XBRL, Excel or PDF? The Effects of Technology Choice on the Analysis of Financial Information

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Abstract

Proponents argue that financial statements created using eXtensible Business Reporting Language (XBRL) will provide more transparent data for users performing financial statement analysis. The more transparent data will simplify the analysis task and allow users to focus more quickly on the financial information they perceive as important. However, U.S. adoption of XBRL-enabled technology has been slow and several standard setters and academics question whether investors will choose to use the XBRL-formatted information the Securities and Exchange Commission (SEC) is now requiring companies to provide. Further, the extant choice literature documents several instances where technology created for a specific purpose was not chosen by the intended users. Therefore, our study examines (1) whether users of financial information (investors) will choose XBRL-enabled technology for financial statement analysis rather than more familiar technologies (i.e., portable document files (PDF) and spreadsheets (Excel)) and (2) *why* they choose the specific technology.

We train participants using all three technologies and then ask them to choose one to complete an investment decision task. We found 58 percent of participants chose to use XBRL-enabled technology, while 42 percent chose Excel. Our analysis suggests that nonprofessional investors chose XBRL-enabled technology because they perceive that it reduces the time required to complete the task (increases task efficiency). Conversely, nonprofessional investors who chose Excel made their choice based on greater experience with Excel relative to XBRL-enabled technology and PDF. Finally, two factors that we hypothesized may explain technology choice, perceived usefulness and perceived ease of use, were not statistically significant. Our findings have implications for technology choice theory development, regulators mandating or considering mandating XBRL-based reporting, and XBRL-enabled technology adoption.

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I. INTRODUCTION

Proponents argue that financial statements created using eXtensible Business Reporting Language (XBRL) will provide more transparent data for investors performing financial analysis tasks. With individual financial statement items tagged, investors are able to quickly select and drill-down to the information they perceive to be important during the financial analysis process. Thus, investors who formerly relied on either spreadsheets (e.g., Excel) or portable document files (e.g., PDF) to perform financial analysis tasks may be able to perform these tasks more efficiently with XBRL-enabled technology, that is parser software designed to manipulate financial information tagged in XBRL (Hodge et al. 2004; Locke et al. 2009). XBRL has also received strong support from many sectors of the business community.[1] Motivated by the goal of assisting nonprofessional investors in understanding financial information (Cox 2006), the Securities and Exchange Commission (SEC) recently mandated that publicly traded firms furnish financial information tagged in XBRL as part of their quarterly and annual filings (SEC 2009).

Despite XBRL's purported benefits to investors, whether investors will use the technology for financial analysis when other, more familiar technologies are available is an open question. This question is important since recent research suggests that some U.S. firms view XBRL implementation as a compliance exercise and question the benefits of providing XBRL-formatted statements (Janvrin and No 2010). Further, recent experimental research (Hodge et al. 2004) finds that despite the purported benefits of XBRL, almost 50 percent of participants did not use XBRL-enabled technology in their information acquisition task. The extant choice

[1] XBRL supporters include a consortium of over 400 CPA firms, companies (e.g., Microsoft), regulators (e.g., Securities and Exchange Commission), standard setters and accounting bodies (e.g., the Financial Accounting Standards Board, the International Accounting Standards Committee and the Canadian Institute of Chartered Accountants (Debreceny and Gray 2001; Debreceny et al. 2005; Trites 1999)).

literature suggests that users do not always choose to use the best technology for the task (Jones and Schkade 1995; Whitecotton and Butler 1998). For example, based on user choice theory, Wheeler and Jones (2003) found that users deciding whether or not to use on a decision aid often made sub-optimal decisions. Pinsker and Wheeler (2009) suggest that investors recognize that XBRL-enabled technology is beneficial for financial analysis. However, Pinsker and Wheeler did not directly address the issue of this paper since their participants were assigned one technology rather than asked to choose between using XBRL-enabled or other technologies to analyze financial information. If firms provide their reports in XBRL format, but users choose to analyze financial information in other more familiar technologies (e.g., PDF or Excel), the SEC's mandate may produce XBRL-formatted information that investors will not use. Thus, XBRL adoption may not provide the expected benefits to investors (see Pinsker and Li (2008) for more details).

We conjecture that nonprofessional investors are likely to choose to use only one technology when analyzing financial information. While the user choice literature finds that users may choose a technology not created for the specific purpose, little is known regarding *why* users may make a choice which appears to be 'irrational.' We expand user choice theory that examines exclusive choice between alternative decision aid features to develop technology choice theory by defining *technology choice* as the decision between alternative *technologies* and developing hypotheses as to *why* users may make these 'irrational' choices. Specifically, based on existing user choice studies, we hypothesize that nonprofessional investors will choose XBRL-enabled technology over Excel and PDF technologies due to efficiency issues (i.e., users perceive the task will take less time to complete using XBRL-enabled technology).

Next, based on the Technology Acceptance Model (TAM) (Davis 1989), we hypothesize that nonprofessional investors will choose Excel over XBRL-enabled technology due to its perceived usefulness and perceived ease of use. Finally, cognitive fit theory provides a mechanism to fit the "task" into human information processing (Vessey 1991). For example, Jones and Schkade (1995) find that for professional analysts typically solve problems with their most experienced problem representation. Thus, relying on cognitive fit theory, we suggest that nonprofessional investors will choose Excel over XBRL-enabled technology since these investors tend to choose the problem representation with which they have the most experience.

