intentions, participants are asked if they would invest their \$10,000 in Alpha and how much of the \$10,000 they would invest both pre and post viewing Alpha's press release. The post press release investment amount is used as a measure of the investment decision.

Data Analysis and Results

This study uses analysis of variance (ANOVA) to first examine the effects of the manipulated experimental conditions on forecast credibility. Thus, hypotheses H1, H2, H3, H4a, H4b, H5a, and H5b are examined in the experimental analyses. A composite score is calculated

as a measure for forecast credibility for the ANOVA analysis based on the mean score on the forecast credibility questions³². For experimental testing purposes, participants are classified as having high or low financial reporting knowledge based on their relative score on the financial literacy quiz. Specifically, participants with scores above (below) the mean financial literacy score within the sample (mean = 7.48) are classified as possessing high (low) financial reporting knowledge³³. Participants are also classified as having high or low need for cognition based on their relative score along the need for cognition scale. Participants with scores above (below) the mean need for cognition score within the sample (mean = 95.92) are classified as having high (low) need for cognition³⁴.

All of the hypothesized relationships and the entire research model are further examined using structural equation modeling. The objective of the experimental analysis is to examine the effect of the manipulated variables (interactivity and argument quality) on perceptions of forecast credibility. On the other hand, the structural model is used to examine how individual perceptions of interactivity and argument quality impact perceptions of credibility and the investment decision. Thus, structural equation modeling is used to examine the relationships in the structural model using latent variable measures. Structural equation modeling facilitates the simultaneous examination of the effects of both the central route (argument quality) and the

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³² Another method of computing a composite score using regression-based factor scores from a principal components analysis was examined (DiStefano et al. 2009). Analyses results did not differ between using the forecast credibility factor score or the forecast credibility composite score. The composite score is used because it retains the original scale metrics and allows for easier interpretation.

³³ Financial reporting knowledge was used as a continuous variable in a regression analysis and a dichotomous variable for ANOVA. The results did not differ between using financial reporting knowledge as a continuous variable or a dichotomous variable so the dichotomous variable was retained for reporting the results of the ANOVA.

³⁴ Need for cognition was used as a continuous variable in a regression analysis and a dichotomous variable for ANOVA. The results did not differ between using need for cognition as a continuous variable or a dichotomous variable so the dichotomous variable was retained for reporting the results of the ANOVA.

peripheral route (interactivity) on forecast credibility and actual behavior because it is "particularly useful in testing theories that contain multiple equations involving dependence relationships" (Hair et al. 2010, p. 612). PLS is used to validate and test the measurement and structural models represented in the research model. PLS is a components-based structural equation modeling technique. PLS analysis is used to assess the reliability of the measurement model and test the structural model because this study includes a latent construct (forecast credibility), which is measured as a second-order formative construct.

ANOVA Results

ANOVAs are conducted to examine the effect of interactivity and argument quality on perceptions of forecast credibility. Table 25 presents the results of this analysis. Panel A of Table 25 summarizes descriptive statistics for the effects of interactivity and argument quality on forecast credibility. The results of the ANOVA are displayed in Panel B of Table 25. H1 predicts that interactivity will have a positive effect on forecast credibility. However, the experimental results indicate that H1 is not supported (F = 0.210, p = 0.647). H2 posits that argument quality will have a positive effect on forecast credibility. However, the results indicate that the effect of argument quality on forecast credibility is not statistically significant (F = 2.797, p = 0.097) and H2 is not supported. H3 predicts that the effect of interactivity on forecast credibility will be mitigated or reduced by argument quality. However, the results indicate that the interacting effect of interactivity and argument quality on forecast credibility is not statistically significant (F = 0.851, p = 0.358). Thus, H3 is not supported.

H4a and H4b examine the moderating effect of need for cognition on the relationship between interactivity and forecast credibility, and the relationship between argument quality and forecast credibility³⁵. Table 26 displays the results of the moderating analyses. Panel A reports the moderating effect of need for cognition on the relationship between interactivity and forecast credibility. Results indicate that H4a is not supported as the moderating effect of need for cognition on interactivity does not have a statistically significant effect on forecast credibility (F = 0.027, p = 0.870). Panel B reports the moderating effect of need for cognition on the relationship between argument quality and forecast credibility. Results indicate that H4b is not supported. The moderating effect of need for cognition on the relationship between argument quality and forecast credibility is not significant (F = 0.411, p = 0.523).

H5a and H5b examine the moderating effect of financial reporting knowledge on the relationship between interactivity and forecast credibility, and the relationship between argument quality and forecast credibility³⁶. Table 27 displays the results of the moderating analyses. Panel A reports the moderating effect of financial reporting knowledge on the relationship between interactivity and forecast credibility. Results indicate that H5a is not supported as the moderating effect of financial reporting knowledge on interactivity does not have a statistically significant effect on forecast credibility (F = 0.004, p = 0.947). Panel B reports the moderating effect of financial reporting knowledge on the relationship between argument quality and forecast credibility. Results indicate that H5b is not supported. The moderating effect of financial

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³⁵ Regression analyses were also conducted to test for the moderating role of need for cognition. Product terms were created for the interaction effect by first, mean centering the need for cognition variable, and second, creating the product terms for the interaction of need for cognition and interactivity, and need for cognition and argument quality. Results from the regression analyses did not differ from the reported ANOVA results.

³⁶ Regression analyses were also conducted to test for the moderating role of financial reporting knowledge. Product

³⁰ Regression analyses were also conducted to test for the moderating role of financial reporting knowledge. Product terms were created for the interaction effect by first, mean centering the financial reporting knowledge variable, and second, creating the product terms for the interaction of financial reporting knowledge and interactivity, and financial reporting knowledge and argument quality. Results from the regression analyses did not differ from the reported ANOVA results.

reporting knowledge on the relationship between argument quality and forecast credibility is not significant (F = 1.071, p = 0.303).

Results: Structural Model Analysis

SmartPLS 2.0 (Ringle et al. 2005) is used to validate and test the measurement and structural models represented in the research model. Bootstrapping resampling (1000 samples) is used to generate t-statistics for conducting the statistical analysis. The measurement model and the structural model are discussed in the following sections.

Construct Reliability and Validity

Factor loadings, composite construct reliability, and average variance extracted are used to assess the convergent and discriminant validity of the reflective constructs in the research model. Table 24 details the descriptive statistics for scale item measures. Convergent validity identifies how well indicators of a specific latent construct capture the variance in the construct (Hair et al. 2010). According to Hair et al. (2010), factor loadings of 0.50 and higher are acceptable, however, factor loadings of at least 0.70 are more desirable. Several items were eliminated from the need for cognition scale due to low loadings. Table 24 details the items that were eliminated. Eliminating these items improved the composite reliability and average variance extracted (AVE) for the need for cognition construct. One item (item 3) is eliminated from the argument quality construct due to low factor loadings and one item (item 2) is eliminated from the forecast quality construct due to high cross loadings with perceived argument quality. Table 28 reports item loadings and cross loadings for the retained items. All item loadings are 0.70 or higher, with the exception of two need for cognition items (items 4 and 9). However, these items are retained in the analyses. Table 29 reports the related composite

reliability and AVE for each reflective construct. The related composite reliability for each construct is greater than the recommended 0.70, and all AVE are greater than 0.50 supporting the convergent validity of the reflective constructs (Fornell and Larcker 1981; Hair et al. 2010). Discriminant validity identifies the extent to which a construct is truly distinct from other constructs (Hair et al. 2010). Table 29 reports the construct correlations and the square root of AVE. The square root of all average variance extracted is larger than the intercorrelations between the constructs, supporting discriminant validity (Chin 1998).

Forecast credibility is modeled as a second-order formative construct comprised of two dimensions, forecast clarity and forecast quality, which are measured reflectively³⁷. Forecast credibility is estimated by first estimating factor scores for the reflective item measures representing forecast clarity and forecast quality using principal components analysis with promax rotation. Construct validity and reliability for the second-order construct are evaluated according to the recommendations specified in Petter et al. (2007). First, to assess validity, principal components analysis with oblique rotation is used to examine item weightings for the two dimensions of forecast credibility using each construct's factor scores. Both items load on the second-order latent construct at 0.928 with 86.03% of variance explained. Second, the presence of multicollinearity is determined in order to evaluate reliability. Variance inflation factors (VIF) are calculated using the factor scores from forecast clarity and forecast quality, and the forecast credibility composite score. The VIFs for both forecast clarity and forecast quality

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³⁷ In Hirst et al. (2007), forecast clarity and forecast quality are described as components of forecast credibility and modeled as antecedents to forecast credibility in the structural model.

was 2.080, which falls below the suggested cutoff of 3.3 (Diamantopoulos and Siguaw 2006; Petter et al. 2007).

Common Method Bias

As with all self-reported data, there is a potential for common method bias. Common method bias represents "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podaskoff et al. 2003, p. 879). The single unmeasured latent common factor method test was performed to rule out the presence of common method bias in this study (Podsakoff et al. 2003; Liang et al. 2007).

Following Podsakoff et al. (2003) and Liang et al. (2007), a common method construct was added to the measurement model. The first step in carrying out this test is to create a single indicator construct for each indicator in the measurement model and link each single indicator to the substantive construct it is designed to measure. Therefore, a single item indicator was created for every item measure in this study and linked to their corresponding substantive construct (e.g. forecast clarity, need for cognition, etc.). Second, a common method factor is added to the model and includes all of the indicators used in the model. Finally, a link is created between the common method construct and each single indicator construct. Common method bias is assessed by examining the path coefficients and significance of the links between the substantive constructs and single item indicator constructs as well as the path coefficients and significance of the links between the common method construct and the single item indicator constructs.

Common method bias is determined to have minimal effect "if the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances" (Liang et al. 2007, p. 87). The results of this test are detailed in Table 30. The results

indicate that the variances of the indicators to the substantive constructs are greater than the variances to the common method construct. In addition, all but four of the loadings on the common method construct are not statistically significant. Finally, the AVE due to the substantive constructs is 72.2 percent compared to 2.3 percent for the common method construct. Thus, common method bias is deemed to be of no concern in this study.

Results of Hypotheses Testing

Figure 16 presents the structural model with path loadings and significance levels relating to the hypothesized relationships. The model explains 72.2% of the variance in forecast credibility and 53.6% of the variance in the final investment decision. H1 and H2 examine the effects of the two different routes to processing on forecast credibility. H1 predicts that interactivity will have a positive effect on user perceptions of forecast credibility. The model results indicate a significant and positive relationship (β = 0.127, p < 0.05) between perceived interactivity and forecast credibility. This finding suggests that interactivity does function as a peripheral cue in influencing attitudes and that the decision-making of nonprofessional investors can be affected by the perception of interactivity. H2 hypothesizes that argument quality will have a positive effect on user perceptions of forecast credibility. Consistent with H2, the results indicate that perceived argument quality has a significant and positive effect on forecast credibility (β = 0.765, p < .001).

H3 examines the expectation that as individuals process information more in the central route, the effect of the peripheral route on credibility will diminish. Thus, H3 predicts that argument quality will weaken the relationship between interactivity and user perceptions of forecast credibility. H3 is examined in the structural model by adding a path for the interaction

term of perceived argument quality and perceived interactivity to forecast credibility. The product indicator method of building moderator variables in PLS is used to add the latent variables for the interaction to the model (Chin et al. 1996; Henseler and Fassott 2010)³⁸. The results of adding this path to the structural model is displayed in Figure 17. The results show that the interaction of perceived argument quality and perceived interactivity on forecast credibility is not statistically significant (β = 0.046, p = 0.230). In addition, although the addition of the interaction term reduced the regression coefficient of the effect of perceived interactivity on forecast credibility, a test for a difference in the effect of perceived interactivity on forecast credibility with and without the interaction term indicates that this change is not statistically significant (t = 0.050, p = 0.961). Thus, H3 is not supported.

H4a and H4b examine the effect of a moderating variable, need for cognition on the relationship between perceived interactivity and forecast credibility, and the relationship between perceived argument quality and forecast credibility. The product indicator method of building moderator variables in PLS is used to add the latent variables for the interaction to the model (Chin et al. 1996; Henseler and Fassott 2010). H4a predicts that the relationship between perceived interactivity and credibility will be weakened with high levels of need for cognition. The results indicate that the moderating effect of need for cognition on perceived interactivity is not significant (β = -0.100, p = 0.956, left-tailed). Thus, H4a is not supported. H4b examines the interaction effect of need for cognition and perceived argument quality on forecast credibility.

³⁸ The moderator variable is created through the interaction of the predictor variable and the moderator variable by obtaining the product terms of all the individual indicators from the two variables. The product indicator then becomes the latent interaction variable used in the model. The variables are mean centered before the product indicator is computed as recommended in Chin et al. (1996) and Henseler and Fassott (2010).

The results indicate that this interaction effect does not have a significant effect on forecast credibility ($\beta = 0.034$, p = 0.256) and H4b is not supported.

H5a predicts that financial reporting knowledge will weaken the relationship between perceived interactivity and forecast credibility. The results show that H5a is not supported (β = -0.013, p = 0.600, left-tailed). H5b predicts that financial reporting knowledge will strengthen the relationship between argument quality and forecast credibility. The results indicate that H5b is not supported as the moderating effect is not statistically significant (β = 0.080, p = 0.081).

H6 examines the relationship between forecast credibility and the investment decision. H6 predicts that perceptions of forecast credibility will have a positive effect on the subsequent investment decision. Results indicate support for H6 as the relationship between forecast credibility and the investment decision is positive and statistically significant (β = 0.435, p < 0.001).

H7 predicts that individuals who form their perceptions of forecast credibility via the central route will exhibit stronger behavioral supporting intentions than individuals who form their perceptions via the peripheral route. H7 examines if there is a difference in the final investment choice made between individuals who are influenced by perceived argument quality (the central route) and individuals who are influenced by perceived interactivity (the peripheral route). To test for H7, the indirect and total effects of perceived argument quality and perceived interactivity on the investment decision are examined and compared. While the path coefficients and t-statistics of the total effects are generated in PLS, the path coefficients of the indirect effects are generated using the product term of the coefficients of the related direct paths and

bootstrap procedures are used to conduct 99 percent (p < 0.01) confidence intervals for testing the significance of the indirect effects (Hayes 2009; Elbashir et al. 2013).

The indirect and total effects of perceived argument quality on the investment decision are reported in Table 31. Panel A of Table 31 displays a summary of the indirect effects of perceived argument quality on the investment decision. The results show that perceived argument quality indirectly affects the investment decision through forecast credibility (indirect effect is 0.765 * 0.435 = 0.333, p < 0.01). The total effect of perceived argument quality on the investment decision is equal to the total indirect effect, given that the structural model does not test for the direct effect of perceived argument quality on the investment decision. Panel B of Table 31 summarizes the total effect and t-statistic for the total effect and it is significant at p < 0.001. The indirect and total effects of perceived interactivity on the investment decision are reported in Table 32. Panel A of Table 32 displays a summary of the indirect effects of perceived interactivity on the investment decision. The results show that perceived interactivity indirectly affects the investment decision through forecast credibility (indirect effect is 0.127 * 0.435 = 0.055, p < 0.01). The total effect of perceived interactivity on the investment decision is equal to the total indirect effect, given that the structural model does not test for the direct effect of perceived interactivity on the investment decision. Panel B of Table 32 summarizes the total effect and t-statistic for the total effect and it is significant at p < 0.001. A test for the difference between the regression coefficient for the total effect of perceived argument quality and the regression coefficient for perceived interactivity indicates that the total effect of perceived argument quality on the investment decision is significantly higher than the total effect of perceived interactivity on the investment decision (t = 4.205, p < 0.001). Overall, these results

provide support for H7 as perceived argument quality contributes more to determining the final investment decision compared to perceived interactivity.

Summary and Conclusions

This research study examines the effect of increasing interactivity in internet financial reporting on investors' perceptions of forecast credibility, and on a firm's attractiveness as a potential investment choice. Extant research on disclosure credibility suggests that one of the factors that influence investor credibility of management's earnings forecasts is the characteristics of the forecast itself, including forecast form, the timing of the forecast, forecast disaggregation, attributions associated with the forecast, and forecast venue (Mercer 2004; Hirst et al. 2008; Elliott et al. 2012; Han 2013). Due to the development of new technologies, the Internet has become a prevalent disclosure and financial reporting venue in recent years (Ettredge et al. 2001; Ettredge et al. 2002; Cho and Roberts 2010). Particularly in 2009, the SEC issued a mandate requiring public companies to provide their financial information to the SEC and on their corporate Websites in an interactive format using XBRL (XBRL; SEC 2009).

Interactivity has increasingly become a more salient element of financial reporting on the Web. Investors now rely heavily on corporate websites for financial statements, press releases, speeches, and links to further information (Lymer and Debreceny 2003). According to the SEC, the new standard for interactive financial statement reporting is intended to improve the usefulness of financial information to investors. However, there is a lack of understanding of how investors perceive disclosures in the presence of increasing interactivity in the disclosure venue. The results from previous research suggest that interactivity potentially induces positive

moods which may override the critical scrutiny of presented information and influence users of financial information (e.g. Kida et al. 1998; Clements and Wolfe 2000; Rose 2001; Rose et al. 2004; Elliott et al. 2012). On the other hand, according to disclosure literature, management's earnings forecast acts as an influencing tool in management's communication with investors (e.g. Hutton et al. 2003; Hirst et al. 2007; Lansford et al. 2007; Davis et al. 2012). This study thus investigates which of the two above mentioned mechanisms shape investors' perceptions of forecast credibility in the context of increasing interactivity in financial reporting.

This study employs the elaboration likelihood model (ELM) as a theoretical lens to understand how investors' perceptions of credibility are shaped. ELM is a dual-process theory of persuasion that posits that there are two routes to information processing. The central route is where critical thinking about issue-relevant information occurs. On the other hand, the peripheral route is primarily governed by non-content elements or cues associated with presented information (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). In addition, the likelihood of which route is taken is dependent on the motivation and ability of the individual decision-maker. Based on the ELM literature, the central route is operationalized in this study as the argument quality of management's earnings forecast, which is manipulated by varying the use of "soft talk" or verifiable forward-looking statements in an earnings forecast. The peripheral route is operationalized as the presence or absence of interactivity, motivation is measured using a need for cognition scale, and ability is operationalized as financial reporting knowledge.

ANOVA is used in the experimental analyses to examine the effects of the manipulated variables on forecast credibility. The results from the experimental analyses indicate that

argument quality and interactivity do not significantly impact forecast credibility. However, this study conceptualizes interactivity according to the perceptual view of interactivity (Liu and Shrum 2002; Voorveld et al. 2011), which asserts that a user's experience and perceptions during involvement with an interactive medium is important in shaping subsequent attitudes. Along similar lines, the basic tenets of ELM suggest that the persuasive success of the central and peripheral routes will be dependent on how an individual perceives message arguments or existing peripheral cues. Specifically in this study, it is expected that the effect of argument quality and interactivity on forecast credibility will be dependent on individual perceptions of argument quality and interactivity, respectively. For instance, if argument quality is strong and the consideration of management's earnings forecast generates positive thoughts, then perceptions of forecast credibility should be high. On the other hand, if strong argument quality generates predominantly negative thoughts, then perceptions of forecast credibility should be low and attitude change will be unsuccessful. Thus, structural equation modeling using PLS analysis is also conducted to examine the effects of perceived interactivity and perceived argument quality on forecast credibility and the investment decision, and to examine the simultaneous effect of both processes in shaping attitudes and behavior.

The results from the structural model suggest that nonprofessional investors are influenced by both the perceived interactivity and perceived argument quality. Both perceived argument quality and perceived interactivity had a significant and positive effect on forecast credibility. This suggests that consideration of both user perceptions of interactivity and perceptions of argument quality are important in explaining forecast credibility in a disclosure

setting. However, perceived argument quality had a stronger effect on forecast credibility than perceived interactivity.