We trained participants to use three technologies (PDF, Excel, and XBRL-enabled) to perform an investment decision task. Following training, participants were given a similar investment decision task and asked to choose one technology to complete the task. Participants completed the task using their chosen technology and then responded to several questions designed to explore the rationale driving their technology choice.

Results indicate 58 percent of participants chose to use XBRL-enabled technology (EDGAR-Online's I-Metrix) to complete their investment decision task, while 42 percent chose Excel. Participants who chose the XBRL-enabled technology indicated their motivation was efficiency (i.e., they perceived the task took them less time to complete using XBRL-enabled technology relative to the other technologies). Participants who chose Excel indicated that their choice was based on greater prior experience with Excel relative to XBRL-enabled technology. Finally, participants did not (1) choose PDF or (2) base their technology choice on perceived usefulness and perceived ease of use.

Our study makes both academic and practical contributions to the extant research. While Hodge et al. (2004) found evidence that XBRL-enabled technology provides better data search functionality, they noted that almost 50 percent of participants did not choose to use XBRL-enabled technology. We extend Hodge et al.'s by examining *why* investors may not choose to use XBRL-enabled technology. We also extend the extant user choice literature to examine technology choice and hypothesize regarding *specific reasons why* nonprofessional investors would choose to use XBRL-related technology or Excel in their investment decisions. Our results may be of interest to both regulators considering mandating XBRL reporting requirements and software designers developing XBRL-enabled technology for investor use.

II. BACKGROUND AND HYPOTHESIS DEVELOPMENT

XBRL represents a unique financial reporting format relative to previous reporting formats, offering investors a choice that facilitates searching activities (Hodge et al. 2004). Clements and Wolfe (2000, 79) observe that "media *choice* in financial reporting is a new phenomenon brought on by the widespread use of multimedia-capable computers and financial reporting on the Internet." We examine financial report users' (e.g., nonprofessional investors) choice of reporting technology for analyzing financial information. Proponents of XBRL argue that XBRL-tagged financial statements increase information transparency by allowing users to directly select the individual financial items they deem to be most important through search technology and use these items in financial analysis tasks (Pinsker and Wheeler 2009; Janvrin and Mascha 2010). In contrast, Excel and PDF formats require investors to sequentially search for and extract specific financial items and then manually enter this information into their financial analysis model.

Research to date has focused either on the practical benefits of XBRL to users (Baldwin et al. 2006) or technical aspects of XBRL implementation (Bartley et al. 2009; Janvrin and Mascha 2010; Plumlee and Plumlee 2008). In addition, prior research and debate throughout the

SEC XBRL mandate implementation process has lamented the slow rate of XBRL-enabled technology adoption by investors (Bartley et al. 2009; Cox 2006; Gunn 2007; Troshani and Rao 2007). For example, Debrecency et al. (2005) suggest that developing investor applications for XBRL-formatted documents is important to XBRL's success. Pinsker and Wheeler (2009) note that users recognize that XBRL-enabled technology is beneficial for financial analysis. Further, Ghani et al. (2009) assigned participants one of three technologies to use: PDF, HTML, or XBRL-enabled. They find that participants using XBRL-enabled technology assigned higher perceived usefulness ratings than did PDF or HTML participants; however, perceptions of ease of use were similar across the three technologies.

Unfortunately, prior research does not require investors to choose between using XBRL-enabled or other technologies to perform financial analysis even though many proponents of XBRL argue that nonprofessional investors will rely on XBRL-enabled technology instead of spreadsheet or portable document file technology (Cox 2006; Locke et al. 2009). Thus, professionals and standard setters assume that nonprofessional investors will choose XBRL-enabled technology rather than spreadsheets or portable document files for financial analysis (Pinsker and Wheeler 2009). Examining technology choice is important since prior research suggests that user choice may be driven by heuristics that may lead to suboptimal performance (Wheeler and Jones 2003). Our study attempts to fill this gap in the research.

Our research assumes that investors must make an exclusive choice of technology due to time constraints and the desire to minimize cognitive effort. That is, the investors must choose between using XBRL-enabled technology or other technologies typically available on firms' investor relations websites (specifically, Excel and PDF) to perform financial statement analysis. For this study, we modify the user choice definition used in prior accounting information systems research (Wheeler and Jones 2003) so that *technology choice* refers to the decision to use one alternative technology to the exclusion of all other alternative technologies.

Further, we note that the information systems' literature suggests that *technology usage* and *technology acceptance* may be two different concepts. *Technology usage* requires individuals to freely engage in a task using a specific technology. User choice leads to technology usage as will be discussed next. *Technology acceptance* is a necessary, but not sufficient, component of usage implying that users may accept a particular technology, but choose not to use it in their task for one or more reasons. We explore technology acceptance theory and its implication for our research in a future section.

The "User Choice" Literature

Making a choice in an ambiguous context is analogous to decision-making under uncertainty. Early psychological and social science research commonly relied on expected utility theory to examine decision-making under uncertainty. However, expected utility theory often failed to predict choice behavior (see Einhorn and Hogarth 1986) since findings from examining simple gambles in highly-controlled laboratory settings may not generalize to complicated uncertainties individuals face in real-world settings. In response, Hogarth and Reder (1987) developed rational choice theory. Rational choice theory relies on rationality to explain choices and assumes that decision-makers pursue behaviors at their lowest possible costs, given their beliefs (Pincione and Teson 2006). Yet, multiple studies in varying contexts indicated that decision-makers did not make rational choices (operationalized as "optimal" choices) due to ambiguity avoidance (Ellsberg 1961), perceived high domain expertise (Arkes et al. 1986), or high self-determination (i.e., self-attribution; Becker 1997). These reasons suggest that individuals make decisions consistent with their own mental models. Once an individual evokes his/her mental model, it may be difficult for him/her to use information not in the model (e.g., a new technology; Lewis et al. 1988).

The user choice literature evolved from rational choice theory. Based on user choice theory, Wheeler and Jones (2003) found that users provided with alternative decision aid features must engage in some form of choice behavior. We expand user choice theory since nonprofessional investors provided with alternative technologies to analyze financial information must make a technology choice. Nonprofessional investors may choose to rely on (1) one technology to the exclusion of the others; (2) one technology for one instance of a task, but use other technologies subsequently; or (3) two or more technologies to varying degrees for the same task (e.g., analyze the same task separately with each technology). Prior research indicates that option (3) is unlikely because of time constraints, the desire to minimize cognitive effort, the opportunity costs incurred by using additional technologies, and the belief that the use of more than one technology is unnecessary due to personal competence (Wheeler and Jones 2003). Consequently, we examine only options (1) and (2).

Dos Santos and Bariff (1988, 461) state that there exists "the common assumption that greater flexibility and *choice* in software aids will promote improved user performance." However, research does not fully support this prediction. A robust finding in decision aid research is that users rarely rely on the decision aid in an optimal manner, systematically either under-relying or over-relying (cf. Rose (2002) for review). A second stream of research investigates conditions under which users have two alternative decision aids (Jones and Schkade 1995; Wheeler and Jones 2003; Whitecotton and Butler 1998). Our study follows this second research stream.

The second research stream, like the first, does not unanimously support Dos Santos and Bariff's (1988) optimistic prediction concerning users' performance and technology choice. Jones and Schkade (1995) found that users tend to choose the problem representation with which they are most familiar, even if this choice involves the unnecessary expenditure of increased cognitive effort. However, with regard to decision aid choices, decision makers choose to use and rely on the aid only if they perceive it will help them complete the given task more efficiently. Wheeler and Jones (2003) found that user choice systematically resulted in sub-optimal decisions, because many users chose not to use the aid. Whitecotton and Butler (1998) find similar results.

In summary, the extant user choice literature finds uncertainty with regard to the relationship between choice and performance/reliance. To the extent that decision makers choose rationally, choice should improve task performance. However, choice may cause a decline in task performance if users choose inappropriately, which may occur if decision makers choose using heuristics (Wheeler and Jones 2003) over rationality. Heurstics tend to introduce biases in decision making because they are often used across diverse conditions for which they are not equally effective (Baron 1994).

Technology Choice Explanation

As noted above, Jones and Schkade (1995) find that decision makers' choice of decision aid is dependent upon perceived task efficiency issues. Applied to a technology choice setting, we argue that decision makers may choose the technology which they perceive can help them complete the task more efficiently by reducing time needed to perform the task. Accordingly, we predict that participants will choose XBRL-enabled technology due to its task efficiency advantage (i.e., perceived less time to complete task) over other technologies. Formally, we hypothesize:

> **H1: Nonprofessional investors will choose XBRL-enabled technology over PDF and Excel due to perceived task efficiency (i.e., perceived less time to complete task).**

Alternative Choice Explanations

The user choice literature cited to support H1 represents one potential reason for technology choice. Yet, this literature is still being developed and is fairly narrow in scope. Specifically, the user choice literature is dominated by research investigating (1) whether or not technology, in the form of a researcher-created decision aid, would be chosen, and (2) if the decision aid would be used/relied upon to form a decision. Consequently, we now consider technology choice decisions using two more established information systems theories: technology acceptance model (TAM) and cognitive fit.

The TAM postulates that when users are provided new technology (e.g., XBRL-enabled technology) to assist them in performing assigned tasks, their perceptions of the technology's usefulness and ease of use significantly influence their acceptance and assumed usage of the technology (Bagozzi et al. 1992; Davis et al. 1989). *Perceived usefulness* is the degree to which a person believes that using a technology could enhance his or her job performance, while *perceived ease of use* is the degree to which a person believes that using a technology could be free from effort. However, TAM does not postulate that a technology's functional superiority to other technologies will necessarily result in its perception by users as superior. In fact, the literature indicates that under-utilization of technology due to users' negative misperceptions is a major problem in business (Mun and Hwang 2003).

TAM research and related findings have important implications for XBRL-enabled technology acceptance. Specifically, our study closely builds from Hodge et al.'s (2004) work. They find that users of XBRL-enabled technology were better than non-XBRL users at acquiring and integrating financial statement information. Although Hodge et al. did not examine whether XBRL-enabled technology users had more positive perceptions of usefulness and ease of use than did non-XBRL-enabled technology users, Pinsker and Wheeler (2009) filled this gap and found such a perception difference between users. Investigating the perceptions of XBRL users is important when examining expectations about the diffusion of XBRL-enabled technology in the business community, since TAM research attempts to link user perceptions of technology to technology use (Pinsker and Wheeler 2009).