According to ELM, an individual may reach the same decision or attitude change via either the central or the peripheral route. However, ELM postulates three differences based on the route taken. ELM posits that attitude changes formed along the central route tend to be more stable, more predictive of behavior, and less susceptible to counter-persuasion (Petty and Cacioppo 1986a; Petty and Cacioppo 1986b). The results of this study indicate that perceived argument quality has a stronger impact on actual investment behavior than perceived interactivity. While perceived argument quality and perceived interactivity both have positive and significant total effects on the investment decision, the regression coefficient of the total effect of perceived argument quality on the investment decision is higher, indicating that perceived argument quality has a greater impact on actual behavior.

The findings in this study contribute to the research on interactivity in financial reporting contexts. To date, prior research (Tang et al. 2014) has focused on the functional view of interactivity and examined the impact of interactivity features on outcome variables such as decision accuracy. This study extends the definition of interactivity in financial reporting to the perceptual view and acknowledges that the perceptual view of interactivity is important when considering the effect of interactivity on user perceptions. The interactivity literature in the marketing and advertising domains (e.g. Song and Zinkhan 2008; Voorveld et al. 2011) advocate the consideration of the experiential effects of interactivity. For example, Voorveld et al. (2011) examined the difference between an expert developed actual interactivity index score for the

website of 65 of the top 100 global brands, and perceptions of interactivity obtained from a survey of users who were asked to browse the company websites. The results from Voorveld et al. (2011) suggests that adding interactive functions to a Website does not guarantee higher perceived interactivity and there may be incompatibility in the level of actual interactivity and perceived interactivity. The results in this study correspond with the functional view and indicate that actual interactivity and perceived interactivity can differ in their effects on attitudes and beliefs.

As with all research, this study has limitations. It is possible that the interactivity manipulation used in this study is relatively simple. Voorveld et al. (2011) discuss the concept of expected interactivity as a possible explanation for the incongruence between actual interactivity and perceived interactivity. Expected interactivity is defined as "the extent of interactivity that a person expects to experience during a prospective interaction with a message vehicle, such as a website" (Sohn et al. 2007, p. 110). Interactive functions (e.g. hyperlinks) may be so common that a user would not consider them interactive, and only unique interactive features would affect interactivity perceptions (Voorveld et al. 2011). It is possible that participants did not consider the interactivity manipulations used in this study (i.e. the drop-down filtering tool, and hyperlinked financial statement item definitions) unique in nature. However, the interactive features used in this study were designed to mirror some of the features found on corporate websites today. Future research may examine the use of more interactive features (e.g. enhanced search capabilities, financial analysis tools, and multimedia) on influences processes in a disclosure setting.

The findings in this study also contribute to the voluntary disclosure research examining investor reactions to management earnings forecasts. This study considers the effects of two forecast characteristics (i.e. forecast attributions and forecast venue) in influencing investor perceptions of forecast credibility. Elliott et al. (2012) find that management's choice of disclosure venue (video versus text) for earnings restatement announcements affects investor trust in management. Along similar lines, the results in this study suggest that user perceptions of the presence of interactivity in IFR influence subsequent perceptions of forecast credibility in the context of management's earnings forecasts. In this study, the effect of perceived interactivity is small relative to the effect of perceived argument quality. However, in light of the concept of expected interactivity, it is possible that perceived interactivity has a greater influence on perceptions of credibility and investment decisions if more unique interactivity techniques are used in IFR. Future research could investigate the possibility that different interactivity techniques may exert more influence on user perceptions in relation to disclosure communication. Future research could also examine the effect of interactivity and disclosure communication on other measures of credibility (e.g. management's credibility).

The findings in this study are important in light of the XBRL mandate issued by the SEC and the move to interactive financial reporting on the Web. Internet financial reporting continues to grow in importance as the Securities and Exchange Commission (SEC) continues to pursue its initiative to make internet delivery of financial information the norm. However, despite the increase in IFR, there is very little understanding of how users utilize or interact with aspects of IFR and the subsequent effects on attitudes and behavior. This research study makes a contribution to the research stream by exploring how interactive financial reporting can induce

perceptions of credibility and a company's attractiveness as a potential investment. Future research could investigate the effects of interactivity on different types of disclosures (e.g. earnings restatement announcements, MD & A) and examine how influence processes might differ depending on the type of disclosure in question. The research in this study focused only on good news earnings forecasts. It is possible that the effects of interactivity on forecast credibility may differ based on the valence of the information contained in a forecast. Future research could also examine if there is a difference in influence processes depending on if the forecast contains good news or bad news.

In this study, the expectation that motivation and ability interact with the central and peripheral route to affect the likelihood of elaboration was not confirmed. This finding is inconsistent with previous research (e.g. Bhattacherjee and Sanford 2006). A limitation of this study might be in the choice of the motivation and ability operationalization. Future research in this area could replicate this study using other measures of motivation and ability (e.g. personal relevance).

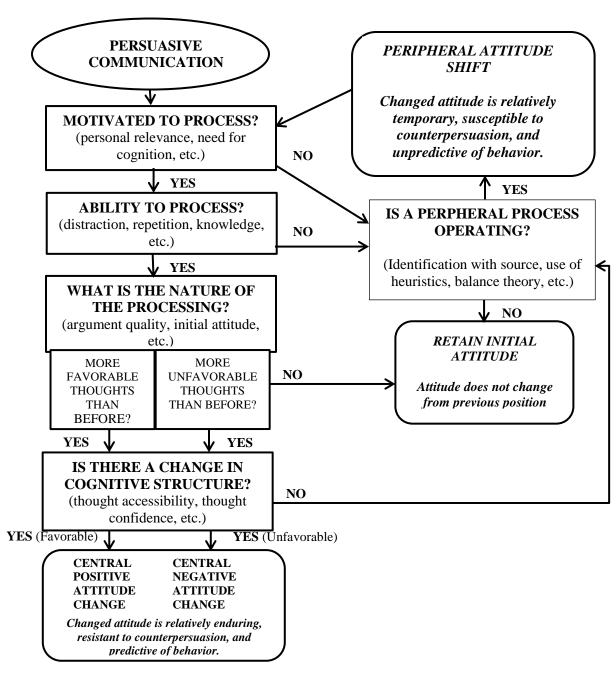


Figure 13: Elaboration Likelihood Model (ELM)³⁹

³⁹ Adapted from Petty et al. (2002).

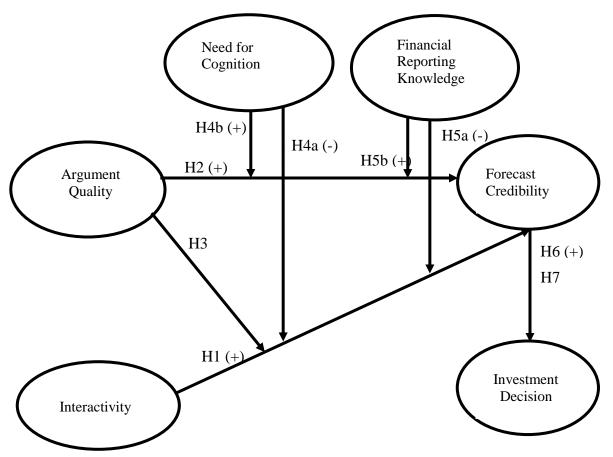


Figure 14: Research Model: Impact of Interactivity and Argument Quality on Forecast Credibility

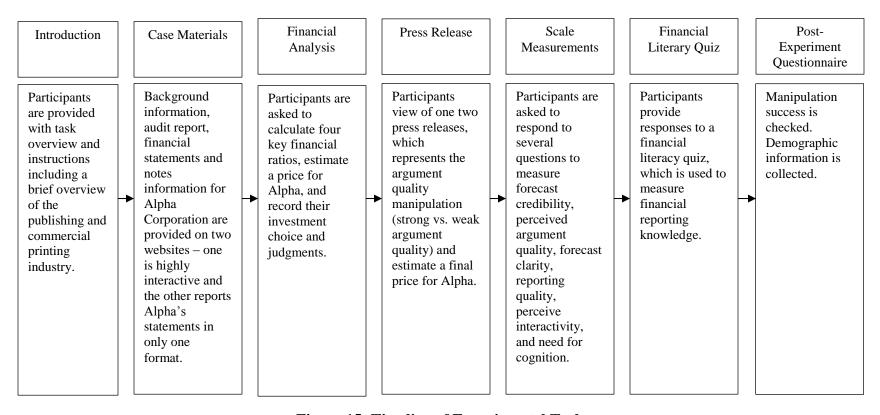


Figure 15: Timeline of Experimental Task

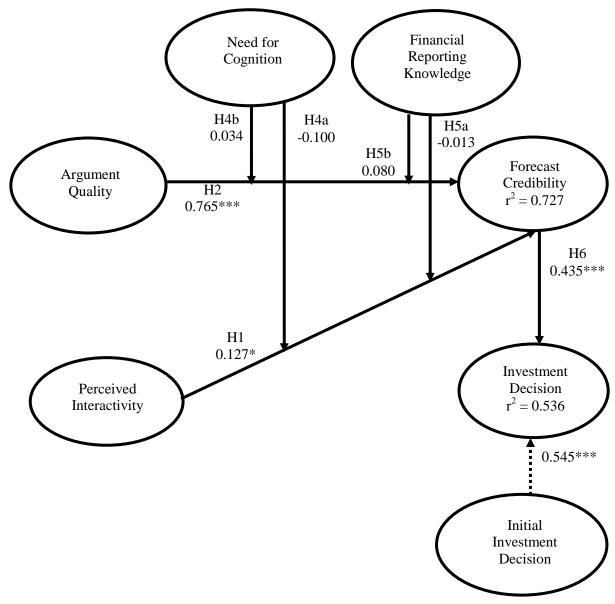


Figure 16: Results of Research Model Testing⁴⁰

 $\begin{array}{ll} * & p < 0.05 \\ ** & p < 0.01 \\ *** & p < 0.001 \end{array}$

-

⁴⁰ Dotted lines represent relationships that are not hypothesized, but controlled for in the research model

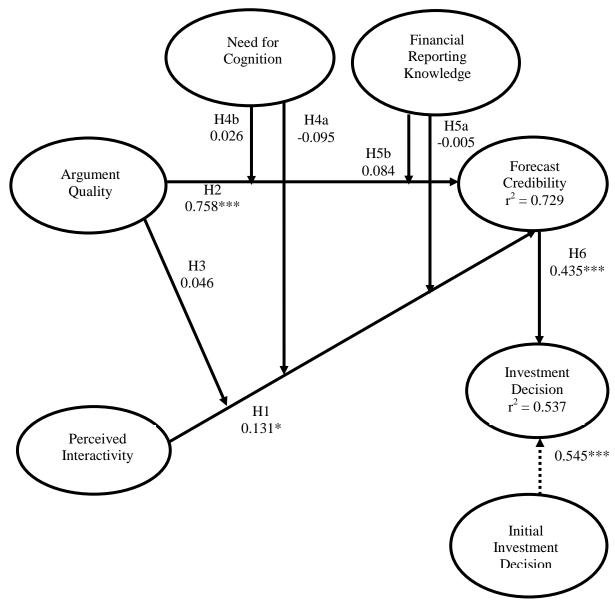


Figure 17: Results of Research Model Testing – Test of H3⁴¹

 $\begin{array}{ll} * & p < 0.05 \\ ** & p < 0.01 \\ *** & p < 0.001 \end{array}$

-

⁴¹ Dotted lines represent relationships that are not hypothesized, but controlled for in the research model

Table 23: Participant Demographics

Item	Frequency (n = 117)	Percent
Panel A: Gender		
Male	71	60.68
Female	46	39.32
Panel B: Age (in years)		
Under 25	39	33.33
25 to 40 years	50	42.74
40+ years	28	23.93
Panel C: Full-time Work Exp	perience (in years)	
None	8	6.84
1 to 2 years	14	11.97
3 to 6 years	31	26.49
7 to 10 years	17	14.53
10+ years	47	40.17
Panel D: Bought or sold com	mon stock or debt securities	
Yes	48	41.03
No	68	58.12
Did not answer	1	0.85
	aluated a company's performance b	y analyzing its
financial statements		
Never	29	24.79
1 to 5 times	57	48.72
6 to 10 times	9	7.69
10+ times	22	18.80
Panel F: Future Investment I		
Yes	91	77.78
No	24	20.51
Did not answer	2	1.71
Panel G: Courses Taken		
Accounting	Mean = $2.63 (3.56)$	75.21
Finance	Mean = $2.21 (2.37)$	70.94

Table 24: Descriptive Statistics for Item Measures

	Item Measure Name	Mean	Median (Range)	Standard Deviation
Forecast Credibility (Hirst et al. 2007)				
Forecast Clarity				
Please indicate your level of agreement or	r disagreement with	the followi	ng statements abo	out Alpha's
net income forecast.				
I believe that Alpha's management is	Clarity1	4.12	4.00	1.445
very clear about how they are going to			(1.00 - 7.00)	
achieve their net income forecast for the				
year.				
I believe that Alpha's forecast very	Clarity2	3.80	4.00	1.458
clearly demonstrated how Alpha could			(1.00 - 7.00)	
achieve their net income number.				
Given the information provided to me	Clarity3	3.95	4.00	1.401
in the case, I thought it was very easy			(1.00 - 7.00)	
for me to determine whether Alpha's				
net income forecast was plausible.				
I believe it is very easy to see how	Clarity4	3.61	3.00	1.358
Alpha could achieve their net income			(1.00 - 7.00)	
forecast.				
Forecast Quality				
Please indicate your level of agreement or	r disagreement with	the follows	ng statements abo	out Alpha's
net income forecast.	0 11: 1	416	1.00	1 402
I believe that Alpha's net income	Quality1	4.16	4.00	1.402
forecast is very plausible.			(1 ()() — / ()()	
	0 1'. 0	2.01	(1.00 - 7.00)	1 450
I believe that Alpha's net income	Quality2	3.81	4.00	1.450
forecast will prove to be very accurate.	Quality2	3.81		1.450
forecast will prove to be very accurate. (Dropped due to high cross loadings)	- ,		4.00 (1.00 – 7.00)	
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's	Quality2 Quality3	3.81	4.00 (1.00 – 7.00) 4.00	1.450
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high.	Quality3	3.97	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00)	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will	- ,		4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00) 4.00	
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net	Quality3	3.97	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00)	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income.	Quality3	3.97	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00) 4.00	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net	Quality3	3.97	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00) 4.00	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility	Quality3 Quality4	3.97	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00) 4.00	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in	Quality3	3.97	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00)	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is	Quality3 Quality4 Credibility1	3.97 3.91 4.65	4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00) 4.00 (1.00 – 7.00)	1.361 1.424 1.199
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in	Quality3 Quality4	3.97	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00)	1.361
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is	Quality3 Quality4 Credibility1 Credibility2	3.97 3.91 4.65	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00)	1.361 1.424 1.199
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in the press release is	Quality3 Quality4 Credibility1 Credibility2 2008)	3.97 3.91 4.65 4.57	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00) 5.00 (1.00 - 7.00)	1.361 1.424 1.199 1.248
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in the press release is Perceived Interactivity (Song and Bucy)	Quality3 Quality4 Credibility1 Credibility2 2008)	3.97 3.91 4.65 4.57	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00) 5.00 (1.00 - 7.00)	1.361 1.424 1.199 1.248
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in the press release is Perceived Interactivity (Song and Bucy Please indicate your level of agreement of	Quality3 Quality4 Credibility1 Credibility2 2008)	3.97 3.91 4.65 4.57	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00) 5.00 (1.00 - 7.00)	1.361 1.424 1.199 1.248
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in the press release is Perceived Interactivity (Song and Bucy Please indicate your level of agreement or experience on Alpha's web site.	Quality3 Quality4 Credibility1 Credibility2 2008) r disagreement with	3.97 3.91 4.65 4.57	$4.00 \\ (1.00 - 7.00)$ $4.00 \\ (1.00 - 7.00)$ $4.00 \\ (1.00 - 7.00)$ $5.00 \\ (2.00 - 7.00)$ $5.00 \\ (1.00 - 7.00)$ ng statements about	1.361 1.424 1.199 1.248
forecast will prove to be very accurate. (Dropped due to high cross loadings) I believe that the quality of Alpha's forecasted net income is very high. I believe it is very likely that Alpha will legitimately meet their forecasted net income. Forecast Credibility I believe that the forecast provided in the press release is I believe that the forecast provided in the press release is Perceived Interactivity (Song and Bucy Please indicate your level of agreement or experience on Alpha's web site. I had a lot of control over my	Quality3 Quality4 Credibility1 Credibility2 2008) r disagreement with	3.97 3.91 4.65 4.57	4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 4.00 (1.00 - 7.00) 5.00 (2.00 - 7.00) 5.00 (1.00 - 7.00) and statements above	1.361 1.424 1.199 1.248

Scale Item	Item Measure Name	Mean	Median (Range)	Standard Deviation
There is a variety of content on Alpha's website.	PI3	3.96	4.00 (1.00 – 7.00)	1.589
My actions decided the kind of	PI4	4.48	5.00	1.448
experience I got on Alpha's website.	114	7.70	(1.00 - 7.00)	1.440
I believe Alpha's website is interactive.	PI5	4.04	4.00	1.447
1 believe Alpha 8 website is interactive.	115	4.04	(1.00 - 7.00)	1,447
Argument Quality (Zhao et al. 2011)				
Please indicate your level of agreement of	r disagreement with	the followi	ng statements abo	out Alpha's
press release.	-			-
How much do you agree or disagree	AQ1	4.35	5.00	1.191
with the statements in Alpha's press			(2.00 - 7.00)	
release?				
I believe the statements in Alpha's	AQ2	4.36	5.00	1.429
press release are convincing.			(1.00 - 7.00)	
Most nonprofessional investors would	AQ3	5.19	5.00	1.203
find the statements in Alpha's press			(2.00 - 7.00)	
release believable. (Dropped due to low				
loading)				
The statements in Alpha's press release	AQ4	4.41	5.00	1.469
put thoughts in my head about wanting			(1.00 - 7.00)	
to invest in Alpha's stock.				
I find the statements in Alpha's press	AQ5	4.37	5.00	1.343
release believable.			(2.00 - 7.00)	
I believe the statements in Alpha's	AQ6	4.35	5.00	1.555
press release helped me feel confident			(1.00 - 7.00)	
about their positive outlook.				
I believe the statements in Alpha's	AQ7	4.44	5.00	1.471
press release are strong.			(1.00 - 7.00)	
Need for Cognition (Cacioppo et al. 198	84)			
Statements that people use to describe the	emselves are given b	below. Pleas	e choose the resp	onse that
indicates how you generally feel.	-		_	
I would prefer complex to simple	NFC1	4.91	5.00	1.326
problems.			(2.00 - 7.00)	
I like to have the responsibility of	NFC2	5.52	6.00	.961
handling a situation that requires a lot			(2.00 - 7.00)	
of thinking. (Dropped due to low				
loading)				
Thinking is my idea of fun. (Dropped	NFC3	5.26	5.00	1.115
due to low loading)			(1.00 - 7.00)	
I would rather do something that is sure	NFC4	5.50	6.00	.970
to challenge my thinking abilities than			(2.00 - 7.00)	
something that requires little thought.				

Scale Item	Item Measure Name	Mean	Median (Range)	Standard Deviation
I am drawn to situations where there is a likely chance I will have to think in depth about something. (<i>Dropped due</i> to low loading)	NFC5	5.32	5.00 (2.00 – 7.00)	.990
I find satisfaction in deliberating hard and for long hours. (<i>Dropped due to low loading</i>)	NFC6	4.82	5.00 (1.00 – 7.00)	1.349
I like to think about problems long and hard rather than just getting by with little thought. (Dropped due to low loading)	NFC7	5.15	5.00 (2.00 – 7.00)	1.111
I prefer to think about long term projects rather than small, daily ones. (Dropped due to low loading)	NFC8	4.97	5.00 (1.00 – 7.00)	1.303
I like tasks that require a lot of thought.	NFC9	5.12	5.00 (1.00 – 7.00)	1.076
The idea of relying on thought to make my way to the top appeals to me. (Dropped due to low loading)	NFC10	5.49	6.00 (2.00 – 7.00)	1.022
I really enjoy a task that involves coming up with new solutions to problems. (Dropped due to low loading)	NFC11	5.60	6.00 (3.00 – 7.00)	.992
Learning new ways to think excites me very much.	NFC12	5.56	6.00 (2.00 – 7.00)	1.163
I prefer my life to be filled with puzzles that I must solve.	NFC13	4.92	5.00 (1.00 – 7.00)	1.359
The notion of thinking abstractly is appealing to me. (<i>Dropped due to low loading</i>)	NFC14	5.39	5.00 (2.00 – 7.00)	1.159
I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought. (<i>Dropped due to low loading</i>)	NFC15	5.30	5.00 (2.00 – 7.00)	1.184
I feel a sense of satisfaction after completing a task that required a lot of mental effort.	NFC16	5.88	6.00 (3.00 – 7.00)	.930
I like knowing how or why something works. (<i>Dropped due to low loading</i>)	NFC17	5.97	6.00 (2.00 – 7.00)	.991
I usually end up deliberating about issues even when they do not affect me personally. (Dropped due to low loading)	NFC18	5.25	5.00 (1.00 – 7.00)	1.364

Table 25: The Effects of Interactivity and Argument Quality on Forecast Credibility

Panel A: Cell Means

	Low Interactivity	High Interactivity	Average
	Mean (Standard	Mean (Standard	Mean (Standard
	Deviation)	Deviation)	Deviation)
Weak Argument	4.267 (1.298)	4.571 (1.238)	4.392 (1.270)
Quality	n = 30	n = 21	n = 51
Strong Argument	4.839 (1.114)	4.737 (1.051)	4.780 (1.071)
Quality	n = 28	n = 38	n = 66
Average	4.543 (1.236)	4.678 (1.113)	4.611 (1.173)
	n = 58	n = 59	n = 117

Panel B: ANOVA Results

Source	Df	Mean Square	F-Ratio	p-value
Intercept	1	2371.505	1741.207	< 0.001
Interactivity	1	.286	.210	.647
Argument Quality	1	3.810	2.797	.097
Interactivity * Argument Quality	1	1.160	.851	.358
Error	113	1.362		
Total	117			

Table 26: Moderating Effects of Need for Cognition on Forecast Credibility

Panel A: Interactivity and Need for Cognition

Source	Df	Mean Square	F-Ratio	p-value
Intercept	1	2412.779	1735.523	< 0.001
Interactivity	1	.349	.251	.617
Need for Cognition	1	1.881	1.353	.247
Interactivity * Need for Cognition	1	.038	.027	.870
Error	113	1.390		
Total	117			

Panel B: Argument Quality and Need for Cognition

Source	Df	Mean Square	F-Ratio	p-value
Intercept	1	2301.707	1692.948	< 0.001
Argument Quality	1	3.429	2.522	.115
Need for Cognition	1	1.161	.854	.357
Argument Quality * Need for	1	.559	.411	.523
Cognition				
Error	113	1.360		
Total	117			

Table 27: Moderating Effects of Financial Reporting Knowledge on Forecast Credibility

Panel A: Interactivity and Financial Reporting Knowledge

Source	Df	Mean Square	F-Ratio	p-value
Intercept	1	2411.580	1722.732	< 0.001
Interactivity	1	.315	.225	.636
Reporting Knowledge	1	.838	.598	.441
Interactivity * Reporting	1	.006	.004	.947
Knowledge				
Error	113	1.400		
Total	117			

Panel B: Argument Quality and Financial Reporting Knowledge

Source	Df	Mean Square	F-Ratio	p-value
Intercept	1	2281.252	1679.919	< 0.001
Argument Quality	1	2.901	2.136	.147
Reporting Knowledge	1	.593	.437	.510
Argument Quality * Reporting	1	1.455	1.071	.303
Knowledge				
Error	113	1.358		
Total	117			

Table 28: Item Loadings and Cross Loadings

Item Measure Name	Argument Quality	Perceived Clarity	Perceived Quality	Need for Cognition	Perceived Interactivity
AQ1	0.896	0.650	0.777	0.103	0.098
AQ2	0.909	0.595	0.762	0.068	0.068
AQ4	0.811	0.545	0.588	0.104	0.044
AQ5	0.919	0.587	0.787	0.112	0.132
AQ6	0.908	0.634	0.730	0.079	0.098
AQ7	0.794	0.531	0.695	0.086	0.234
Clarity1	0.563	0.867	0.658	0.156	0.133
Clarity2	0.633	0.934	0.722	0.147	0.151
Clarity3	0.540	0.850	0.593	0.145	0.211
Clarity4	0.658	0.893	0.726	0.078	0.129
Quality1	0.819	0.720	0.937	0.177	0.244
Quality3	0.641	0.615	0.871	0.080	0.168
Quality4	0.817	0.760	0.946	0.135	0.243
NFC1	0.004	0.081	0.117	0.717	0.124
NFC12	0.049	0.055	0.117	0.762	0.142
NFC13	0.079	0.191	0.078	0.806	0.077
NFC16	0.173	0.087	0.141	0.737	0.013
NFC4	-0.013	-0.020	0.033	0.660	0.051
NFC9	-0.004	0.002	0.003	0.640	0.016
PI1	0.065	0.137	0.136	0.164	0.829
PI2	0.124	0.124	0.198	0.144	0.836
PI3	0.034	0.104	0.161	0.055	0.768
PI4	0.006	-0.016	0.089	0.100	0.716
PI5	0.169	0.204	0.270	0.029	0.865

Table 29: Tests of Convergent and Discriminant Validity⁴²

	Average Variance Extracted	Composite Reliability	1	2	3	4	5
Argument	0.764	0.951	0.874				
Quality							
Need for	0.522	0.867	0.107	0.722			
Cognition							
Forecast Clarity	0.786	0.936	0.677	0.150	0.887		
Perceived	0.648	0.901	0.128	0.112	0.174	0.805	
Interactivity							
Forecast Quality	0.844	0.942	0.831	0.146	0.763	0.240	0.918

 42 The square root of the AVE is shown on the diagonal in bold.

Table 30: Analysis for Common Method Bias

Construct	Indicator	Substantive Factor Loading	Variance Explained	Method Factor Loading	Variance Explained
Argument Quality	AQ1	0.741***	0.548	0.165	0.027
	AQ2	0.978***	0.956	-0.074	0.006
	AQ4	1.028***	1.057	-0.228	0.052
	AQ5	0.926***	0.857	-0.007	0.000
	AQ6	0.927***	0.860	-0.020	0.000
	AQ7	0.640***	0.410	0.163	0.027
Forecast Clarity	CLARITY1	0.908***	0.824	-0.047	0.002
	CLARITY2	0.921***	0.848	0.015	0.000
	CLARITY3	0.942***	0.888	-0.105	0.011
	CLARITY4	0.781***	0.610	0.129	0.017
Forecast Quality	QUALITY1	0.738***	0.545	0.212*	0.045
	QUALITY3	1.335***	1.782	-0.495***	0.245
	QUALITY4	0.719***	0.517	0.242**	0.058
Perceived Interactivity	PI1	0.845***	0.715	-0.010	0.000
	PI2	0.831***	0.691	0.034	0.001
	PI3	0.779***	0.606	-0.027	0.001
	PI4	0.827***	0.684	-0.106*	0.011
	PI5	0.786***	0.618	0.104	0.011
Need for Cognition	NFC1	0.744***	0.554	0.011	0.000
	NFC4	0.809***	0.654	-0.065	0.004
	NFC9	0.764***	0.583	-0.060	0.004
	NFC12	0.788***	0.621	0.025	0.001
	NFC13	0.656***	0.430	0.081	0.007
	NFC16	0.680***	0.463	0.105	0.011
Average		0.837	0.722	0.002	0.023

^{*} p < 0.05, ** p < 0.01, *** p < 0.001

Table 31: Indirect and Total Effects of Perceived Argument Quality on Investment Decision

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Perceived Argument Quality	Path to:
Through:	Investment Decision
	0.333**
Forecast Credibility	(0.327 - 0.337)
Total Indirect Effects	0.333

Panel B: Total Effects of Perceived Argument Quality

On	Coefficient	t-statistics	p-value
Investment Decision	0.333	5.399	p < 0.001

 $*p < .05; \ **p < 0.01; \ ***p < 0.001$

Table 32: Indirect and Total Effects of Perceived Interactivity on Investment Decision

Panel A: Indirect Effects and 99% Bootstrap Confidence Intervals (in parenthesis)

The Effect of Perceived Interactivity	Path to:
Through:	Investment Decision
	0.055**
Forecast Credibility	(0.052 - 0.056)
Total Indirect Effects	0.055

Panel B: Total Effects of Perceived Interactivity

On	Coefficient	t-statistics	p-value
Investment Decision	0.055	2.338	p < 0.05

 $^*p < .05; \ ^{**}p < 0.01; \ ^{***}p < 0.001$

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GENERAL CONCLUSION

Each of the three studies presented in this dissertation provides a unique perspective into the impact of characteristics of interactive data visualization on the decision-making of nonprofessional investors in financial reporting contexts. Based on literature reviews by Dilla et al (2010) and Lurie and Mason (2007), two characteristics of interactive data visualization (i.e. interactivity and visualization) that can potentially affect decision environments are identified and explored. Study one examines the effect of interactivity and visualization on task-technology fit, task performance during a financial statement analysis task, and on user attitudes and beliefs about interactive data technology use. Study two extends the first study by exploring how the experiential feedback (i.e. previous assessments of task-technology fit and perceptions of performance) from initial interactive data technology use affects future choice or continued use of the technology. Study three examines the effect of interactivity on nonprofessional investors' perceptions of forecast credibility and final investment decisions. Taken together, these three studies provide insights into user-machine interaction while using interactive data technology in financial reporting and analysis contexts. The results from these three studies provide unique contributions to theory and practice as described in more detail in the following paragraphs.

The results from study one provides important insights into how characteristics of interactive data visualization affect performance in a financial analysis context. One of the proposed benefits of the SEC XBRL mandate and interactive financial reporting is to enable the efficient acquisition and analysis of financial information. The results from study one indicate that higher levels of interactivity provide a better match between interactive data visualization technology and task requirements while conducting a financial analysis task. In addition, the

match between the task and interactive technology subsequently impacts perceptions of performance in a financial statement analysis task. Although perceptions of interactivity and visualization as assessed by nonprofessionals both increase task-technology fit, actual visualization does not have an effect on task-technology fit according to the experimental results. This might suggest that interactivity alone is a sufficient element of interactive data visualization for a financial analysis task. However, the effects of interactivity and visualization might be dependent on the task or decision environment. For instance, visualization might have a greater impact on the task environment for a task that requires that individuals both acquire and integrate information obtained in order to complete their analysis. Future research may explore other financial analysis tasks with varying levels of complexity and examine the impact of interactivity and visualization in those contexts.

Study one also provides additional insights by exploring an expanded model of decision-making in a financial analysis context – one that incorporates theories from IS (task-technology fit, technology acceptance) and cognitive psychology (cognitive load). This study contributes to the research stream by examining a model of performance which considers that the interaction of task requirements and technology characteristics may impose mental workloads on a decision-maker and detract from performance. The results indicate that although actual interactivity and visualization did not affect cognitive load, perceptions of interactivity affected cognitive load. However, this effect was not in the expected direction as the results indicate that interactivity may reduce cognitive load. Future research should examine this relationship in more detail.

Study one also contributes to the research stream by not only examining the impact of technology and task requirements on performance, but also examining the relationship between

the match between task and technology and the precursors to interactive data technology acceptance and use. The results show that task-technology fit does lead to an increase in perceptions of usefulness and intentions to use interactive data visualization technology. In addition, examining the indirect effects of interactivity and visualization indicates that both interactivity and visualization affect performance and the behavioral intention to use interactive data technology through the effects on task-technology fit. This suggests that nonprofessional investors will be more likely to respond positively to the potential use of interactive technology if the technology closely meets the needs of the investor while performing a financial analysis task. This finding provides valuable insight to the factors that potentially affect the use of interactive data technology since previous research has shown that nonprofessional investors did not use an interactive technology even when it was made available to them (e.g. Hodge et al. 2004).

The results from study two suggest that assessments of performance and the fit between interactive data technology and task requirements in a financial analysis task serve as antecedents to the extent a user's expectation about interactive data technology is confirmed or disconfirmed following initial use. This study provides insights by incorporating insights from Goodhue and Thompson's (1995) technology-performance chain model in examining Bhattacherjee' (2001) IS continuance model. In order for the benefits of interactive financial reporting to be realized, investors will have to use interactive technology beyond their initial or first use. The results indicate that both task-technology fit and assessments of performance positively affect post-use perceptions of the usefulness of interactive data technology and post-use assessments of satisfaction with interactive data technology use. In addition, perceived

usefulness and satisfaction both impact continuance intention, which affects utilization. Finding that nonprofessional investors will choose to use an interactive financial reporting technology based on their evaluation of performance impacts and the match between the technology and task is important because it provides software developers and the SEC with information on how to add value and encourage utilization in developing XBRL-enabled viewers.

Study two provides additional insights into the process through which nonprofessional investors may make their choice of interactive data technology by examining the research model for participants who chose the low interactivity viewer and participants who chose the high interactivity viewer separately. The results of this analysis suggest that task-technology fit is an appropriate antecedent to understanding continuance intention and utilization for participants who chose the low interactivity viewer, and for participants who chose the high interactive viewer. However, performance appears to have differential effects on continuance intention and utilization between the two groups. In addition, most of the participants in this study chose to use the highly interactive data viewer compared to the low interactive viewer. Overall, these findings are important because it suggests that characteristics of interactive data visualization do matter in determining future choice to use an interactive technology. Previous research that has examined the choice to use interactive data technology has only compared the choice to use XBRL instead of an Excel or PDF reporting format (e.g. Janvrin et al. 2013). Examining the choice to use one of two interactive reporting technologies is important because an individual's choice is more likely based on the extent to which elements of interactive data visualization are present and beneficial to the decision process, rather than the discrepancy between the capabilities of interactive data technology and more static financial reporting formats.

The results from study three suggest that nonprofessional investors are influenced by both their perceptions of interactivity and the information content of management's earnings forecast. This finding is important because it suggests that the presence of interactivity in financial reporting contexts could potentially function as a non-issue relevant cue and interfere with the information processing of nonprofessional investors. However, the evidence from study three indicates that management's earnings disclosure has a more influencing role on investor beliefs than interactivity. Future research can examine the effects of increasing interactivity and different types of disclosures on investor perceptions of credibility to determine if the influence on increasing interactivity differs depending on the type of disclosure. Future research can also examine if there is a difference in the influence process related to interactivity depending on if a disclosure contains good news or bad news. Study three also provides important insights into the effects of interactivity on actual behavior. The results from this study indicate that although interactivity affects individual perceptions of forecast credibility, its indirect effect on actual behavior or the investment decision is smaller compared to the effect of the information contained in management's earnings forecast. This finding is consistent with the propositions of the elaboration likelihood model and suggests that interactivity in financial reporting may not be a great concern if its impact on actual behavior is minimal.

These three studies contribute to our understanding of how nonprofessional investors might interact with interactive financial reporting technology. The SEC has been encouraging developers to build XBRL-enabled tools to meet the needs of investors (Clements et al. 2011). These studies present an in-depth examination of elements characteristic of interactive financial reporting technology in the context of the proposed benefits of interactive data to

nonprofessional investors. In addition to the theoretical contributions, these studies therefore also provide practical contributions to standard setters and software developers on how interactive financial reporting technology affects decision-making and the characteristics of interactive technology that lend to improved decisions and continued use by nonprofessional investors.

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APPENDIX A: STUDY 1 EXPERIMENTAL MATERIALS



EXPLANATION OF RESEARCH

Title of Project: Research on Nonprofessional Investors

Principal Investigator: Kemi Osidipe

Faculty Supervisor: Steve Sutton

You are being invited to take part in a research study. Whether you take part is up to you. The purpose of this study is to enhance our understanding of how nonprofessional investors make decisions using financial reporting technology. This research study consists of two phases. In both phases, you will be asked to assume the role of an investor evaluating companies for a potential investment. You will be asked to view both financial and nonfinancial information about the companies using a financial reporting technology. In the first phase, you will be introduced to two different financial reporting technologies. In the second phase, you will be asked to make a choice between the two financial reporting technologies previously used. Finally, in both phases, you will be asked to answer several questions about the information presented and asked to make judgments about the companies you analyzed, the task, and using financial reporting technology. You may complete the study at your earliest convenience. The estimated time to complete Phase 1 is approximately 60 minutes. You will be directed to Phase 2 after completing Phase 1. The estimated time to complete Phase 2 is approximately 30 minutes.

You must be 18 years of age or older to take part in this research study.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints please contact Kemi Osidipe, Doctoral Candidate, Dixon School of Accounting by email at oluwakemi.osidipe@ucf.edu or Dr. Steve Sutton, Faculty Supervisor at steve.sutton@ucf.edu.

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901.

GENERAL INSTRUCTIONS

Thank you for participating in this study. For purposes of this study, you are asked to assume the role of an investor evaluating companies for potential investment. In this phase, you will be evaluating four companies, divided equally into two groups – Group A and Group B. All four companies are firms in the retail sector. Your task is to evaluate the financial condition and earnings potential of the companies in each group. Professional analysts consider the following factors critical to the financial performance and earnings potential of firms in the retail sector:

- Return on Assets (Net Income/Total Assets)
- Current Ratio (Current Assets/Current Liabilities)
- Inventory Turnover (Cost of Goods Sold/Inventory)
- Gross Profit Margin (Gross Profit/Revenue)
- Return on Equity (Net Income/Stockholder's Equity)
- Trends in Earnings Per Share (EPS) and Revenue

For each group of companies, you must decide which company you would invest in at the conclusion of your analysis. You will also be asked to describe the reasons for your choice. You will view financial information about each company using a financial reporting technology. After evaluating both groups, you will respond to questions about the task and your experience with using financial reporting technology. Please base your decisions only on the information obtained while completing this study.

Your answers will be completely confidential as it is important to the integrity of our study that you answer to the best of your ability. We greatly appreciate your participation.

Please indicate y	your agreement or	disagreement to	completing thi	is study by s	selecting the
appropriate option	on below.				

O	Agree
O	Disagree

NOTE: The information in the following pages includes information about each company that will be presented to participants.

Description of Task

Group A (Low Interactivity Condition)

The two companies to evaluate in this group are DSW, Inc. (NYSE: DSW) and Genesco, Inc. (NYSE: GCO). DSW, Inc. is a specialty branded retailer of footwear and accessories for men and women with over 350 stores in the United States. Genesco, Inc. is a retailer of branded footwear, licensed and branded headwear, and licensed sports apparel and accessories. Genesco operates over 2,000 retail stores throughout the United States, Puerto Rico, and Canada.

Your Task:

Assume you are an investor with \$10,000 to potentially invest in either DSW, Inc. or Genesco, Inc. Evaluate DSW, Inc. and Genesco, Inc. relative to one another using the financial metrics described in the beginning of the case.

Recently, in an effort to improve the usefulness of financial statement information to investors, the Securities and Exchange Commission (SEC) issued a mandate requiring public companies to report their financial statements using an interactive financial reporting technology. The SEC is now encouraging software developers to build tools enabled with interactive technology in order to help investors in their financial analysis.