Nonprofessional investors using XBRL-based information for analysis are likely to use less cognitive effort, since XBRL-enabled technology allows them to gather, integrate, and compare firm data more rapidly, and therefore, at a lower cost, compared to using paper-based data (Hodge et al. 2004). This effect should improve perceived ease of use. Additionally, Hodge et al. (2004) and Pinsker and Wheeler (2009) find that investors benefit when using XBRL-enabled technology to review, compare, and integrate data from multiple firms. Since XBRL formatted financial data is more easily searchable and retrievable, higher perceived usefulness should lead to higher acceptance of XBRL-enabled technology.

Despite the positive perceptions predicted by the TAM constructs described above, acceptance does not imply usage. The TAM findings do not consider choice in the decision-making process. Specifically, results from the previously-cited user choice literature suggest that users, given a choice, may not act as rationally as predicted by TAM and Dos Santos and Bariff (1988). Specifically, the extant user choice literature suggests that XBRL-enabled technology users will not respond as predicted by TAM to XBRL-enabled technology's perceived usefulness and perceived ease of use increase. In the extreme, XBRL-enabled technology use will decline as perceived usefulness and perceived ease of use increase. A more moderate prediction is that XBRL-enabled technology use by nonprofessional investors will not be affected by perceived usefulness and perceived ease of use. Next, since the user choice literature contradicts TAM, we predict that possible acceptance of XBRL-enabled technology does not imply usage. In other words, *technology acceptance* is a necessary, but not sufficient, component of use implying that users may accept a particular technology, but choose not to use it in their task for one or more reasons. Therefore, we propose the following hypotheses, in null form.

> **H2a: Nonprofessional investors' choice of XBRL-enabled technology over PDF and Excel will not be affected by perceived usefulness.**

> **H2b: Nonprofessional investors' choice of XBRL-enabled technology over PDF and Excel will not be affected by perceived ease of use.**

Cognitive Fit Theory

Cognitive fit theory suggests that task effectiveness increases as the three-way match among (1) the problem representation, (2) the problem-solving task, and (3) the users' problem-solving skill set increases (Vessey 1991; Vessey and Galletta 1991). The theory suggests that decision makers correctly perceive improvements in cognitive fit (Vessey and Galletta 1991). Users typically resist giving up familiar software and learning new software, even though the new software is perceived to be better (Hayes 2004). This is consistent with the findings in the task familiarity literature (see Pinsker and Church (2007) for a review) and cognitive fit theory. Thus, we argue that nonprofessional investors will choose the technology they perceive to increase their competence with technology (i.e., the technology that best matches their self-assessed problem-solving skills). This prediction is supported by Jones and Schkade's (1995) results indicating that decision makers tend to choose the problem representation with which they have the most experience and to a lesser extent by Arkes et al.'s (1986) finding that those with perceived higher levels of domain expertise tend not to use a given technology. Thus, we expect that the greater amount of experience with PDF and Excel, relative to experience with XBRL-enabled technology, will lead to inertia with regard to XBRL-enabled technology.[2] This will negatively affect the choice to use XBRL-enabled technology. Our next set of hypotheses is now given:

> **H3a: Nonprofessional investors will choose PDF over XBRL-enabled technology due to their greater prior experience with PDF relative to XBRL-enabled technology.**
>
> **H3b: Nonprofessional investors will choose Excel over XBRL-enabled technology due to their greater prior experience with Excel relative to XBRL-enabled technology.**

III. METHOD

Participants

Participants were 45 graduate business students enrolled in a financial statement analysis course at a medium-sized state university. Each participant received course credit for completing the experiment. Table 1 provides descriptive statistics for our sample. Libby et al. (2002) argue that experiments that focus on the judgments of nonprofessional investors only require participants who possess basic accounting and investing knowledge. Our student participants had completed at least two undergraduate financial accounting courses and almost 40 percent had previously bought or sold common stock or mutual funds. Further, two-thirds of the participants intend on buying stock in the next five years. On average, participants had analyzed financial

[2] We have no basis to predict any differences between PDF and Excel, since investors potentially are equally familiar with PDF and Excel.

statements over seven times. Thus, these demographics suggest that the participants had the requisite course and "hands-on" experience to perform the investment decision task.

[Insert Table 1 about here]

Procedures

We used software to conduct the experiment online. As illustrated in Figure 1, the first screen in Phase I provided a brief introduction to the experimental task. Participants then navigated to an overview of the task and three technologies: PDF, Excel, and XBRL-enabled.[3] In Phase I, the participants were trained to use each technology to complete the investment decision task. Specifically, the training guided participants through step-by-step instructions of how to use each technology to calculate the investment decision model for two sample firms, Abaxis and Blackbaud. Consistent with Wheeler and Arunachalam (2008), the investment decision model comprised three common financial ratios. All participants viewed the exact same training tasks although the order of presentation (PDF, Excel, and XBRL-enabled) was randomized. Participants could go back and retrain if they felt uncomfortable with any technology.

[Insert Figure 1 – Experimental Procedure – about here]

In phase II, participants navigated to an overview screen, which presented summary financial statement information for two new companies, Concur Technologies and CommVault,

[3] We used EDGAR-Online's I-Metrix tool as our XBRL-enabled technology. To ensure that our task consisted of a test of the XBRL technology in general, rather than a test of the specific tool we chose, our task was designed to be completed using many of the XBRL tools currently available in the marketplace.

in a neutral Word format.[4] Participants were asked to review the summary financial information and make judgments regarding which of these companies to invest in. Next, participants were asked to calculate the investment decision model for each company using *only* one of the three technologies. This decision represents the dependent variable TECHNOLOGY CHOICE. Once participants made their technology choice, the software prevented them from backtracking and changing their choice. After calculating and recording the investment decision model for both companies, participants again made investment judgments.