DSW, Inc. and Genesco, Inc. report information about their financial operations using an interactive financial reporting technology known as the EDGAR tool and can be viewed on the next page. Please only use the EDGAR financial reporting tool provided to you in the following page to view information about DSW and Genesco's financial operations.

Please watch the following video demonstration on using the EDGAR tool before proceeding. After viewing the video, scroll down the screen for further instructions and to use the EDGAR reporting technology.

Using the EDGAR Tool

- In the box below the 'Fast Search' tool, search for DSW's company filings using their ticker symbol, DSW. Note: You will need to repeat this search for Genesco, Inc. Genesco's ticker symbol is GCO.
- For both companies, please use their most recent annual report (10-K) for fiscal year 2012 (most recent 10-K filed) operations to conduct your analysis. Look in the column titled 'Filings' for the most recent 10-K report.

- To open each company's 10-K report and begin your analysis, click on the 'Interactive Data' link. Your answers to each of the financial metrics are required in the questions that follow.
- To return to the Edgar home page to search for Genesco, click on the 'Company Search' folder link located above the search results.

Description of Task

Group A (High Interactivity Condition)

The two companies to evaluate in this group are DSW, Inc. (NYSE: DSW) and Genesco, Inc. (NYSE: GCO). DSW, Inc. is a specialty branded retailer of footwear and accessories for men and women with over 350 stores in the United States. Genesco, Inc. is a retailer of branded footwear, licensed and branded headwear, and licensed sports apparel and accessories. Genesco operates over 2,000 retail stores throughout the United States, Puerto Rico, and Canada

Your Task:

Assume you are an investor with \$10,000 to potentially invest in either DSW, Inc. or Genesco, Inc. Evaluate DSW, Inc. and Genesco, Inc. relative to one another using the financial metrics described in the beginning of the case.

Recently, in an effort to improve the usefulness of financial statement information to investors, the Securities and Exchange Commission (SEC) issued a mandate requiring public companies to report their financial statements using an interactive financial reporting technology. The SEC is now encouraging software developers to build tools enabled with interactive technology in order to help investors in their financial analysis.

DSW, Inc. and Genesco, Inc. report information about their financial operations using an interactive financial reporting technology known as the CALCBENCH tool that can be viewed on the next page. Please only use the CALCBENCH financial reporting tool provided to you in the following page to view information about DSW and Genesco's financial operations.

Please watch the following video demonstration on using the Calcbench tool before proceeding. After viewing the video, scroll down the screen for further instructions and to use the Calcbench reporting technology.

Using the CALCBENCH Tool

- You are required to login to be able to use this website. The Join/Log On link is located in the top right corner of the Calcbench home page.
- Use the following credentials to login:
 - o Email Address: user001@researchinais.com
 - o Password: research
 - Uncheck the Remember me box and click ok
- To access the Calcbench analysis tool, click on the 'Go Now' link next to Benchmark, Screen, Query & Search.

- To conduct your analysis, you are required to first create a dataset for the companies you want to analyze. Click on 'create' next to 'My Saved Peer Groups'. A create/edit peer group box opens.
- Enter Group A in the Title box.
- In the 'Add a Company box', add DSW, Inc. and Genesco, Inc. one at a time using their ticker symbols, DSW and GCO, respectively. Click 'Save'.
- Next, a list of saved peer groups is displayed, select the 'Group A' peer group you just created to begin the analysis for DSW, Inc. and Genesco, Inc. For both companies, a set of financial statement items are displayed. You can remove items by clicking on the 'X' next to the item name. You can also add other financial statement items and/or financial ratios by selecting from the drop-down arrows under 'Data Points' 'Ratios'. Note: New columns are added to the right on the Calcbench tool. Please scroll to the right to view all added columns.
- For a quick visual of the features of the analysis tool, click on the '? Interactive Help' link. Your answers to each of the financial metrics are required in the following questions.
- For missing ratios/financial statement items in the analysis tool, you can refer to a company's original financial statement filings to obtain the items by clicking on the Company Name in the analysis tool. The single company filing page opens. The default view is for quarterly financial reports. Click on the 'Yearly View' link to view the annual financial statement reports.
- When you are finished using the Calcbench tool, log out of the website.

Description of Task (continued)

Group B (Low Interactivity Condition)

The two companies to evaluate in this group are Gap, Inc. (NYSE: GPS) and Nordstrom, Inc. (NYSE: JWN). Gap, Inc. is a specialty clothing and accessories retailer with over 3,000 stores in the United States and worldwide. Nordstrom, Inc. is an American upscale fashion retailer of shoes, clothing, accessories, jewelry, cosmetics, and fragrances. Nordstrom, Inc. has over 200 stores throughout the United States.

Your Task:

Assume you are an investor with \$10,000 to potentially invest in either Gap or Nordstrom. Evaluate Gap, Inc. and Nordstrom, Inc. relative to one another using the financial metrics described in the beginning of the case.

Recently, in an effort to improve the usefulness of financial statement information to investors, the Securities and Exchange Commission (SEC) issued a mandate requiring public companies to report their financial statements using an interactive financial reporting technology.

Gap, Inc. and Nordstrom, Inc. report information about their financial operations using an interactive financial reporting technology known as the EDGAR tool and can be viewed on the next page. Please only use the EDGAR financial reporting tool provided to you in the following page to view information about Gap and Nordstrom's financial operations.

Please watch the following video demonstration on using the EDGAR tool before proceeding. After viewing the video, scroll down the screen for further instructions and to use the EDGAR reporting technology.

Using the EDGAR Tool

- In the box below the 'Fast Search' tool, search for Gap's company filings using their ticker symbol, GPS. Note: You will need to repeat this search for Nordstrom, Inc. Nordstrom's ticker symbol is JWN.
- For both companies, please use their most recent annual report (10-K) for fiscal year 2012 (most recent 10-K filed) operations to conduct your analysis. Look in the column titled 'Filings' for the most recent 10-K report.
- To open each company's 10-K report and begin your analysis, click on the 'Interactive Data' link. Your answers to each of the financial metrics are required in the questions that follow
- To return to the Edgar home page to search for Nordstrom, click on the 'Company Search' folder link located above the search results.

Group B (High Interactivity Condition)

The two companies to evaluate in this group are Gap, Inc. (NYSE: GPS) and Nordstrom, Inc. (NYSE: JWN). Gap, Inc. is a specialty clothing and accessories retailer with over 3,000 stores in the United States and worldwide. Nordstrom, Inc. is an American upscale fashion retailer of shoes, clothing, accessories, jewelry, cosmetics, and fragrances. Nordstrom, Inc. has over 200 stores throughout the United States.

Your Task:

Assume you are an investor with \$10,000 to potentially invest in either Gap or Nordstrom. Evaluate Gap, Inc. and Nordstrom, Inc. relative to one another using the financial metrics described in the beginning of the case.

Recently, in an effort to improve the usefulness of financial statement information to investors, the Securities and Exchange Commission (SEC) issued a mandate requiring public companies to report their financial statements using an interactive financial reporting technology.

Gap, Inc. and Nordstrom, Inc. report information about their financial operations using an interactive financial reporting technology known as the CALCBENCH tool that can be viewed on the next page. Please only use the CALCBENCH financial reporting tool provided to you in the following page to view information about Gap and Nordstrom's financial operations.

Please watch the following video demonstration on using the Calcbench tool before proceeding. After viewing the video, scroll down the screen for further instructions and to use the Calcbench reporting technology.

Using the CALCBENCH Tool

- You are required to login to be able to use this website. The Join/Log On link is located in the top right corner of the Calcbench home page.
- Use the following credentials to login:
 - o Email Address: user001@researchinais.com
 - o Password: research
 - Uncheck the Remember me box and click ok
- To access the Calcbench analysis tool, click on the 'Go Now' link next to Benchmark, Screen, Query & Search.
- To conduct your analysis, you are required to first create a dataset for the companies you want to analyze. Click on 'create' next to 'My Saved Peer Groups'. A create/edit peer group box opens.
- Enter 'Group B' in the Title box.

- In the 'Add a Company box', add Gap, Inc. and Nordstrom, Inc. one at a time using their ticker symbols, GPS and JWN, respectively. Click 'Save'.
- Next, a list of saved peer groups is displayed, select the 'Group B' peer group you just created to begin the analysis for Gap, Inc. and Nordstrom, Inc. For both companies, a set of financial statement items are displayed. You can remove items by clicking on the 'X' next to the item name. You can also add other financial statement items and/or financial ratios by selecting from the drop-down arrows under 'Data Points' 'Ratios'.
 Note: New columns are added to the right on the Calcbench tool. Please scroll to the right to view all added columns.
- For a quick visual of the features of the analysis tool, click on the '? Interactive Help' link. Your answers to each of the financial metrics are required in the following questions.
- For missing ratios/financial statement items in the analysis tool, you can refer to a company's original financial statement filings to obtain the items by clicking on the Company Name in the analysis tool. The single company filing page opens. The default view is for quarterly financial reports. Click on the 'Yearly View' link to view the annual financial statement reports.
- When you are finished using the Calcbench tool, log out of the website.

FINANCIAL ANALYSIS QUESTIONNAIRE (GROUP A)

Calculate the following financial ratios for DSW, Inc. and Genesco, Inc. Fill in the numbers in each formula and the ratio will automatically populate. Alternatively, you can calculate the ratio on your own and record your answer in the appropriate box.

1. Return on Assets (Net Income/Total Assets)

Definition: Return on Assets or ROA measures how efficiently a company is using its assets to generate profits. The higher the percentage, the better, because that means the company is doing a good job of using its assets to generate profits.

	DSW, Inc.	Genesco, Inc.
Net Income		
/ Total Assets		
= Return on Assets		

2. Current Ratio

Definition: The current ratio measures whether or not a company has enough resources to pay its debts over the next 12 months. The higher the current ratio, the more capable the company is of paying its obligations if they came due at that point.

	DSW, Inc.	Genesco, Inc.
Current Assets		
/ Current Liabilities		
= Current Ratio		

3. Inventory Turnover

Definition: The inventory turnover ratio measures how many times a company's inventory is sold and replaced over a period. In general, a low turnover implies excess inventory and poor sales, while a high turnover indicates better performance. The average inventory turnover for companies like DSW and Genesco is 3.9.

	DSW, Inc.	Genesco, Inc.
Cost of Goods Sold		
/ Inventory		
= Inventory Turnover		

4. Gross Profit Margin

Definition: The gross profit margin measures a company's financial health by revealing the percentage of money left over from revenues after accounting for the costs associated with generating the revenue. The higher the percentage, the better.

	DSW, Inc.	Genesco, Inc.
Gross Profit		
/ Revenue		
= Gross Profit Margin		

5. Return on Equity

Definition: Return on Equity or ROE measures a company's profitability by revealing how much a company generates with the money its shareholders have invested. The higher the ROE, the better.

	DSW, Inc.	Genesco, Inc.
Net Income		
/ Stockholder's Equity		
= Return on Equity		

• Review the trend in DSW's and Genesco's revenue and basic earnings per share (EPS) from continuing operations for the most recent 3 years. A company's EPS is an indicator of their profitability and is the portion of profits allocated to each share of common stock outstanding.

Both Revenue and EPS are reported on the Income Statement or Statement of Operations.

Note: The second half of this question represents the visualization manipulation.

No Visualization Condition

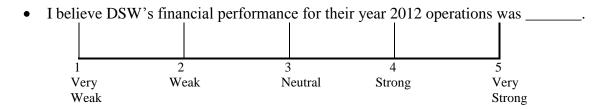
To examine the trend:

- Add DSW and Genesco's revenue and EPS to your analysis using the 'Add Column' drop-down feature under Data Points.
- Examine the trend in revenue and EPS by clicking on 'prev' under each column name to view the revenue and EPS amounts for previous years.

Visualization Condition

Use the graphs provided in the Calcbench tool to examine the trend:

- Add DSW and Genesco's revenue and EPS to your analysis using the 'Add Column' drop-down feature under Data Points.
- Examine the trend in revenue and EPS by right-clicking on each number and viewing the graph generated.
- o Check here to confirm you have looked at the graphs before proceeding.



I believe Genesco's financial performance for their year 2012 operations was ______.

	1	2	3	4	5	
	Very Weak	Weak	Neutral	Strong	Very Strong	
•	If you had to in	nvest all \$10,00	0 in one firm, wh	nich firm would	you invest in (check	one)?
	DSW, Geneso					
•	Briefly describ	e the reason for	your choice.			
•	If you could in must add up to		ns, what percent	age would you i	nvest in each (the to	tal
	DSW, i Geneso	co, Inc.	% 100 %			

FINANCIAL ANALYSIS QUESTIONNAIRE (GROUP B)

Calculate the following financial ratios for Gap, Inc. and Nordstrom, Inc. Fill in the numbers in each formula and the ratio will automatically populate. Alternatively, you can calculate the ratio on your own and record your answer in the appropriate box.

1. Return on Assets (Net Income/Total Assets)

Definition: Return on Assets or ROA measures how efficiently a company is using its assets to generate profits. The higher the percentage, the better, because that means the company is doing a good job of using its assets to generate profits.

	Gap, Inc.	Nordstrom, Inc.
Net Income		
/ Total Assets		
= Return on Assets		

2. Current Ratio

Definition: The current ratio measures whether or not a company has enough resources to pay its debts over the next 12 months. The higher the current ratio, the more capable the company is of paying its obligations if they came due at that point.

	Gap, Inc.	Nordstrom, Inc.
Current Assets		
/ Current Liabilities		
= Current Ratio		

3. Inventory Turnover

Definition: The inventory turnover ratio measures how many times a company's inventory is sold and replaced over a period. In general, a low turnover implies excess inventory and poor sales, while a high turnover indicates better performance. The average inventory turnover for companies like Gap and Nordstrom is 3.9.

	Gap, Inc.	Nordstrom, Inc.
Cost of Goods Sold		
/ Inventory		
= Inventory Turnover		

4. Gross Profit Margin

Definition: The gross profit margin measures a company's financial health by revealing the percentage of money left over from revenues after accounting for the costs associated with generating the revenue. The higher the percentage, the better.

	Gap, Inc.	Nordstrom, Inc.
Gross Profit		
/ Revenue		
= Gross Profit Margin		

5. Return on Equity

Definition: Return on Equity or ROE measures a company's profitability by revealing how much a company generates with the money its shareholders have invested. The higher the ROE, the better.

	Gap, Inc.	Nordstrom, Inc.
Net Income		
/ Stockholder's Equity		
= Return on Equity		

• As part of your decision, you want to look at the trend in Gap's and Nordstrom's revenue and basic earnings per share (EPS) from continuing operations for the most recent 3 years. A company's EPS is an indicator of their profitability and is the portion of profits allocated to each share of common stock outstanding.

Note: The second half of this question represents the visualization manipulation.

No Visualization Condition

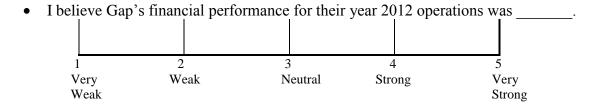
To examine the trend:

- Add DSW and Genesco's revenue and EPS to your analysis using the 'Add Column' drop-down feature under Data Points.
- Examine the trend in revenue and EPS by clicking on 'prev' under each column name to view the revenue and EPS amounts for previous years.

Visualization Condition

Use the graphs provided in the Calcbench tool to examine the trend:

- Add DSW and Genesco's revenue and EPS to your analysis using the 'Add Column' drop-down feature under Data Points.
- Examine the trend in revenue and EPS by right-clicking on each number and viewing the graph generated.
- o Check here to confirm you have looked at the graphs before proceeding.



• If you had to invest all \$10,000 in one firm, which firm would you invest in (check one)?

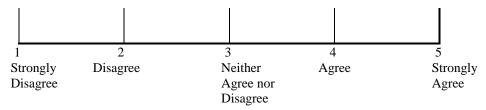
	Gap, Inc. Nordstrom, Inc.		
•	Briefly describe the reason	for your	choice.
•	If you could invest in both must add up to 100)?	firms, wh	nat percentage would you invest in each (the total
	Gap, Inc.		%
	Nordstrom, Inc.		%
		100	%

Note: Participants will get these set of follow-up questions after their analysis of Group B. Either EDGAR or CALCBENCH will be evaluated depending on which tool is used last.

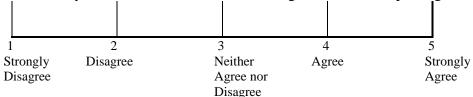
Please answer the following questions regarding your experience while using the EDGAR/CALCBENCH tool.

Perceived Interactivity Scale

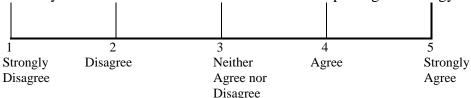
1. I had a lot of control over my experience while using the financial reporting technology.



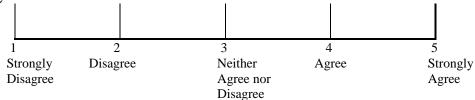
2. I could choose freely what I wanted to see while using the financial reporting technology.



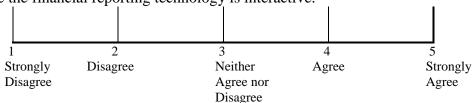
3. There is a variety of content available within the financial reporting technology.



4. My actions decided the kind of experience I got while using the financial reporting technology.

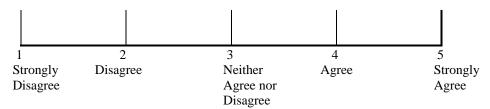


5. I believe the financial reporting technology is interactive.

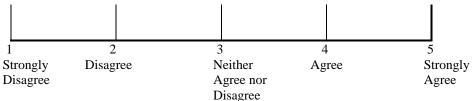


Perceived Visualization Scale

1. In addition to text, this financial reporting technology enabled the visualization of financial data.



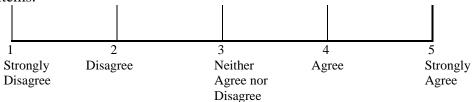
2. This financial reporting technology helps me to visually see the relationships among financial items.



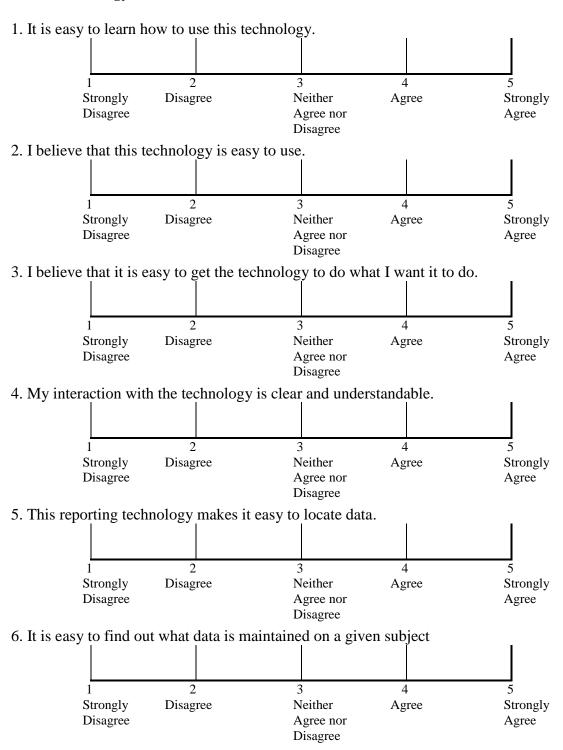
3. Using this financial reporting technology enabled me to graphically compare the financial results.