In phase III, participants completed a post-test questionnaire containing demographic questions (including prior experience with PDF, Excel, and XBRL-enabled technologies; TAM questions on perceived usefulness and perceived ease of use consistent with Davis' (1989) seminal work, and both open- and close-ended questions on why the participants chose the particular technology).

We conducted three pretests prior to data collection. Our pretests occurred in two environments: computer labs and online. The first and second pretest consisted of two tasks: simple (i.e., calculating the current ratio) and complex (the task used in the current study). Feedback from this process resulted in elimination of the simple task due to time constraints and minor changes to the experimental materials. Our final pretest indicated that the experimental materials were successful in capturing the required data in a reasonable amount of time.

Dependent Variable

[4] We chose two unfamiliar companies for the training and two other unfamiliar companies for the actual test in order to avoid familiarity demand effects. Results from demographic questions suggest that participant familiarity with each company in the actual task was low (mean familiarity with both Concur and CommVault were less than one on an 11 point scale where 0 = unfamiliar and 10 = very familiar).

Similar to user choice research (Wheeler and Jones 2003), we use technology choice as our dependent variable. To operationalize technology choice, participants were required to choose one technology (PDF, Excel, or XBRL-enabled) to use to complete the investment decision task following training for all three technologies.

Explanatory Variables

As noted above, our design consisted of training in three technologies, followed by the experimental task of choosing one technology to perform an investment decision task. All participants saw the same training tasks. Our explanatory variables consisted of the potential reasons *why* participants would choose a particular technology for their investment decision task as indicated in our hypotheses: efficiency (i.e., takes less time to complete task), perceived usefulness, perceived ease of use, and prior experience.[5] Each variable was measured on an 11-point scale (0-10) with higher scores indicating higher perceived importance. Consistent with prior research (e.g., Pinsker and Wheeler 2009), we operationalized efficiency as taking less time to complete the task.

IV. RESULTS

Manipulation Checks

Two manipulation check questions were used. The first question asked whether the participants understood that they had a choice of technology to use to complete the investment task (after the training phase). Using a binary "True/False" response, participants responded to the following statement in the post-test questionnaire, "In the second part of the study, I was allowed to choose whether I wanted to perform the task using Excel-only, PDF, or I-Metrix

[5] We also included two other potential reasons for choosing a technology for the task: (1) "because the researchers wanted me to choose it" and (2) "because I thought it was the latest state-of-the-art technology." Both relate to potential demand effects in the experiment, but neither was statistically significant in our upcoming analyses; thus, we do not discuss them further.

(please respond by choosing True or False)."[6] Forty-one out of 45 participants (91.1 percent) correctly responded "True." We conclude, therefore, that participants properly understood they could choose any of the three technologies to complete the task.[7]

The second item was a statement related to understanding the type of task performed. Specifically, the statement read, "I was asked to make investment judgments." All 45 participants correctly answered "True." Thus, the participants appeared to understand the task at hand. In sum, both manipulation check questions were successful.[8]

Hypothesis Testing

We began hypothesis testing by analyzing the dependent variable TECHNOLOGY CHOICE. Specifically, we explored whether one technology dominated participants' choice. Twenty-six of 45 participants chose XBRL-enabled technology (I-Metrix) to perform their task; 19 chose Excel, and none chose PDF. Since no participants chose PDF to perform the task, we can immediately reject H3a. A Chi-Square test did not show any significance differences between the number of participants choosing Excel and XBRL-enabled technology ($\chi^2 = 1.09$, *p*-value = 0.30).

We test our hypotheses regarding *why* nonprofessional investors' chose a certain technology (Excel or XBRL-enabled) to perform a investment analysis task using a combination

[6] We note that I-Metrix uses Excel sparingly as part of its interface. Thus, we clearly specified Excel on its own versus I-Metrix and its occasional Excel appearance.

[7] Removing the four participants who did not answer this question correctly did not materially affect our results. Thus, we left them in our upcoming analyses.

[8] We also inquired as to the salience of the course credit and if the participants could identify the type of software application I-Metrix was (since we specifically asked them about I-Metrix in some of the questionnaire items and since I-Metrix used the Excel format). Only 1 participant (2.2 percent) did not respond correctly about receiving course credit. Thirty-seven participants (82.2 percent) correctly identified I-Metrix as an XBRL-enabled decision-making tool, rather than a database, spreadsheet, word processor, or none of the above. Removing the one incorrect respondent from the course credit questionnaire item or the eight incorrect respondents on the I-Metrix item did not materially change our results. Thus, we kept all 45 participants in our upcoming analyses.

of the following statistical techniques: correlation analysis, stepwise logistic regression (parametric), and Kruskal-Wallis (non-parametric). Normality plots indicated some skewness of the data suggesting the need for non-parametric tests. Additionally, the latter two statistical techniques provide a ranking of the potential reasons for choosing a technology.[9]

Correlation Analysis

We coded our dependent variable TECHNOLOGY CHOICE as follows: 0 = Excel, 1 = XBRL-enabled. First, we used correlation analysis. Table 2 provides the Spearman correlations among our dependent variable and our four potential explanatory variables.[10] H1 predicts that efficiency is a driving force for choosing XBRL-enabled technology over PDF and Excel. As previously outlined, we operationalized efficiency as TAKES LESS TIME. Examining Table 2, we find that TAKES LESS TIME (corr. = 0.440, *p*-value < 0.01) is positively and significantly correlated with TECHNOLOGY CHOICE. Given our coding, we interpret this correlation to mean participants chose XBRL-enabled technology (as the higher code) since they perceive that they can perform the task in less time using XBRL-enabled technology than using either PDF or Excel. This result supports H1.

[Insert Table 2 Here]

With regard to H2a (PERCEIVED USEFULNESS) and H2b (PERCEIVED EASE OF USE), both stated in the null, neither variable is significantly correlated with TECHNOLOGY

[9] We also investigated the effect of demographic differences identified in Table 1, with the exception of the last two items related to task realism and task difficulty, as possible covariates in our analyses. No demographic characteristics were significant at a *p*-value < 0.10. Additionally, we considered risk preference as a factor in technology choice. We used three questions adapted from Kahneman and Tversky (1979), summed them into a single index (Cronbach's Alpha = 0.92), and performed a correlation analysis with technology choice. The results were not statistically significant (corr. = 0.04, *p*-value = 0.80).

[10] Our statistical analysis found that Pearson correlations are almost identical to the Spearman correlations.

CHOICE (corr. = 0.195; corr. = -0.00, respectively; *p*-value > 0.10 for both). We, therefore, fail to reject H2a and H2b.

Our last hypothesis, H3b, predicts that participants' prior experience with technology will affect their choice of Excel over XBRL. Table 2 indicates that PRIOR EXPERIENCE is negative and significantly correlated with TECHNOLOGY CHOICE (corr. = - 0.538, *p*-value < 0.01). Given our coding, higher prior experience will result in a "lower" level of TECHNOLOGY CHOICE (Excel choosers were coded '0'). This finding supports H3b.

Stepwise Logistic Regression

In order to rank order the importance of each explanatory variable and confirm/disconfirm the reasons for technology choice found in the correlation analysis, we next employed stepwise logistic regression. Stepwise regression is a data reduction tool commonly used where there is no a prior reason to support inclusion/exclusion of one variable over another. It can result in greater explanatory and predictive power by lowering the mean square error (Stine and Foster 2002).

In general, stepwise regression goes through a series of steps eliminating unlikely (statistically insignificant) predictors of the phenomenon of interest. Using our sample data, these steps are summarized in Table 3. Step one lists all four explanatory variables with their statistical significance. Step two eliminated PERCEIVED USEFULNESS as an explanatory variable. The final step eliminated PERCEIVED EASE OF USE, leaving the efficiency variable (TAKES LESS TIME) and PRIOR EXPERIENCE as significant predictors of technology choice. These results confirm the correlation analysis.

[Insert Table 3 about here]

Kruskal-Wallis

We also tested our hypotheses using the Kruskal-Wallis test. The Kruskal-Wallis test rank-ordered the technology choice explanatory variables. As shown in Table 4, the only mean ranks that are different between the technology choices are for PRIOR EXPERIENCE (mean rank of the Excel choice = 31.13; mean rank of the XBRL-enabled technology choice = 17.06; χ^2 = 12.76, p-value < 0.001) and TAKES LESS TIME (mean rank of the Excel choice = 16.42; mean rank of the XBRL-enabled technology choice = 27.81; χ^2 = 8.52, p-value < 0.01). The mean rank differences for PERCEIVED USEFULNESS (χ^2 = 1.68, p-value = 0.20) and PERCEIVED EASE OF USE (χ^2 = 0.00, p-value = 0.98) were not significant. These findings are consistent with the previous hypothesis tests and provide additional empirical support for H1 and H3b, while once again failing to reject H2a and H2b.

[Insert Table 4 about here]

Further Analysis

Prior Technology Experience

Our hypothesis testing indicated that prior experience was a key factor as to why participants chose Excel over XBRL-enabled technology in their investment decision task. We performed an additional paired-samples t-test to provide empirical support for this finding. We examined the participants' reported prior experiences with both Excel and XBRL-enabled technology. Both of these measurements were on 11-point scales (0-10) with higher scores indicating higher levels of experience. The participants' mean prior experience with Excel (7.56, S.D. = 1.66) was significantly higher than their mean prior experience with XBRL-enabled technology (3.56, S.D. = 2.92; t-statistic = 9.11, p-value < 0.001).

Relating the Technology Choice to Investment Choice

Similar to the method used by Hodge et al. (2004), we chose our sample companies such that one company seemed to be the "better" investment choice just looking at the face financials, but the other company *should* be chosen if the participants correctly calculated and relied upon the investment decision model (a proxy for accuracy). Since the experiment was run over two years with different graduate business students, and we used actual firm data, the companies reversed as to the "right" company to invest in (using the investment decision model). In the first year, CommVault had the "better" financials, but Concur Technologies had the higher investment decision model score. The opposite was true in the second year. Thus, this reversal of firm performance biases us against finding an effect.