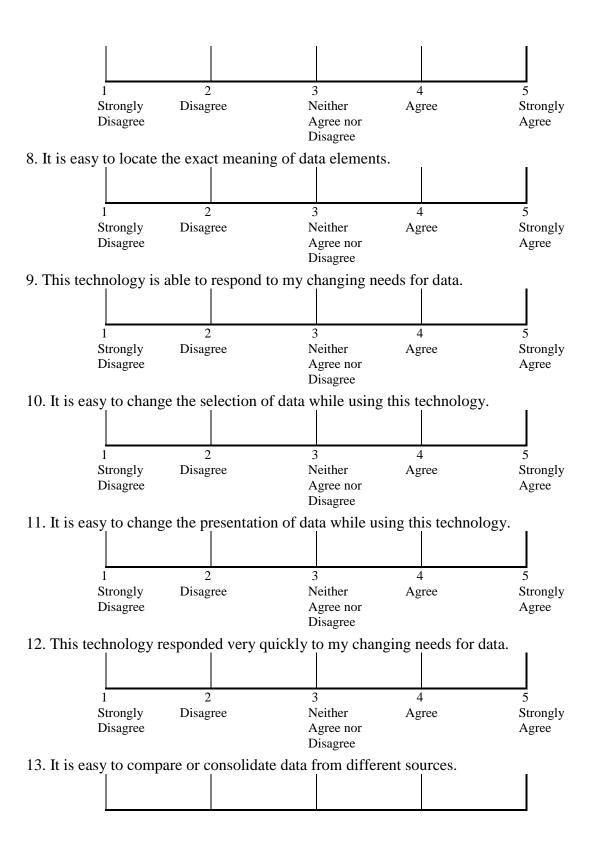
4. Using this financial reporting technology enabled me to graphically view the trend in financial statement items.

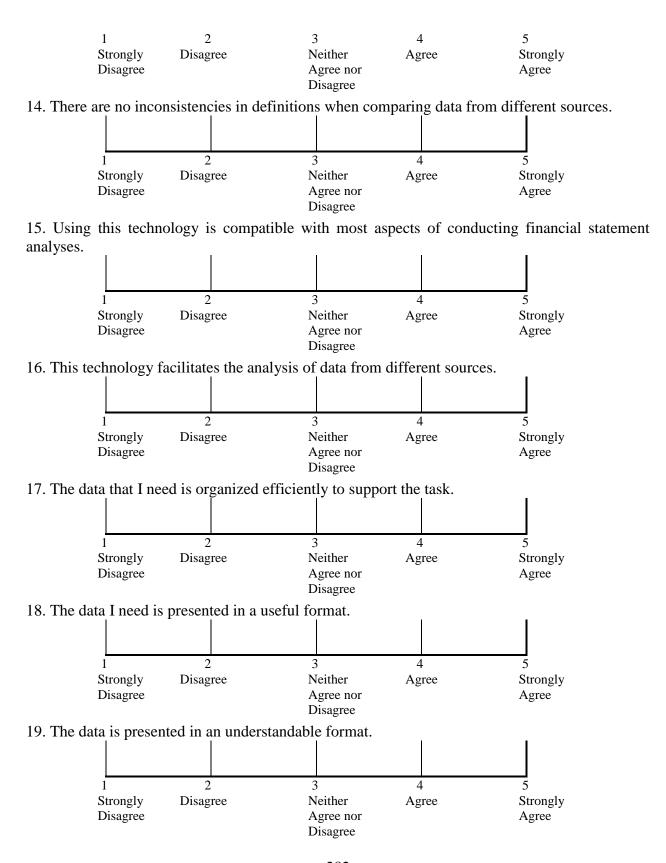


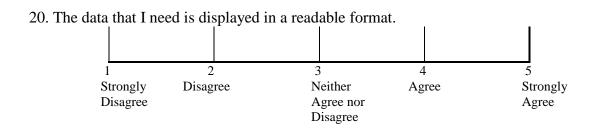
Task-Technology Fit Scale



7. The exact definition of the data fields relevant to this task are easy to find out.

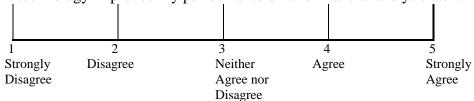




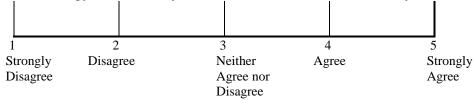


Perceived Usefulness Scale

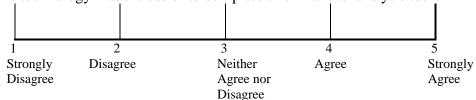
1. Using this technology improved my performance on this financial analysis task.



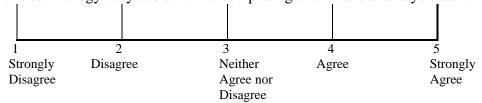
2. Using this technology enhanced my effectiveness on this financial analysis task.



3. Using this technology made it easier to complete this financial analysis task.

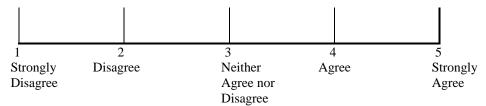


4. I found this technology very useful while completing this financial analysis task.

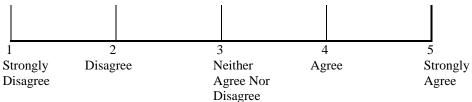


Behavioral Intention to Use Scale

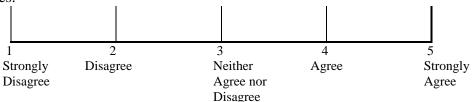
1. Assuming this technology was available, I would use it in future financial analysis tasks.



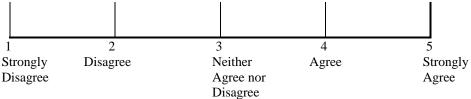
2. Assuming this technology was available, I predict I would use it in future financial analysis tasks.



3. Assuming this technology was available, I would not use alternative financial analysis technologies.

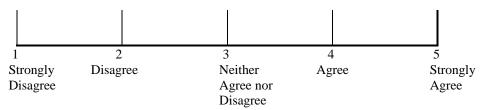


4. Assuming this technology was available, I plan to use it again for future financial analysis tasks.

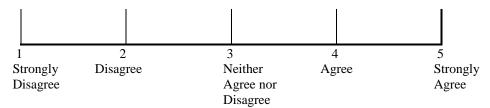


Performance Impact Scale

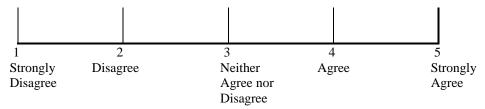
1. Using this technology had a large, positive impact on my effectiveness and productivity in this financial analysis task.



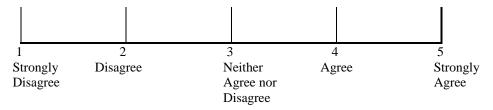
2. This technology is an important and valuable aid to me in the performance of financial analysis.



3. This technology greatly contributed to the improvement of my financial statement analysis.



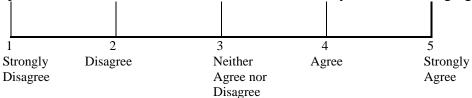
4. Using this technology helped me efficiently manage my financial statement analysis.



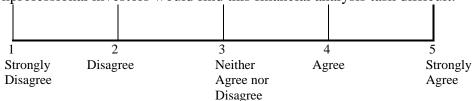
Task Complexity Scale

Please indicate your level of agreement of disagreement with the following statements about your experience during this task.

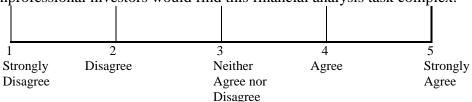
1. Most nonprofessional investors would find this financial analysis task challenging.



2. Most nonprofessional investors would find this financial analysis task difficult.



3. Most nonprofessional investors would find this financial analysis task complex.



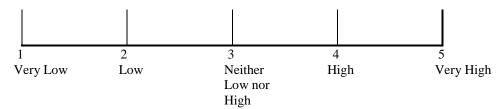
4. Most nonprofessional investors would say that this task requires a lot of thought and problem-solving.



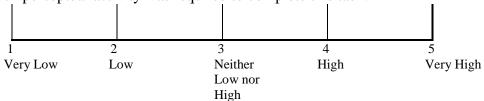
Cognitive Load Scale

Please indicate your level of agreement of disagreement with the following statements about your experience during this task.

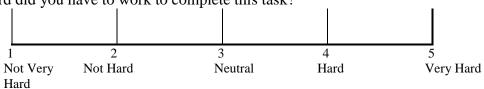
1. How much mental effort was required to complete this task?



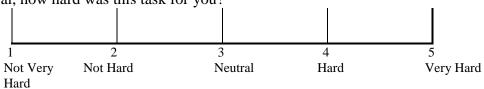
2. How much perceptual activity was required to complete this task?



3. How hard did you have to work to complete this task?



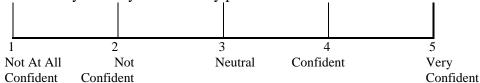
4. In general, how hard was this task for you?



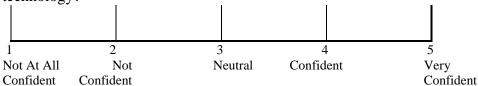
Confidence in Performance Scale

Please indicate your level of agreement of disagreement with the following statements about your experience during this task.

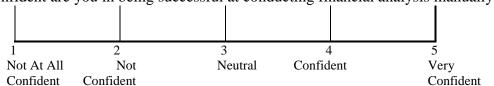
1. How confident are you that you accurately performed this task?



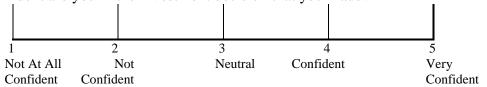
2. How confident are you in being successful at conducting financial analysis with the use of interactive technology?



3. How confident are you in being successful at conducting financial analysis manually?



4. How confident are you in the investment decision that you made?



FINANCIAL LITERACY QUIZ

The following questions are asked to obtain a general idea of your knowledge of financial reporting. Please select the best answer for each of the following questions. After you have answered a question, please DO NOT go back and change your response.

- 1. The four financial statements commonly presented in a firm's annual report are:
 - a. income statement, balance sheet, statement of cash flows, statement of shareholders' equity
 - b. income statement, balance sheet, statement of change in financial position, statement of cash flows
 - c. income statement, bank reconciliation statement, statement of shareholders' equity, statement of cash flows
 - d. none of the above
- 2. What are the three sections of an indirect statement of cash flows?
 - a. financing, reporting, investing
 - b. current, short-term, long-term
 - c. purchasing, operating, lending
 - d. financing, investing, operating

3. Deferred revenue

- a. represents the portion of Accounts Receivable that may be difficult to collect from customers
- b. represents an estimate of the cash the firm may have to refund to customers if the customers return goods as defective
- c. represents cash that has been received but for which the firm has not yet delivered goods/services
- d. more than one of the above
- 4. What is the purpose of the income statement?
 - a. To summarize all changes in assets and liabilities for an accounting period
 - b. To summarize all financing and investing activities for an accounting period
 - c. To summarize the results of operations for an accounting period
 - d. To summarize financial position at the end of an accounting period
- 5. Which of the following statements is true?
 - a. Assets + Shareholder's Equity = Liabilities
 - b. Assets Liabilities = Shareholder's Equity
 - c. Assets + Liabilities = Shareholder's Equity
 - d. None of the above are true
- 6. The accounting for inventories in the US can be based on either LIFO or FIFO. Which of the following statements describes LIFO and FIFO accounting under US GAAP?

- a. LIFO inventory accounting always results in lower financial statement income
- b. LIFO inventory accounting always reduces income taxes paid for a given period
- c. A given firm must use either LIFO or FIFO for all its inventories
- d. A firm that uses LIFO must display the difference between costs of beginning and ending inventories as reported, and the costs of inventories that would have been reported had the firm been using FIFO [or current cost]
- 7. Where can one find the inventory method used by a particular company?
 - a. In the audit report
 - b. In the notes to the financial statements
 - c. In the income statement
 - d. In the statement of shareholder's equity
- 8. Retained Earnings on the balance sheet is an account usually referring to:
 - a. Cash and other liquid assets, generated by income, with which the firm can pay dividends
 - b. Net assets that the firm can distribute as dividends
 - c. The amount, generated by income, that the firm can distribute as dividends
 - d. None of the above
- 9. What does the balance sheet summarize for a company?
 - a. Operating results for an accounting period.
 - b. Financial position at the end of an accounting period.
 - c. Financing and investing activities for an accounting period.
 - d. Profit or loss at the end of accounting period.
- 10. Under U.S. accounting principles, property, plant, and equipment
 - a. appears on the balance sheet at cost less accumulated depreciation, except if the asset has been deemed impaired.
 - b. appears on the balance sheet at fair value (the amount that would be received if the assets were sold in an arms-length transaction) if the asset has been deemed impaired
 - c. Both a and b are possible in certain circumstances

To help us better understand why your responses might differ from those of your colleagues, please answer the following questions.

1.	Have you ever bought or sold an individual's company's common (not through a mutual or pension fund)? YES	stock or debt securities NO				
	If yes, approximately how many times? times					
2.	Please indicate if you have used any of the following technologies Edgar Calcbench	prior to this study.				
3.	How many times have you evaluated a company's performance by analyzing its financial statements?					
4.	Do you plan to invest in the common stock of a company at some t YES NO	ime in the future?				
5.	How many years of previous work experience do you have?					
6.	How many <u>undergraduate and graduate</u> finance and accounting co including those you are taking this semester? Finance Accounting	urses have you taken,				
7.	Have you ever worked in the following capacities?					
	If yes, fill in the number of years. If no, leave blank.					
	Corporate finance	years				
	Corporate accounting	years				
	Engineering, operations, or other technical position	years				
	Public accounting	years				
	Management	years				
	Other	years				
	What is your age? years.					
9.	What is your gender? Female	Male				

THANK YOU FOR PARTICIPATING

APPENDIX B: STUDY 2 EXPERIMENTAL MATERIALS

GENERAL INSTRUCTIONS

In this phase, you will be evaluating Gordmans Stores, Inc. and Zumiez, Inc. Both firms are companies in the retail sector. You will evaluate both companies relative to each other and indicate which company you would invest in. Assume you have \$10,000 to potentially invest in Gordmans Stores, Inc. or Zumiez, Inc. Professional analysts consider the following factors critical to the financial performance and earnings potential of firms in the retail sector:

- Return on Assets (Net Income/Total Assets)
- Current Ratio (Current Assets/Current Liabilities)
- Inventory Turnover (Cost of Goods Sold/Inventory)
- Gross Profit Margin (Gross Profit/Revenue)
- Return on Equity (Net Income/Stockholder's Equity)
- Trends in Earnings Per Share (EPS) and Revenue

Your task is to evaluate the financial condition and earnings potential of Gordmans Stores, Inc. and Zumiez, Inc. At the conclusion of your analysis, you must decide how you will invest your \$10,000. You will also be asked to describe the reasons for your choice. You will view financial information about each company using a financial reporting technology of your choice. You will also be asked to answer several questions about the financial reporting technology you choose.

Your answers will be completely confidential as it is important to the integrity of our study that you answer to the best of your ability. We greatly appreciate your participation.

Description of Task

The two companies to evaluate are Gordmans Stores, Inc (NASDAQ: GMAN) and Zumiez, Inc. (NASDAQ: ZUMZ). Gordmans is a value retailer of name brand apparel and home fashions with over 90 stores in 19 states nationwide. Zumiez is a specialty apparel store that sells action-sports related clothing for sports like skateboarding, snowboarding, and surfing. Zumiez currently operates over 500 stores in the United States and Canada.

Your Task:

Assume you are an investor with \$10,000 to potentially invest in either Gordmans Stores, Inc. or Zumiez, Inc. Evaluate Gordmans Stores, Inc. and Zumiez, Inc. relative to one another using the financial metrics described in the beginning of the case.

Recently, you conducted two financial analysis tasks using two interactive financial reporting technologies – the SEC's interactive web reporting technology and Calcbench's online XBRL analysis tool. For this task, you are required to choose one of the two reporting technologies to use during your analysis. Please refer to your previous experience with these two financial reporting technologies when making your choice.

Please select the <u>one</u> technology you wish to use below. Once you select your technology choice, you <u>cannot</u> go back or switch technologies.

The EDGAR Tool

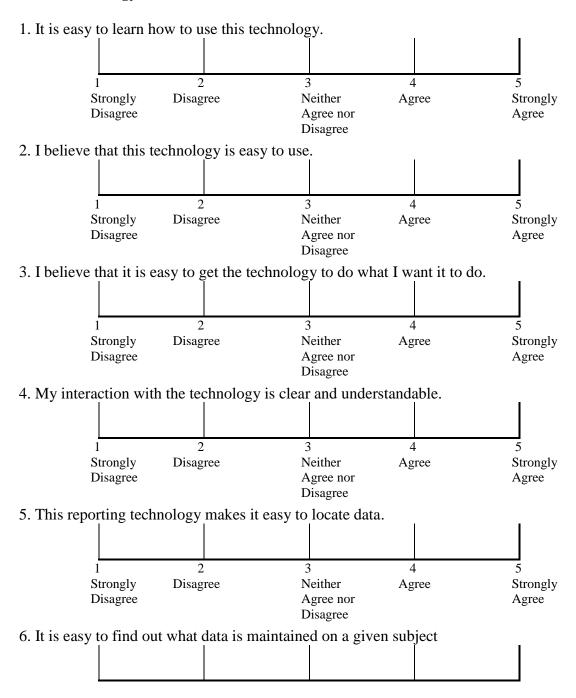
The CALCBENCH Tool

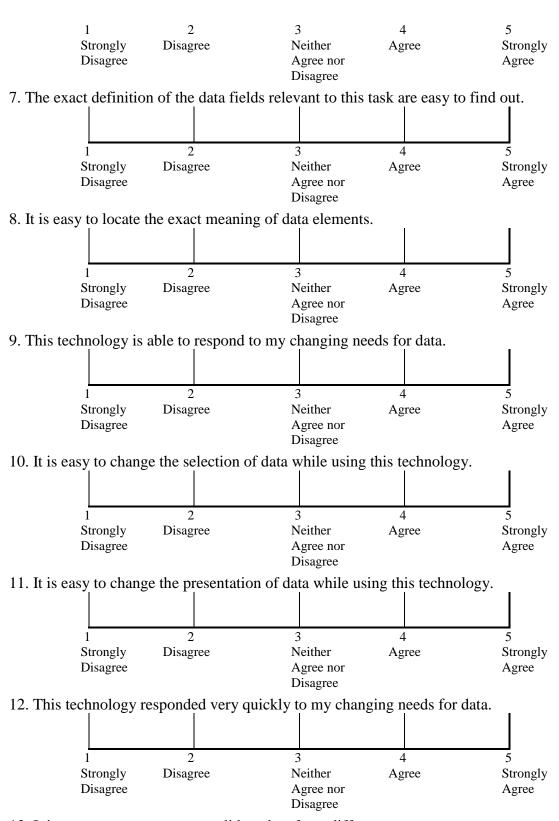
Follow Up Questions					
Please, briefly state why you chose the EDGAR/CALCBENCH tool.					