Rather than only coding the individual companies, we used a binary coding of 0 = the "wrong company" and 1 = the "right" company to invest in given the investor decision model scores. Twenty-four participants chose the "right" company to invest in; 16 chose the "wrong" company; five participants did not provide a choice. Correlation analysis (corr. = 0.04, *p*-value =0.79), Chi-Square testing ($\chi^2 = 0.80$; *p*-value = 0.67) and logistic regression (*p*-value = 0.79) all find no relationship between technology choice and choosing the "right" company (i.e., no accuracy differences in favor of a given technology).[11]

Single Reason for Technology Choice

We asked our participants to identify which explanatory variable (TAKES LESS TIME, PERCEIVED USEFULNESS, PERCEIVED EASE OF USE, or PRIOR EXPERIENCE) was their most important reason for their technology choice. There was no significant differences

[11] Since we initially asked participants to choose a company solely given their financial data, we attempted to link this initial decision to technology choice. Twenty-six participants chose the "right" company to invest in given the initial financial information in Word format; 12 participants chose the "wrong" company; seven did not provide a choice. A logistic regression indicated no statistically significant relationship (*p*-value = 0.11). Further, correlation analysis did not find any accuracy effect for those who changed their mind or did not change their mind to either the "right" or "wrong" decision when later asked for their investment choice (see above) relative to their initial decision (based solely on the financials; corr. = .131, *p*-value = .46).

among the top three reasons chosen (TAKES LESS TIME, PERCEIVED USEFULNESS, PRIOR EXPERIENCE; $\chi^2 = 2.00$, p-value = 0.37). We then separated the responses by technology choice (i.e. Excel vs. XBRL-enabled technology) and found results consistent with previous testing. Specifically, the Excel choosers stated PRIOR EXPERIENCE as their most important reason ($\chi^2 = 6.40$, p-value = 0.04) and the XBRL-enabled technology choosers stated PRIOR EXPERIENCE the least important reason (only one participant chose this reason; $\chi^2 = 8.00$, p-value = 0.02). Thus, we were unable to identify one single reason for technology choice.

Investment Decision Model and Acquisition Technology

We asked participants two questions relating to the investment decision model they completed. Specifically, we examined (1) the technology chosen when calculating the investment decision model, and (2) the perceived importance of the technology choice in the investment decision model. Regarding the first question, the participants' choices included paper-and-pencil, calculator, spreadsheet (Excel), mental methods, I-Metrix (XBRL), PDF, and other. Only 19 participants responded to this question. Of the 19 respondents, nine chose spreadsheet and 8 chose I-Metrix, with one answer each for calculator and PDF. These descriptive results add credence to the dominant choices of spreadsheet and XBRL-enabled technology found in the hypothesis testing.

Regarding the second question, we explored whether the importance (or lack thereof) of technology choice on the investment decision model. We used a 11-point scale (0-10) with the higher scores meaning higher perceived importance. Using a t-test, we found that the mean of the Excel choosers (7.16, S.D. = 1.26) was not significantly higher than the XBRL-enabled technology choosers (6.50, S.D. = 1.45). Therefore, we do not find any evidence linking the importance of technology choice to the investor decision model.

Lastly, we asked participants which technology (PDF, Excel, or XBRL-enabled) they would prefer to use to *acquire* a company's financial information. Twenty-four participants chose XBRL-enabled (53.3 percent), 19 chose Excel (42.2 percent), and 2 chose PDF (4.4 percent). A Chi-Square test did not show any significant differences between XBRL-enabled and Excel choices for acquiring financial information (χ^2 = .58, p-value = 0.45).

V. CONCLUSION

We examine whether nonprofessional investors will choose XBRL-enabled technology over more familiar technologies such as spreadsheets and portable document files for financial statement analysis tasks. We also extend the extant choice literature to examine "technology choice" and provide *specific reasons why* nonprofessional investors choose to use XBRL-related or Excel technology in their investment decisions. Our work is important since recent evidence suggests investor adoption of XBRL-enabled technology is slow despite the regulation requirements (SEC 2009) and emphasis on XBRL-formatted information (Hodge et al. 2004; Locke et al. 2009). For example, despite its benefits, almost 50 percent of participants in Hodge et al. (2004) research did not use XBRL-enabled technology. Furthermore, some U.S. firms view XBRL implementation as a compliance exercise and question the benefits of providing XBRL-formatted statements (Janvrin and No 2010). In other words, XBRL and its related technology may be under-utilized in terms of its main intended purposes: increased efficiency, increased reusability, and increased transparency of data (SEC 2009).

We trained nonprofessional investors to use three technologies (PDF, Excel, and XBRL-enabled) to perform a financial analysis task. We then asked participants to choose which technology they would use to complete the same financial analysis task for two different companies.[12] Results indicate 58 percent of participants chose to use XBRL-enabled technology while 42 percent chose Excel. Further, no participants chose PDF. Apparently, no participant believed that PDF was superior to Excel and XBRL-enabled technology in terms of efficiency, perceived usefulness, perceived ease of use, or prior experience.

When considering the reasons for technology choice, efficiency in performing the task (i.e., taking less time) is the primary reason participants chose XBRL-enabled technology. Thus, if nonprofessional investors obtain access to XBRL-enabled technology, they may choose to use it because they will perceive it will save them time. As stated at the beginning of this section, increased efficiency in analyzing financial information is a main purpose for using XBRL-enabled technology as advocated by proponents. Our finding is a positive sign for those who advocate XBRL-enabled technology use in the public domain. Regarding user choice of Excel, prior experience with the technology was the dominant factor. Further testing provided evidence that Excel choosers shied away from XBRL-enabled technology because they felt they had insufficient XBRL experience.