Follow Up Questions

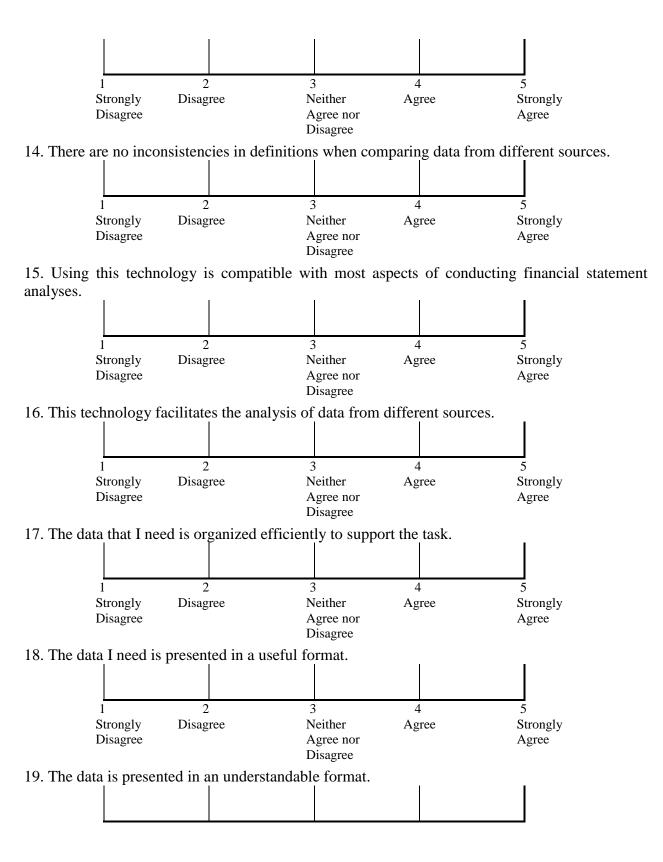
Please answer the following questions regarding the financial reporting technology you chose. Please indicate your level of agreement of disagreement with the following statements.

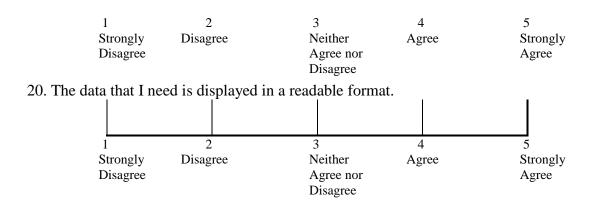
Task-Technology Fit Scale





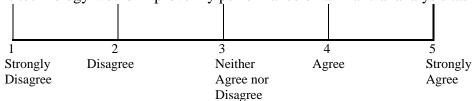
13. It is easy to compare or consolidate data from different sources.



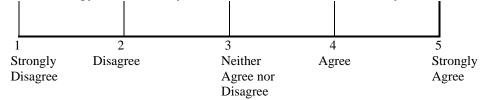


Perceived Usefulness Scale

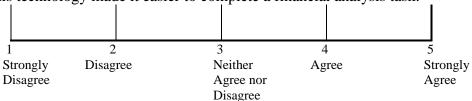
1. Using this technology would improve my performance on a financial analysis task.



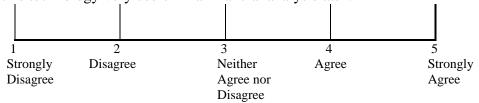
2. Using this technology enhanced my effectiveness on a financial analysis task.



3. Using this technology made it easier to complete a financial analysis task.

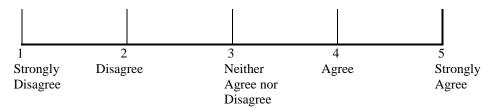


4. I found this technology very useful in a financial analysis task.

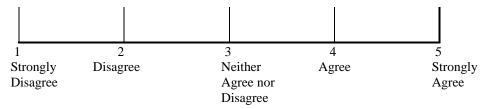


Performance Impact Scale

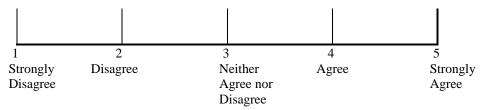
1. Using this technology has a large, positive impact on my effectiveness and productivity in a financial analysis task.



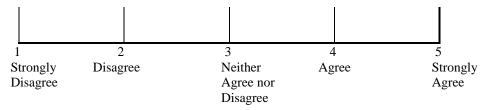
2. This technology is an important and valuable aid to me in the performance of financial analysis.



3. This technology greatly contributed to the improvement of my financial statement analysis.

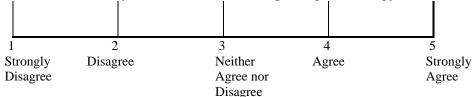


4. Using this technology helped me efficiently manage my financial statement analysis.

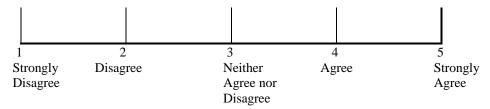


Satisfaction Scale.

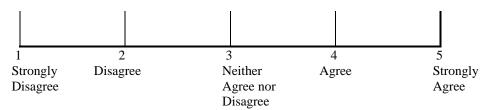
1. I was satisfied with my use of this financial reporting technology.



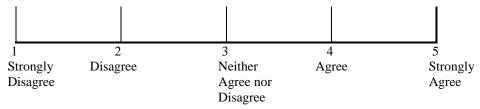
2. My choice to use this financial reporting technology is a wise one.



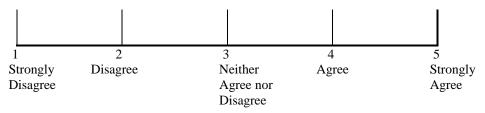
3. My experience with using this financial reporting technology was very satisfactory.



4. I think I did the right thing by deciding to use this financial reporting technology.



5. If I were to do it again, I would feel the same way about using this financial reporting technology.



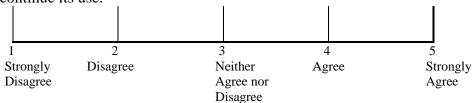
6. I was pleased with my use of this financial reporting technology.



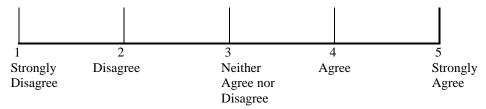
1	2	3	4	5
Strongly	Disagree	Neither	Agree	Strongly
Disagree		Agree nor		Agree
		Disagree		

Note: Continuance Intention Scale.

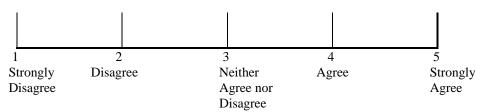
1. If I could, I intend to continue using this financial reporting technology rather than discontinue its use.



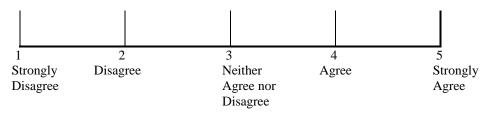
2. If possible, my intentions are to continue using this financial reporting technology rather than any alternative financial reporting tools.



3. I would like to continue the use of this financial reporting technology.



4. If I could, I would continue using this financial reporting technology for financial analysis tasks.



INSTRUCTIONS: FINANCIAL ANALYSIS TASK

Note: Participants will see this if they chose to use the SEC's interactive web viewer.

You are now ready to complete the financial analysis task. Your task is to evaluate the performance and financial condition of Gordmans Stores, Inc. and Zumiez, Inc., and decide how you will invest your \$10,000. Please only use the financial reporting tool provided to you based on your choice to view information about Gordmans Stores' and Zumiez's financial operations.

To begin, please:

- In the box below the 'Fast Search' tool, search for Gordmans' company filings using their ticker symbol, GMAN. **Note**: You will need to repeat this search for Zumiez, Inc. Zumiez's ticker symbol is ZUMZ.
- For both companies, please use their most recent annual report (10-K) for fiscal year 2012 (most recent 10-K filed) operations to conduct your analysis. Look in the column titled 'Filings' for the most recent 10-K report.
- To open each company's 10-K report and begin your analysis, click on the 'Interactive Data' link. Your answers to each of the financial metrics are required in the questions that follow.
- To return to the Edgar home page to search for Zumiez, click on the 'Company Search' folder link located above the search results.

Note: Participants will see this if they choose to use Calcbench's online analysis tool.

You are now ready to complete the financial analysis task. Your task is to evaluate the performance and financial condition of Gordmans Stores, Inc. and Zumiez, Inc., and decide how you will invest your \$10,000. Please only use the financial reporting tool provided to you based on your choice to view information about Gordmans Stores' and Zumiez's financial operations.

To begin, please:

- You are required to login to be able to use this website. If you are already logged in, skip this step. The 'Join/Log On' link is located in the top right corner of the Calcbench home page. Use the following credentials to login:
 - o Email Address: user\${e://Field/UserNumber}@researchinais.com
 - o Password: research
 - O Uncheck the 'Remember me?' box and click 'ok'
- To access the Calcbench analysis tool, click on the 'Go Now' link next to Benchmark, Screen, Query & Search.

- To conduct your analysis, you are required to first create a dataset for the companies you want to analyze. Click on 'create' next to 'My Saved Peer Groups'. A create/edit peer group box opens.
- Enter 'Group C' in the Title box.
- In the 'Add a Company' box, add Gordmans Stores, Inc. and Zumiez, Inc. one at a time using their ticker symbols, GMAN and ZUMZ, respectively. Click 'Save'.
- Next, a list of saved peer groups is displayed, select the 'Group C' peer group you just created to begin the analysis for Gordmans Stores, Inc. and Zumiez, Inc.
- For both companies, a set of financial statement items are displayed. You can remove items by clicking on the 'X' next to the item name. You can also add other financial statement items and/or financial ratios by selecting from the drop-down arrows under 'Data Points' and 'Ratios'. Note: New columns are added to the right on the Calcbench tool. Please scroll to the right to view all added columns.
- For a quick visual of the features of the analysis tool, click on the '? Interactive Help' link. Your answers to each of the financial metrics are required in the following questions.
- For missing ratios/financial statement items in the analysis tool, you can refer to a company's original financial statement filings to obtain the items by clicking on the company's name in the analysis tool. The single company filing page opens. The default view is for quarterly financial reports. Click on the 'Yearly View' link to view the annual financial statement reports.
- When you are finished using the Calcbench tool, log out of the website.

FINANCIAL ANALYSIS QUESTIONNAIRE

Calculate the following financial ratios for Gordmans Stores, Inc. and Zumiez, Inc. Fill in the numbers in each formula and the ratio will automatically populate. Alternatively, you can calculate the ratio on your own and record your answer in the appropriate box.

1. Return on Assets (Net Income/Total Assets)

Definition: Return on Assets or ROA measures how efficiently a company is using its assets to generate profits. The higher the percentage, the better, because that means the company is doing a good job of using its assets to generate profits.

	Gordmans Stores, Inc.	Zumiez, Inc.
Net Income		
/ Total Assets		
= Return on Assets		

2. Current Ratio

Definition: The current ratio measures whether or not a company has enough resources to pay its debts over the next 12 months. The higher the current ratio, the more capable the company is of paying its obligations if they came due at that point.

	Gordmans Stores, Inc.	Zumiez, Inc.
Current Assets		
/ Current Liabilities		
= Current Ratio		

3. Inventory Turnover

Definition: The inventory turnover ratio measures how many times a company's inventory is sold and replaced over a period. In general, a low turnover implies excess inventory and poor sales, while a high turnover indicates better performance. The average inventory turnover for companies like Gordmans Stores and Zumiez is 3.9.

	Gordmans Stores, Inc.	Zumiez, Inc.
Cost of Goods Sold		
/ Inventory		
= Inventory Turnover		

4. Gross Profit Margin

Definition: The gross profit margin measures a company's financial health by revealing the percentage of money left over from revenues after accounting for the costs associated with generating the revenue. The higher the percentage, the better.

	Gordmans Stores, Inc.	Zumiez, Inc.
Gross Profit		
/ Revenue		
= Gross Profit Margin		

5. Return on Equity

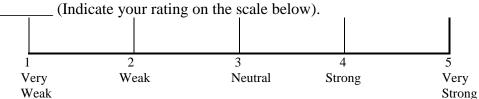
Definition: Return on Equity or ROE measures a company's profitability by revealing how much a company generates with the money its shareholders have invested. The higher the ROE, the better.

	Gordmans Stores, Inc.	Zumiez, Inc.
Net Income		
/ Stockholder's Equity		
= Return on Equity		

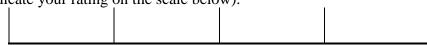
 Review the trend in Gordmans Stores' and Zumiez's revenue and basic earnings per share (EPS) from continuing operations for the most recent 3 years. A company's EPS is an indicator of their profitability and is the portion of profits allocated to each share of common stock outstanding.

Both Revenue and EPS are reported on the Income Statement or Statement of Operations.

• I believe Gordmans Stores' financial performance for their year 2012 operations was



• I believe Zumiez's financial performance for their year 2012 operations was ______ (Indicate your rating on the scale below).



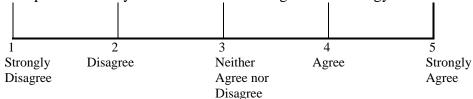
	1	2	3	4	5	
	Verv	Weak	Neutral	Strong	Very	
	Weak			21.31.8	Strong	
	· · · can				Strong	
•	If you had to i	nvest all \$10,000	in one firm, wh	ich firm would	you invest in (check of	one)?
	•				· `	ŕ
	Gordm	nans Stores, Inc.				
	Zumie	z. Inc.				
		,				
_	Driafly dagaril	ha tha rassan for	your aboing			
•	briefly describ	be the reason for	your choice.			
•	If you could in	vest in both firm	s what percenta	ge would you i	nvest in each (the tota	1
-	must add up to		is, what percenta	ge would you i	iivest iii eacii (tiic tota	.1
	must add up to) 100):				
	Gordm	nans Stores, Inc.		%		
	Zumie	z, Inc.	(%		
		,	100	%		
			100	/ U		

FOLLOW-UP QUESTIONS

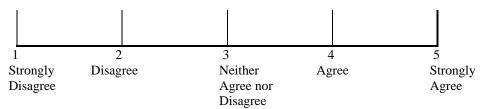
Please indicate your level of agreement or disagreement with the following statements about your use of interactive data technology for this task.

Note: Utilization Scale

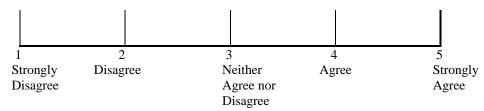
1. I would prefer to always conduct this task using this technology.



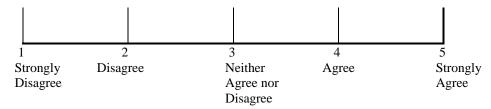
2. I heavily relied on this technology while completing the financial analysis task.



3. I extensively used this technology during my decision process.



4. I am confident in the conclusion of my analysis as a result of using this technology.



5. Did you use the graphing tool during your analysis?

____ No ___ Yes

APPENDIX C: STUDY 3 EXPERIMENTAL MATERIALS



EXPLANATION OF RESEARCH

Title of Project: Effects of Increasing Interactivity on User Perceptions of Credibility and Investment Choice.

Principal Investigator: Kemi Osidipe

Faculty Supervisor: Steve Sutton

You are being invited to take part in a research study conducted by Kemi Osidipe, Doctoral Candidate, University of Central Florida and Steve Sutton, PhD, University of Central Florida. The case will take approximately 30 minutes of your time. Please complete the case in one sitting. There are no anticipated potential risks associated with this study. The purpose of this study is to enhance our understanding of how nonprofessional investors make potential investment judgments and decisions. You will be asked to assume the role of a potential investor and make investments decisions and judgments about a hypothetical company based on your analysis of the information you gather on the company's website.

As the results of this study could be helpful to accounting educators and accounting professionals, it is important that you answer each question in a serious and thoughtful manner. Your responses will be completely anonymous and only aggregated data will be included in any resulting publication or presentations.

You must be 18 years of age or older to take part in this research study.

<u>Study contact for questions about the study or to report a problem</u>: If you have questions, concerns, or complaints please contact Kemi Osidipe, Doctoral Candidate, Dixon School of Accounting at oluwakemi.osidipe@ucf.edu or Dr. Steve Sutton, Faculty Supervisor at steve.sutton@ucf.edu.

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901.

NOTE: This represents the instructions for participants in the high interactivity condition.

INSTRUCTIONS

You are to assume the role of an investor with \$10,000 to potentially invest in the common stock of one company, Alpha Corporation. Alpha is a company in the publishing and commercial printing industry. Professional analysts consider the following factors critical to the financial performance and earnings potential of firms like Alpha in the publishing and commercial printing industry.

- Return on Assets (Net Income/Total Assets)
- Current Ratio (Current Assets/Current Liabilities)
- Inventory Turnover (Inventory/(Cost of Goods Sold/365 days))
- Return on Sales (Operating Income before Taxes/Sales)

Your task is to evaluate the financial condition and earnings potential of Alpha based on information that will be provided to you in this case study. Your analysis will include making an investment decision and several judgments about Alpha and the information provided to you. At the conclusion of your analyses, you must estimate a share price for Alpha and decide if, and how much of the \$10,000 you will invest in Alpha. You will also be asked to describe the reasons for your choice.

Alpha's website (http://www.aisstudies.com) includes general information about Alpha and Alpha's most recent annual report available on their Investor Relations page. Please review and use this information to complete the financial analysis questionnaire on the following pages.

The case information you will receive is not intended to be fully representative of the information that would be available to you if you were undertaking a detailed evaluation of Alpha. However, while completing the case, please base your judgments only on the information provided. There are no "correct" answers to your judgments of Alpha. Following your analysis, you will be asked questions designed to help us gain insights into your decision-making process.

NOTE: This represents the instructions for participants in the low interactivity condition.

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- Return on Sales (Operating Income before Taxes/Sales)

Your task is to evaluate the financial condition and earnings potential of Alpha based on information that will be provided to you in this case study. Your analysis will include making an investment decision and several judgments about Alpha and the information provided to you. At the conclusion of your analyses, you must estimate a share price for Alpha and decide if, and how much of the \$10,000 you will invest in Alpha. You will also be asked to describe the reasons for your choice.

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The case information you will receive is not intended to be fully representative of the information that would be available to you if you were undertaking a detailed evaluation of Alpha. However, while completing the case, please base your judgments only on the information provided. There are no "correct" answers to your judgments of Alpha. Following your analysis, you will be asked questions designed to help us gain insights into your decision-making process.

NOTE: The information in the following pages includes information about Alpha that participants will find on Alpha's website.

ALPHA'S HOME PAGE

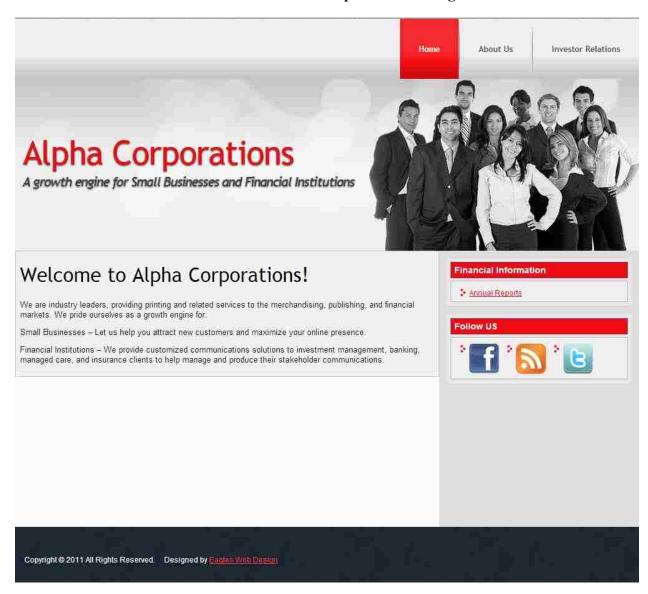
Welcome to Alpha Corporations!

We are industry leaders, providing printing and related services to the merchandising, publishing, and financial markets. We pride ourselves as a growth engine for:

Small Businesses – Let us help you attract new customers and maximize your online presence.

Financial Institutions – We provide customized communications solutions to investment management, banking, managed care, and insurance clients to help manage and produce their stakeholder communications.

Note: Screenshot of Alpha's Home Page



ALPHA'S ABOUT US PAGE

Company Description

Alpha is a provider of printing and related services to the merchandising, publishing, and financial markets. Alpha was founded in 1990. Since then, Alpha has continually drawn on a range of proprietary and commercially available digital and conventional technologies to develop many more innovations, helping beat out the competition and emerging as the industry leader it is today. Alpha works with more than 20,000 customers in North America to develop custom communications solutions that reduce costs, enhance ROI, and ensure compliance. Alpha is a growth engine for small businesses and financial institutions. The company employs a suite of leading Internet based capabilities and other resources to provide premedia, printing, logistics and business process outsourcing services to leading clients in virtually every private and public sector. Alpha has three business segments: Print, Logistics, and Financial.

- The Print segment is comprised of its businesses serving the following end markets: Magazines, Catalogs and Retail; Books; and Technology Services.
- The Logistics segment represents Alpha's logistics and distribution services operations for its print customers and other mailers.
- The Financial segment serves the compliance and transactional documentation needs of the domestic and international capital markets and provides customized communications solutions to investment management, banking, managed care, and insurance clients to help manage and produce their stakeholder communications.

Traditionally, Alpha's core competence has been producing books, magazines, and paper business forms. In recent years, the company has invested in three main areas:

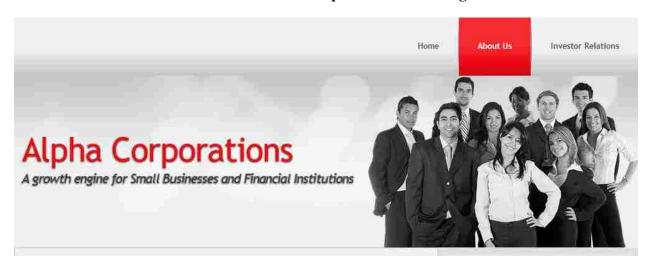
Electronic forms / HTML conversion: Converting paper forms to electronic versions, which allows end-users to enter data into an electronic form on their PC and then print the completed form.

Customized solutions: Services for capital markets, financial services, and insurance customers to help them deliver communications across multiple channels, maintain regulatory transparency, and offer investor-friendly disclosure.

Logistics: Delivering books, magazines, or paper forms to the end-users' mailboxes (in paper form) or personal computers (in electronic form).

With the company's customers increasingly demanding electronic delivery of forms and an increasingly complex environment for the company's financial services customer base, Alpha appears poised to grow. Alpha is traded on the New York Stock Exchange.

Note: Screenshot of Alpha's About Us Page



About Us

Company Description

We are a provider of printing and related services to the merchandising, publishing, and financial markets. Alpha was founded in 1990. Since then, we have continually drawn on a range of proprietary and commercially available digital and conventional technologies to develop many more innovations, helping beat out the competition and emerging as the industry leader we are today.

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Customized solutions: Services for capital markets, financial services, and insurance customers to help them deliver communications across multiple channels; maintain regulatory transparency, and offer investor-friendly disclosure.

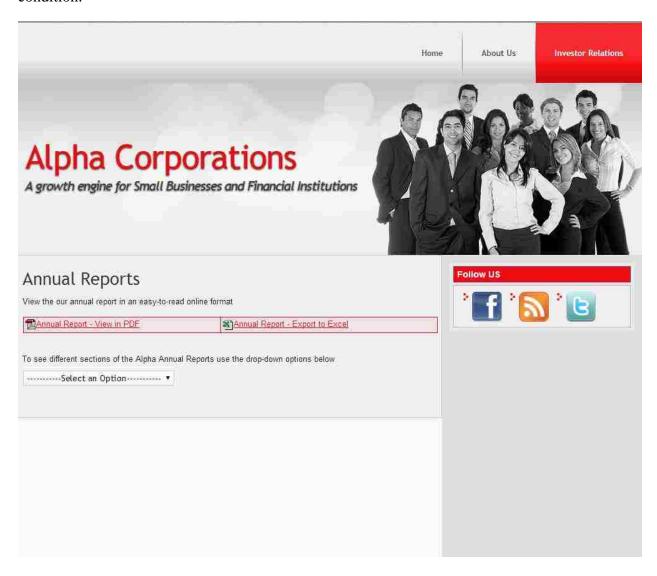


Note: This page shows a screenshot of Alpha's Investor Relations page in the low interactivity condition



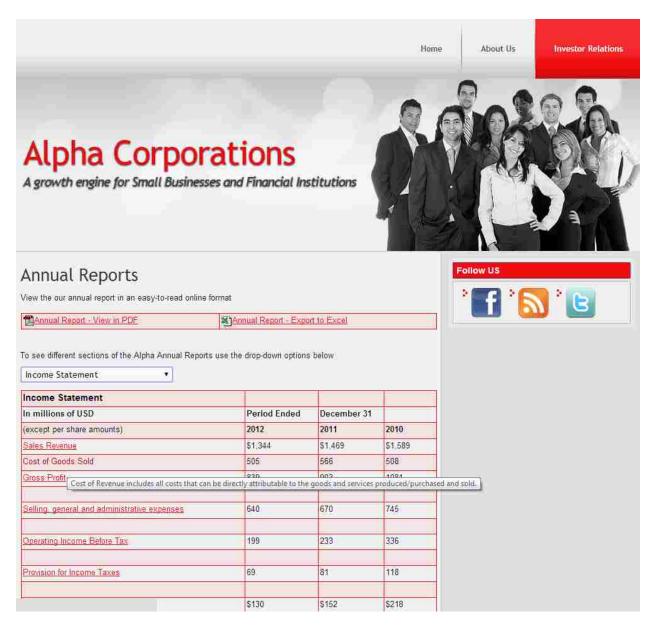
Note: This page shows a screenshot of Alpha's Investor Relations page in the high interactivity condition

This page shows the three different viewing options participants have in the high interactivity condition.



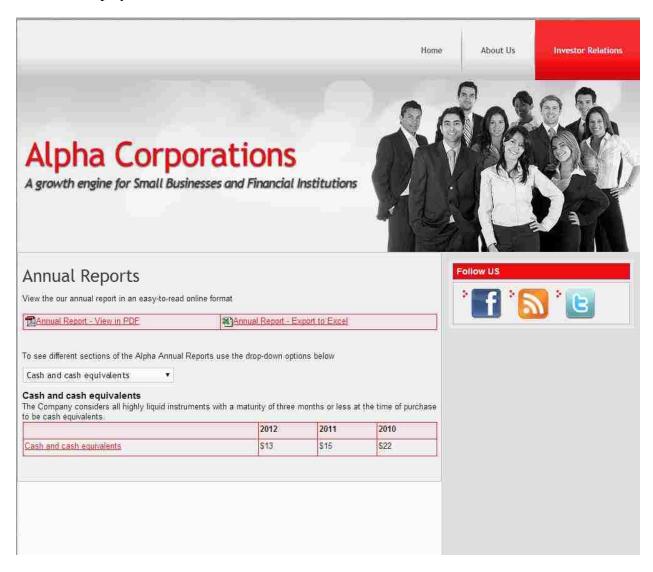
Note: This page shows a screenshot of Alpha's Investor Relations page in the high interactivity condition

This page shows the use of the drop-down list box to get to a specific financial statement report and the use of the abstract/elaborate technique to display definitions for financial statement items.



Note: This page shows a screenshot of Alpha's Investor Relations page in the high interactivity condition

This page shows the use of the drop-down list box to drill down to specific financial statement items and display the related notes information.



ALPHA'S FINANCIAL STATEMENT INFORMATION

Report of Independent Auditors

To the Shareholders and Board of Directors of Alpha Corporation:

In our opinion, the accompanying balance sheets and the related statements of income, and cash flows present fairly, in all material respects, the financial position of Alpha Corporation from 2010 - 2012, and the results of their operations and their cash flows for each of the three years in the period ended December 31, 2012 in conformity with accounting principles generally accepted in the United States of America. Also in our opinion, the Company maintained, in all material respects, effective internal control over financial reporting as of December 31, 2012 based on criteria established in Internal Control - Integrated Framework issued by the Committee of Sponsoring Organizations of the Treadway Commission (COSO). The Company's management is responsible for these financial statements, for maintaining effective internal control over financial reporting and for its assessment of the effectiveness of internal control over financial reporting, included in the accompanying Management's Report on Internal Control over Financial Reporting. Our responsibility is to express opinions on these financial statements and on the Company's internal control over financial reporting based on our integrated audits. We conducted our audits in accordance with the standards of the Public Company Accounting Oversight Board (United States). Those standards require that we plan and perform the audits to obtain reasonable assurance about whether the financial statements are free of material misstatement and whether effective internal control over financial reporting was maintained in all material respects. Our audits of financial statements included examining, on a test basis, evidence supporting the amounts and disclosures in the financial statements, assessing the accounting principles used and significant estimates made by management, and evaluating the overall financial statement presentation. Our audit of internal control over financial reporting included obtaining an understanding of internal control over financial reporting, assessing the risk that a material weakness exists, and testing and evaluating the design and operating effectiveness of internal control based on the assessed risk. Our audits also included performing such other procedures as we considered necessary in the circumstances. We believe that our audits provide a reasonable basis for our opinions.

A company's internal control over financial reporting is a process designed to provide reasonable assurance regarding the reliability of financial reporting and the preparation of financial statements for external purposes in accordance with generally accepted accounting principles. A company's internal control over financial reporting includes those policies and procedures that (i) pertain to the maintenance of records that, in reasonable detail, accurately and fairly reflect the transactions and dispositions of the assets of the company; (ii) provide reasonable assurance that transactions are recorded as necessary to permit preparation of financial statements in accordance with generally accepted accounting principles, and that receipts and expenditures of the company are being made only in accordance with authorizations of management and directors of the company; and (iii) provide reasonable assurance regarding prevention or timely detection of unauthorized acquisition, use, or disposition of the company's assets that could have

a material effect on the financial statements. Because of its inherent limitations, internal control over financial reporting may not prevent or detect misstatements. Also, projections of any evaluation of effectiveness to future periods are subject to the risk that controls may become inadequate because of changes in conditions, or that the degree of compliance with the policies or procedures may deteriorate.

Big-Four Accounting Firm February 22, 2013

ALPHA CORPORATION INCOME STATEMENT

(in millions, except per share amounts)

Year Ended December 31,

	2012	2011	2010
Revenue	\$ 1344	\$ 1469	\$ 1589
Cost of Goods Sold	505	 566	 508
Gross Profit	839	903	1081
Selling, general and administrative expenses	640	 670	 745
Operating Income Before Tax	199	233	 336
Provision for Income Taxes	69	 81	 118
Net Income	\$ 130	\$ 152	\$ 218
Earnings (Loss) per share – basic	\$ 2.55	\$ 2.98	\$ 4.19
Earnings(Loss) per share – diluted	\$ 2.54	\$ 2.97	\$ 4.19
Weighted Average Shares	51	51	52

See Accompanying Notes to Financial Statements

ALPHA CORPORATION BALANCE SHEET

(in millions)

	December 31,				
		2012		2011	2010
Assets					
Cash and cash equivalents	\$	13	\$	15	\$ 22
Accounts receivable, net		66		75	84
Inventory		22		26	30
Other current assets		21		20	 14
Current Assets		122		136	150
Property, plant, and equipment, net		122		128	139
Intangibles and Other Non-current assets		323		345	 356
Total Assets	\$	567	\$	609	\$ 645
Liabilities and Shareholder's equity					
Accounts Payable	\$	61	\$	62	\$ 79
Current portion of long-term debt		-		2	2
Other current liabilities		53		69	 67
Current Liabilities		114		133	148
Long-term notes payable		402		425	 445
Total Liabilities		516		558	593
Shareholder's Equity		51		51	52
Total Liabilities & Shareholder's Equity	\$	567	\$	609	\$ 645

See Accompanying Notes to Financial Statements

Alpha, Inc. Notes to Financial Statements

Cash and equivalents

The Company considers all highly liquid instruments with a maturity of three months or less at the time of purchase to be cash equivalents.

Inventories

Inventories are stated at the lower of cost (primarily last-in, first-out) or market.

Property, plant and equipment

Property, plant and equipment are carried at cost. Depreciation is computed using the straight-line method over the estimated useful life of the related assets, generally ranging from three to seven years for equipment and 40 years for buildings.

Intangibles

Intangible assets are a result of acquisitions. The Company continually monitors conditions that may affect the carrying value of its intangible assets. When conditions indicate potential impairment of an intangible asset, the asset is written down to its net realizable value. The Company currently has no goodwill.

Notes payable

The Company maintains several lines of credit with various lending institutions. Currently, the only outstanding debt consists of:

(in millions)	Decemb	er 31, 2012	Decemb	per 31, 2011	Decemb	per 31, 2010
Medium-term notes (6.35% and 6.85%)	\$	402	\$	425	\$	445

Interest expense is recognized in "other" expenses on the income statement.

Revenue Recognition

We recognize revenue when (1) persuasive evidence of an arrangement exists, (2) delivery has occurred or services have been rendered, (3) the sales price is fixed or determinable, and (4) collectability is reasonably assured.

Employee stock option plans

The Company has a stock option plan for all employees. At December 31, 2012, options for five million shares were vested. These options are accounted for using SFAS 123 and, in accordance with the fair value approach in SFAS 123, the company recognized compensation expense related to options on the income statement.

Income Taxes

The Company computes income taxes using the asset and liability method, under which deferred income taxes are provided for the temporary differences between the financial reporting basis and the tax basis of the Company's assets and liabilities.

FINANCIAL ANALYSIS QUESTIONNAIRE

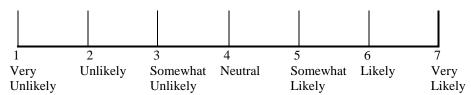
- You may go back and view the materials while answering this questionnaire.
- Please answer the following questions by filling in the blank or selecting the choice that indicates your judgment.
- After you have answered a question, please do not go back and change your response.

1.	Please fill in the numerator and denominator for the following four ratios for Alpha.
	• Return on Assets (Net Income/Total Assets)/
	• Current Ratio (Current Assets/Current Liabilities)/
	• Inventory Turnover (Inventory/(Cost of Goods/365 days))
	Inventory turnover represents the average time inventory is held (unsold) by the firm. An inventory turnover number that is too high indicates risk of not being able to sell inventory. It is important to benchmark this number with other firms in the industry. The industry average for firms in the publishing and commercial printing industry is 21 days.
	• Return on Sales (Operating Income before taxes/Sales)
	Return on Sales is a measure of how much profit is being produced by dollar of sales. It is best to compare a company's return on sales over time to look for trends, and compare it to other companies in the industry. The industry average for firms in the publishing and commercial printing industry is 0.15 or 15%.

2. I believe Alpha's financial performance for the year ended December 31, 2012 was

1 2 3 4 5 6 7
Very Weak Slightly Neutral Slightly Strong Very
Weak Weak Strong Strong

- 3. You decide to determine a fair price for Alpha's shares. A common approach for valuing stock is using a price/earnings (P/E) multiple. Using the information in this case, please estimate a P/E multiple for Alpha and then multiply your estimate by Alpha's earnings to arrive at a price estimate. Assume that other firms in Alpha's industry trade at multiples of trailing (i.e. 2012) earnings of between 10 and 30 times earnings. NOTE: A low multiple means you wouldn't be willing to pay much for the company, while a higher multiple means you would be willing to pay more for the company.
 - For the year ending December 31, 2013, I estimate Alpha's P/E multiple to be
 - For the year ending December 31, 2013, I estimate Alpha's price (2012 Net income per share x P/E multiple) to be
- 4. Assume you have \$10,000 to invest in one firm, what is the likelihood that you would invest in Alpha's stock versus a fixed yield savings account?



5. Assume you have \$10,000 to invest in one firm, how much of the \$10,000 would you invest in Alpha's stock versus a fixed yield savings account (total must equal \$10,000)?



6.	Briefly describe the reason(s) for your choice.				

After your initial analysis of Alpha, you decide to do some more searching and you found the following press release issued by Alpha

NOTE: THIS PAGE REPRESENTS THE WEAK ARGUMENT QUALITY CONDITION (PARTICIPANTS ARE GIVEN EITHER 'WEAK' OR 'STRONG' ARGUMENT QUALITY)

Press Release

On March 31, 2013, Alpha voluntarily issued the following press release.

Alpha Provides Outlook for 2013

ORLANDO, FL., March 31, 2013 – Alpha today provided an earnings forecast for the full year which ends on December 31, 2013. We expect net income to be up 47% to \$191 million. In 2013, we anticipate that revenue from continuing operations will increase from 2012 primarily as a result of organic growth driven by an anticipated continued moderate economic recovery. We anticipate a trend of further improvements in sales and earnings as cost savings are realized and technology solutions for customers are fully integrated.

- Within the Print segment, net sales are anticipated to increase, driven by direct mail
 opportunities in the financial industry. In addition, the Company is expecting increases in
 net sales in forms and office products, primarily resulting from growth in outsourced
 office product volume. Commercial print sales are anticipated to increase from improved
 transactional volume and higher marketing and advertising spending.
- In the Logistics segment, services are expected to increase, driven by continuing growth in mail center and commingling services, along with third party print logistics.
- In the Financial segment, sales of financial print products and services are expected to increase due to continued strength in capital markets transactions.

Our primary focus is on growing revenue and investing in our future with better products and service offers. We are playing offense, making positive strategic moves to reposition the Company for sustainable longer-term growth. For the remainder of 2013, our portfolio is becoming better positioned to deliver sustainable future revenue growth as hopefully the broader economy recovers. This is driven by exciting new product offerings, enhanced internet capabilities, and our new business services offerings.

About Alpha

Alpha is a provider of printing and related services to the merchandising, publishing, and financial markets.

Forward-Looking Statements

Statements made in this release with respect to Alpha's current plans, estimates, strategies and beliefs and other statements that are not historical facts are unaudited, forward-looking statements about the future performance of Alpha. These statements are based on management's assumptions and beliefs in light of the information currently available to it.

After your initial analysis of Alpha, you decide to do some more searching and you found the following press release issued by Alpha

NOTE: THIS PAGE REPRESENTS THE STRONG ARGUMENT QUALITY CONDITION (PARTICIPANTS ARE GIVEN EITHER 'WEAK' OR 'STRONG' ARGUMENT QUALITY)

Press Release

On March 31, 2013, Alpha voluntarily issued the following press release.

Alpha Provides Outlook for 2013

ORLANDO, FL., March 31, 2013 – Alpha today provided an earnings forecast for the full year which ends on December 31, 2013. We expect net income to be up 47% to \$191 million. In 2013, we anticipate that revenue from continuing operations will increase to \$1,402 million from \$1,344 million in 2012 primarily as a result of organic growth driven by an anticipated continued moderate economic recovery. We anticipate a trend of further improvements in sales and earnings as cost savings are realized and technology solutions for customers are fully integrated. The gross margin percentage is projected to be 65%. We expect selling, general, and administrative expenses as a percentage of sales to be 44%.

- Within the Print segment, net sales are anticipated to increase, driven by direct mail
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 net sales in forms and office products, primarily resulting from growth in outsourced
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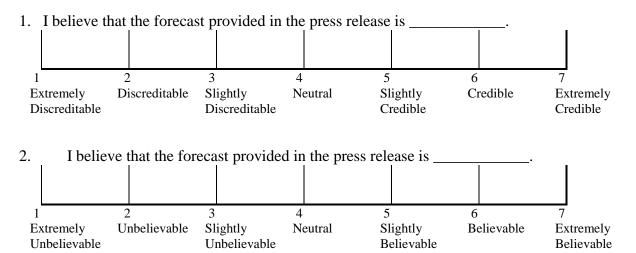
Forward-Looking Statements

Statements made in this release with respect to Alpha's current plans, estimates, strategies and beliefs and other statements that are not historical facts are unaudited, forward-looking statements about the future performance of Alpha. These statements are based on management's assumptions and beliefs in light of the information currently available to it.

FOLLOW-UP QUESTIONS

Please answer the following questions incorporating the new information you received in the preceding press release.