Our findings build upon the existing user choice theory to examine *technology choice* where an individual chooses between multiple technologies. Based upon existing user choice theory, we hypothesized that non professional investors will choose XBRL-enabled technology if they perceive that it will help them complete the task in less time (i.e., more efficiently). We rely upon TAM and cognitive fit theories to develop alternative explanations for *why* users choose one technology over another. Specifically, we suggest that nonprofessional investors may choose XBRL-enabled technology over Excel due to high perceived usefulness and perceived ease of

[12] Consistent with Hodge et al. (2004), we define our task as "complex," because it consisted of information acquisition (from the financial statements) and information integration (in the form of an investment decision model).

use. We also purpose that investors may chose Excel over XBRL-enabled technology since decision makers tend to choose the problem representation with which they have the most experience. Interesting, while we find support for our first (efficiency) and third (experience) hypotheses, the two TAM constructs, perceived usefulness and perceived ease of use, were not significantly related to technology choice using multiple statistical tests.

As with all experimental work, we acknowledge research limitations. Several limitations may suggest future research opportunities. First, our participants were required to choose one of three technologies. While we believe we have chosen the three most common technologies to display financial information, we may have missed a technology. Second, our experiment assumes a cost-free investing environment. Whereas nonprofessional investors may already have access to PDF and Excel technologies, they may need to purchase XBRL-enabled technology. This consideration was not part of our research design, but represents an interesting avenue for future research. Third, we use a single task to measure nonprofessional investor technology choice. Future research should consider multiple tasks of varying complexity to determine if our results generalize or if investor technology choice rationale varies by task complexity.

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TABLE 1
Participant Demographics

Demographics	Frequencies	Mean or % (Std. Dev.)
Age		29.62 (7.58)
Years of business work experience		4.69 (6.51)
Gender	Male = 19 Female = 26	42.2% 57.8%
Bought or sold individual company's common stock or mutual fund	No = 28 Yes = 17	62.2% 37.8%
Bought or sold individual company's common stock or mutual fund as part of class exercise	No = 38 Yes = 7	84.4% 15.6%
Plan to invest in individual company's common stock in the next five years	No = 15 Yes = 30	33.3% 66.7%
Number of times evaluating a company's performance by analyzing its financial statements		7.89 (19.43)
Used an investment model to buy a stock/mutual fund	No = 40 Yes = 5	88.9% 11.1%
Experience level:[a]		
Working with spreadsheets		7.56 (1.66)
Working with XBRL-enabled technology		3.56 (2.92)
Working with portable document files		6.40 (2.38)
Difficulty of investment decision task[b]		4.91 (2.05)
Rate the realism of this task[c]		6.89 (1.60)

[a] Participants were asked to rate their experience on an 11 point scale where 0 = novice and 10 = expert.
[b] Participants were asked to rate the difficulty on an 11 point scale where 0 = extremely simple and 10 = extremely complex
[c] Participants were asked to rate the realism of the task on an 11 point scale where 0 = unrealistic and 10 = very realistic

TABLE 2
Spearman Correlations for All Variables of Interest Trying to Predict Technology Choice

	TECHNOLOGY CHOICE (DV)	PERCEIVED EASE OF USE	PERCEIVED USEFULNESS	PRIOR EXPERIENCE WITH TECHNOLOGY	TAKES LESS TIME
TECHNOLOGY CHOICE (DV)	1.00				
PERCEIVED EASE OF USE	-0.00	1.00			
PERCEIVED USEFULNESS	0.195	0.53***	1.00		
PRIOR EXPERIENCE WITH TECHNOLOGY	-0.538**	0.10	-0.27*	1.00	
TAKES LESS TIME	.440**	0.44***	0.54***	-0.24	1.00

* *p*-value < 0.10
** *p*-value < 0.05
*** *p*-value < 0.01

TABLE 3
Stepwise Logistic Regression Results for Technology Choice

	β	***p*-value**
Step 1:		
PERCEIVED USEFULNESS	-0.16	0.66
PERCEIVED EASE OF USE	-0.25	0.50
PRIOR EXPERIENCE	-0.48	0.01
TAKES LESS TIME	0.96	0.01
Constant	-1.51	0.52
Step 2:		
PERCEIVED EASE OF USE	-0.31	0.25
PRIOR EXPERIENCE	-0.46	0.01
TAKES LESS TIME	0.91	0.01
Constant	-1.85	0.42
Step 3:		
PRIOR EXPERIENCE	-0.49	0.01
TAKES LESS TIME	0.73	0.02
Constant	-1.97	0.31

TABLE 4
Results of Kruskal-Wallis Testing for Technology Choice Factors

Variable	Choice	N	Mean Rank	χ^2	*p*-value
PERCEIVED USEFULNESS	Excel	19	20.08	1.68	0.20
	XBRL	26	25.13		
PERCEIVED EASE OF USE	Excel	19	23.05	.00	0.98
	XBRL	26	22.96		
PRIOR EXPERIENCE	Excel	19	31.13	12.76	<0.001
	XBRL	26	17.06		
TAKES LESS TIME	Excel	19	16.42	8.52	<0.01
	XBRL	26	27.81		

FIGURE 1
Experimental Procedure