Judgments about Alpha's Forecast



Judgments about Alpha's Stock Price

1. After incorporating the information contained in the press release, you decide to determine a final fair price for Alpha's shares. A common approach for valuing stock is using a price/earnings (P/E) multiple. Using the information in this case, please estimate a P/E multiple for Alpha and then multiply your estimate by Alpha's earnings to arrive at a price estimate.

Assume that other firms in Alpha's industry trade at multiples of trailing (i.e. 2012) earnings of between 10 and 30 times earnings. NOTE: A low multiple means you wouldn't be willing to pay much for the company, while a higher multiple means you would be willing to pay more for the company.

- For the year ending December 31, 2013, I estimate Alpha's P/E multiple to be
- For the year ending December 31, 2013, I estimate Alpha's price (2012 Net income per share x P/E multiple) to be
- 2. Assume you have \$10,000 to invest in one firm, what is the likelihood that you would invest in Alpha's stock versus a fixed yield savings account?

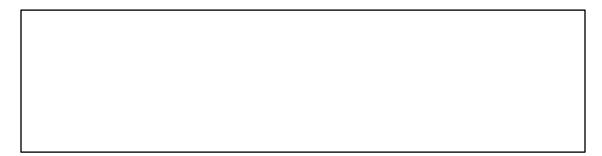


1 2 3 4 5 6 7 Very Unlikely Somewhat Neutral Somewhat Likely Very Unlikely Unlikely Likely Likely

3. Assume you have \$10,000 to invest in one firm, how much of the \$10,000 would you invest in Alpha's stock versus a fixed yield savings account (total must equal \$10,000)?

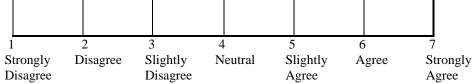


4. Briefly describe the reason(s) for your choice.

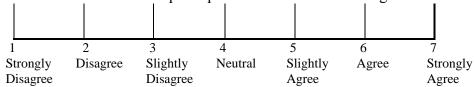


Questions about the statements in Alpha's Press Release (Note: these questions represent perceptions related to the argument quality of Alpha's press release.

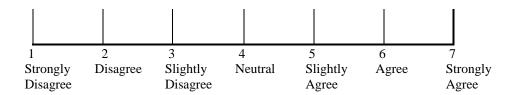
1. How much do you agree or disagree with the statements in Alpha's press release?



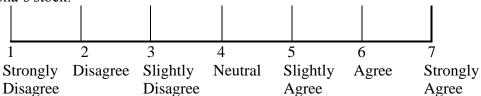
2. I believe the statements in Alpha's press release are convincing.



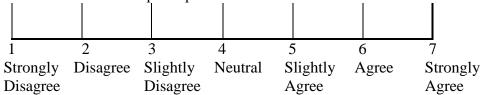
3. Most nonprofessional investors would find the statements in Alpha's press release believable.



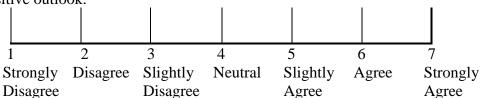
4. The statements in Alpha's press release put thoughts in my head about wanting to invest in Alpha's stock.



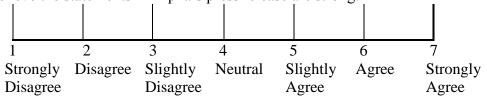
5. I find the statements in Alpha's press release believable.



6. I believe the statements in Alpha's press release helped me feel confident about their positive outlook.



7. I believe the statements in Alpha's press release are strong.



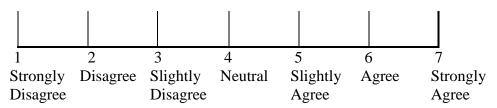
Questions about Alpha's Net Income Forecast (Note: these questions represent perceptions related to the clarity of Alpha's forecast.

1. I believe that Alpha's management is very clear about how they are going to achieve their net income forecast for the year.

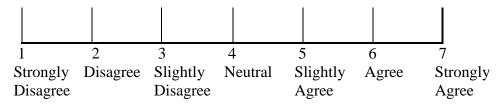


1 2 3 4 5 6 7 Strongly Disagree Slightly Strongly Neutral Slightly Agree Disagree Disagree Agree Agree

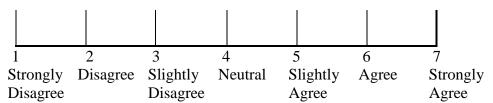
2. I believe that Alpha's forecast very clearly demonstrated how Alpha could achieve their net income number.



3. Given the information provided to me in the case, I thought it was very easy for me *to determine whether* Alpha's net income forecast was plausible.

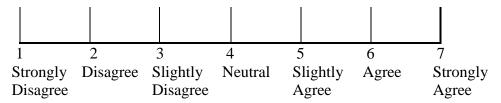


4. I believe it is very easy to see how Alpha could achieve their net income forecast.

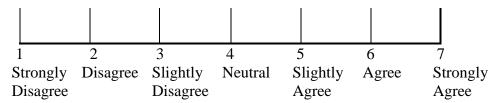


Questions about Alpha's Net Income Forecast (Note: these questions represent perceptions related to the quality of Alpha's forecast.

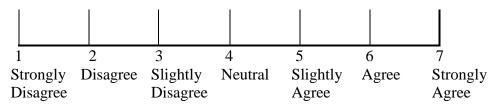
1. I believe that Alpha's net income forecast is very plausible.



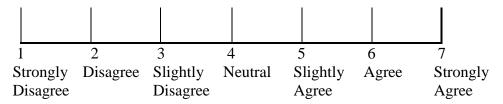
2. I believe that Alpha's net income forecast will prove to be very accurate.



3. I believe that the quality of Alpha's forecasted net income is very high.



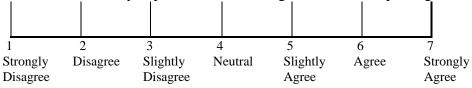
4. I believe it is very likely that Alpha will legitimately meet their forecasted net income.



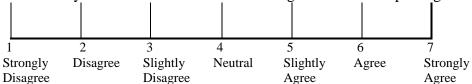
Please indicate your level of agreement or disagreement with the following statements about your experience on Alpha's Web site.

Perceived Interactivity Scale

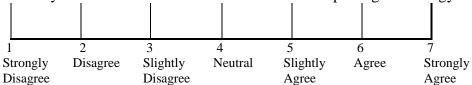
1. I had a lot of control over my experience while using the financial reporting technology.



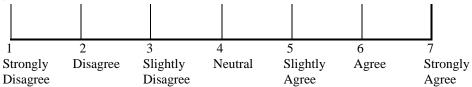
2. I could choose freely what I wanted to see while using the financial reporting technology.



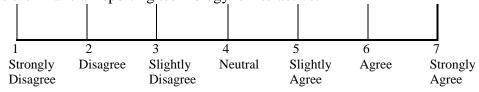
3. There is a variety of content available within the financial reporting technology.



4. My actions decided the kind of experience I got while using the financial reporting technology.



5. I believe the financial reporting technology is interactive.



FINANCIAL REPORTING QUESTIONNAIRE

The following questions are to obtain a general idea of nonprofessional investor's knowledge of financial reporting. Please select the best answer for each of the following questions. After you have answered a question, please DO NOT go back and change your response.

- 1. The four financial statements commonly presented in a firm's annual report are:
 - e. income statement, balance sheet, statement of cash flows, statement of shareholders' equity
 - f. income statement, balance sheet, statement of change in financial position, statement of cash flows
 - g. income statement, bank reconciliation statement, statement of shareholders' equity, statement of cash flows
 - h. none of the above
- 2. What are the three sections of an indirect statement of cash flows?
 - e. financing, reporting, investing
 - f. current, short-term, long-term
 - g. purchasing, operating, lending
 - h. financing, investing, operating

3. Deferred revenue

- e. represents the portion of Accounts Receivable that may be difficult to collect from customers
- f. represents an estimate of the cash the firm may have to refund to customers if the customers return goods as defective
- g. represents cash that has been received but for which the firm has not yet delivered goods/services
- h. more than one of the above

4. Stock options granted to employees

- a. are always accounted for as compensation expense (like cash compensation payments made to employees)
- b. are never accounted for as compensation expense
- c. can be structured to generate substantial tax savings for the employer, with the tax savings shown as a source of cash from operations in the employer's Statement of Cash Flows
- d. both b and c
- 5. What is the purpose of the income statement?

- e. To summarize all changes in assets and liabilities for an accounting period
- f. To summarize all financing and investing activities for an accounting period
- g. To summarize the results of operations for an accounting period
- h. To summarize financial position at the end of an accounting period
- 6. Under U.S. accounting principles, an asset impairment
 - a. requires that management measure and report the impaired asset at its fair value
 - b. always provides an immediate tax deduction
 - c. is an operating use of cash on the Statement of Cash Flows
 - d. can be reversed, if management later concludes the asset did not lose value after all
- 7. Which of the following will properly be labeled a *reserve* in the financial statements?
 - a. Cash used to pay for insurance claims larger than management had anticipated
 - b. An estimate of the liability for warranty repairs promised at the time of sale
 - c. Both a and b
 - d. Neither a nor b
- 8. Which of the following statements is true?
 - e. Assets + Shareholder's Equity = Liabilities
 - f. Assets Liabilities = Shareholder's Equity
 - g. Assets + Liabilities = Shareholder's Equity
 - h. None of the above are true
- 9. If a firm uses the indirect method for the Statement of Cash Flows (SCF), which of the following is true?
 - a. The SCF lists cash receipts from customers
 - b. The SCF shows cash spent for acquiring other firms, in the financing section of the Statement
 - c. The SCF shows dividends declared but not paid
 - d. The SCF shows the change in Accounts Receivable
- 10. The accounting for inventories in the US can be based on either LIFO or FIFO. Which of the following statements describes LIFO and FIFO accounting under US GAAP?
 - e. LIFO inventory accounting always results in lower financial statement income
 - f. LIFO inventory accounting always reduces income taxes paid for a given period
 - g. A given firm must use either LIFO or FIFO for all its inventories
 - h. A firm that uses LIFO must display the difference between costs of beginning and ending inventories as reported, and the costs of inventories that would have been reported had the firm been using FIFO [or current cost]

- 11. Where can one find the inventory method used by a particular company?
 - e. In the audit report
 - f. In the notes to the financial statements
 - g. In the income statement
 - h. In the statement of shareholder's equity
- 12. Retained Earnings on the balance sheet is an account usually referring to:
 - e. Cash and other liquid assets, generated by income, with which the firm can pay dividends
 - f. Net assets that the firm can distribute as dividends
 - g. The amount, generated by income, that the firm can distribute as dividends
 - h. None of the above
- 13. Which actions can management legitimately take to change earnings per share by an amount that is immaterial (that is, small in relation to net income)?
 - a. Increase the Bad Debt Expense by whatever amount is needed to reduce current period earnings by the desired number
 - b. Increase Sales Revenue by shipping more goods to distributors who have not requested the goods, and who have the right to return the goods later
 - c. Defer maintenance on factory equipment until next year
 - d. None of the above
- 14. What does the balance sheet summarize for a company?
 - e. Operating results for an accounting period.
 - f. Financial position at the end of an accounting period.
 - g. Financing and investing activities for an accounting period.
 - h. Profit or loss at the end of accounting period.
- 15. Under U.S. accounting principles, property, plant, and equipment
 - d. appears on the balance sheet at cost less accumulated depreciation, except if the asset has been deemed impaired.
 - e. appears on the balance sheet at fair value (the amount that would be received if the assets were sold in an arms- length transaction) if the asset has been deemed impaired
 - f. Both a and b are possible in certain circumstances
 - g. Neither a nor b is correct

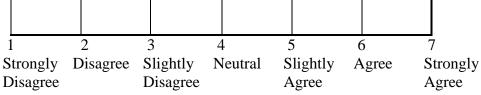
INDIVIDUAL ASSESSMENT (NEED FOR COGNITION SCALE)

Statements that people use to describe themselves are given below. Please choose the response that indicates how you generally feel. There is no right or wrong answer. Do not spend too much time on any one statement.

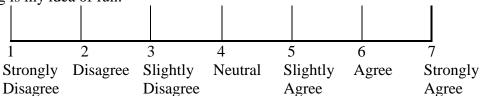
1. I would prefer complex to simple problems.

1 2 3 4 5 6 7
Strongly Disagree Slightly Neutral Slightly Agree Strongly Disagree Disagree Agree Agree

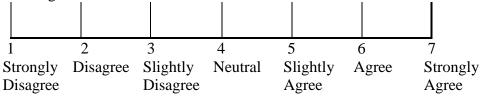
2. I like to have the responsibility of handling a situation that requires a lot of thinking.



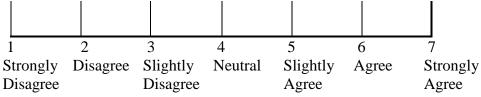
3. Thinking is my idea of fun.



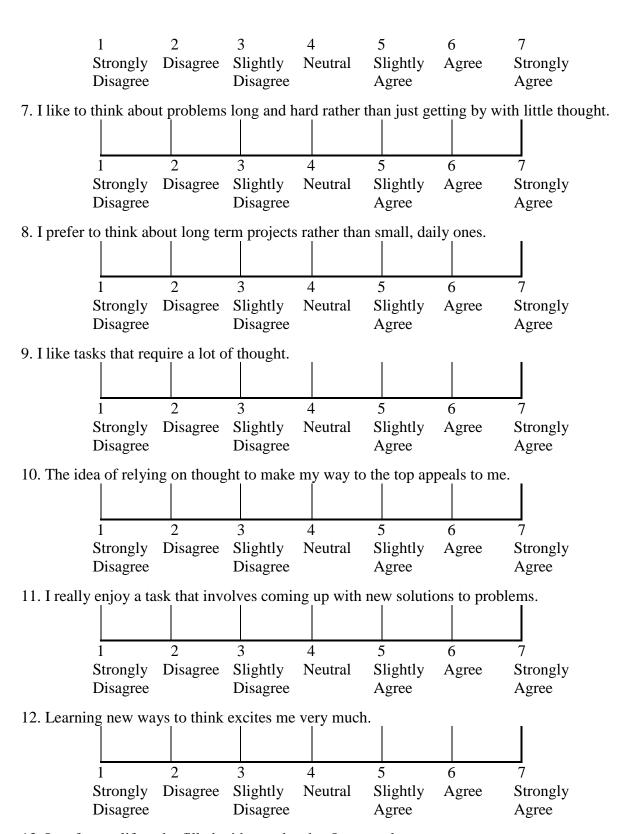
4. I would rather do something that is sure to challenge my thinking abilities than something that requires little thought.



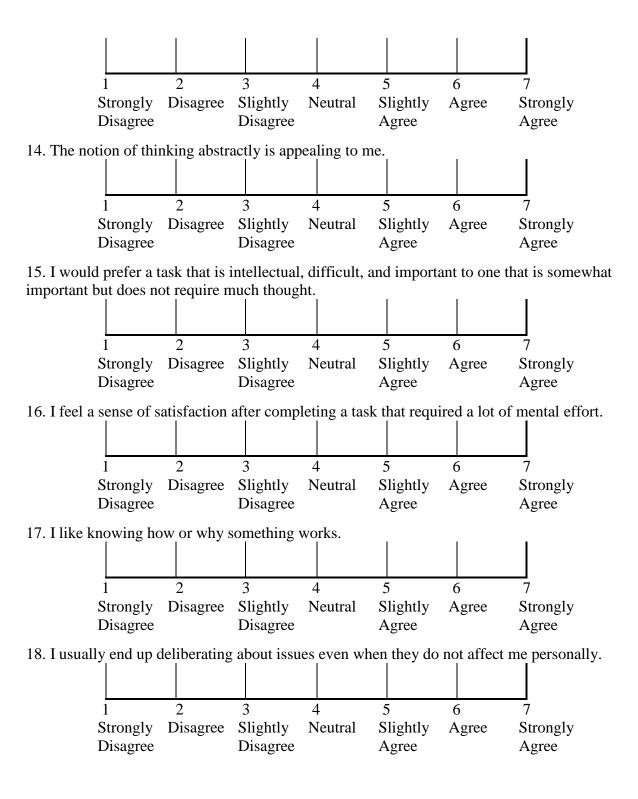
5. I am drawn to situations where there is a likely chance I will have to think in depth about something.



6. I find satisfaction in deliberating hard and for long hours.



13. I prefer my life to be filled with puzzles that I must solve.



NOTE: This page represents manipulation check questions.

Please do not refer back to the previous pages when answering the following questions.

General questions about the case

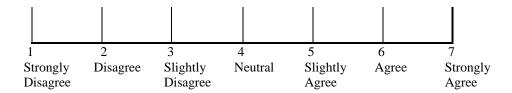
1. The *forecasted* information provided by Alpha in their press release contained: (check one)

A forecast of net income for 2013 alone. *Forecasts* of other income statement line items *were not* provided to me.

A forecast of 2013 net income along with a forecast of other line items on the income statement, including *forecast* of revenue, a *forecast* of cost of sales, a *forecast* of SG&A, etc.

I don't recall

2. I believe that Alpha's earnings forecast was very detailed.



NOTE: This page represents demographic questions.

TO HELP US BETTER UNDERSTAND WHY YOUR RESPONSES MIGHT DIFFER FROM THOSE OF YOUR COLLEAGUES, PLEASE ANSWER THE FOLLOWING QUESTIONS.

1. Have you ever bought or sold an i		nmon stock or debt securities
(not through a mutual or pension fund	d)? YES	NO
If yes, approximately how ma	ny times? tin	nes
2. How many times have you evalua statements?	ated a company's performar	nce by analyzing its financial
3. Do you plan to invest in the commYES	non stock of a company at s	some time in the future?
4. How many <u>undergraduate and grad</u> including those you are taking this		g courses have you taken,
Finance	Accounting	
5. How many years of previous work	k experience do you have?	
6. Have you ever worked in the follow If yes, fill in the number of years. If n	<u> </u>	
Corporate finance Corporate accounting Engineering, operations, or other Public accounting Management Other		years years years years years years
7. What is your age? ye		
8. What is your gender?	Female	Male
Thank yo	ou for participating in this st	tudy.

APPENDIX D: IRB APPROVAL



University of Central Florida Institutional Review Board Office of Research & Commercialization 12201 Research Parkway, Suite 501 Orlando, Florida 32826-3246 Telephone: 407-223-2901 or 407-182-2276 www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

UCF Institutional Review Board #1 From

FWA00006351, IRB00001138

To: Olamakemi Osidipe

Date: June 26, 2013

On 6/26/2013, the IRB approved the following activity as human participant research that is exempt from

regulation:

Type of Review: Exempt Determination

Project Title: Interactive Data Visualization: A Model of Task-Technology Fit

and the Technology-Performance Chain

Oluwakemi Osidipe Investigator. IRB Number

SBE-13-09457

Funding Agency: Grant Title:

Research ID:

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in IRIS so that IRB records will be accurate

In the conduct of this research, you are responsible to follow the requirements of the <u>Investigator Manual</u>.

On behalf of Sophia Deseglelewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Joanne Muratori on 06/26/2013 02:07:22 PM EDT

IRB Coordinator

grave muntori

Page 1 of 1



University of Central Florida Institutional Review Board Office of Research & Commercialization 12201 Research Parkway, Suite 501 Orlando, Florida 32826-3246 Telephone: 407-823-2901 or 407-882-2276

www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: UCF Institutional Review Board #1

FWA00000351, IRB00001138

To: Oluwakemi Osidipe

Date: March 09, 2012

Dear Researcher:

On 3/9/2012, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review: Exempt Determination

Project Title: The Effects of Increasing Interactivity on User Perceptions of

Credibility and Investment Choice.

Investigator: Oluwakemi Osidipe IRB Number: SBE-12-08301

Funding Agency:

Grant Title:

Research ID: N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Joanne Muratori on 03/09/2012 04:53:39 PM EST

IRB Coordinator

Joanne puratori