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The Impact of Data Type and Graphical Presentation Type on Financial and Non-Financial Information Literacy in Undergraduate Accounting Students: Two Experiments with Business Analytics Dashboards

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Abstract

There is increased demand to teach Business Analytics (BA) in accounting curricula. Dashboards are an important part of BA training. Another key element of BA is variety of data, especially non-financial data. Yet accounting students are significantly less familiar with the use of non-financial than financial data. Little is known about how accounting students will react to this mixture of new IT (BA dashboards) and unfamiliar (non-financial) data. In two experiments, we find that: (1) undergraduate accounting students weight the importance of unfamiliar and familiar data equally when the graphical presentation is aggregated; (2) when the graphical presentation is disaggregated, students weight unfamiliar data more heavily; (3) when students received unfamiliar data versus familiar data, they had a greater response to the information on the graphs; and (4) when students incorporated more unfamiliar data, their reaction to graphical information was enhanced. These results have important implications for AIS education. To teach BA more effectively, accounting educators should be aware of how students react to familiar and unfamiliar information when graphically presented on BA dashboards. Equally important, accounting students as future accountants need to understand how clients react to BA dashboard presentations and ensure that clients use the information correctly.

Keywords: Big Data; Data Analytics; Dashboard; Information literacy; Proximity compatibility principle; Data type; Graphical presentation type.

Data availability: *Contact the authors*

Introduction

There is increasing demand from accounting employers for new accounting graduates to have skills for analyzing Big Data (Moffit and Vasarheyli, 2013; Vasarheyli et al., 2017; PwC, 2015). A 2016 McKinsey Global Institute study finds that, even with new university programs in business analytics[1] becoming steadily available, demand for business analytics' skills will significantly outpace supply (MGI, 2016). The study estimates while the number of data science programs graduates could increase by 7% per year, with a 12% annual growth in demand for data analysts, results show an annual shortfall of as many as 250,000 data scientists. *The Economist* conducted a survey of over 400 European and U.S. executives in 2016. They found that these executives believe that business analytics and Big Data will be the most important digital skills for their organizations through the foreseeable future (The Economist, 2016). Similarly, in PwC's (2014a) survey of global CEOs, 85 percent of CEOs place a high value on data analytics for their company, and in another PWC survey (PWC, 2014b), more than 1,400 business leaders put business analytics as the area of investment that tops their list of priorities.

In the area of education, the Association to Advance Collegiate Schools of Business (AACSB) includes data analytics in Business Standard 9 (Curriculum Content) and Accounting Standard A7 (Information Technology Skills and Knowledge for Accounting Graduates), describing it as an important area for accreditation (AACSB, 2019). We see similar emphasis among the Big 4 on the importance of business analytics in accounting education. For example, PwC (2015) specifically addresses "what accounting students need" in the new "data driven" business environment. They particularly emphasize the need for accounting students to have skills in mining new sources of data, visualizing accounting data, and extracting the right data. When teaching undergraduate accounting students, two widely used tools for teaching business analytics skills are Tableau and Power BI. They utilize multi-functional dashboards displaying both textual and graphical information. Since these dashboards (see Figure 1) often incorporate data from multiple Big Data sources (e.g., ERP systems, corporate social responsibility reports, and the social media), it is practically certain that much of the data displayed will be unfamiliar to entry-level accountants.

Many accounting department programs are creating analytics courses which are frequently designed and delivered by AIS faculty members. Further, many of these programs are embedding analytics in traditional accounting courses such as financial, managerial, audit, and tax. The topic of student interpretation of visualizations is important to all who teach accounting course as this phenomenon continues to occur. Thus, while it is important to teach undergraduate accounting students the use of new IT tools (e.g., BI and Tableau) for business analytics (BA), it is equally important for both educators and accounting students to realize that there may be interactions between the tools and the types of data used for analysis. These interactions may cause biases that impact the educational benefits of teaching BA, and, once accounting students enter the workplace, these biases may affect how accurately they react to graphical presentations of data with differing degrees of familiarity. Thus, accounting students need to be aware of reactions to data familiarity and unfamiliarity so that (1) they can counter these reactions in their own perceptions and use of such data, and, (2) as future accountants presenting graphical information to clients, they can assist the clients in recognizing and debiasing the clients' reactions to and use of that information. FASB (2010) in defining the "faithful representation" of useful financial reporting, specifies repeatedly that the representation of information must be "unbiased." To meet this FASB requirement, the presenters (i.e., accountants) must be aware of biases in themselves and in those to whom the information is being presented—and not only aware of the biases but also able to counter any harmful impact on the uses of the financial reports.[2] These are areas that have received little if any attention in accounting education research. In this study, we ask the following research question: What are the

[1] We use the term *business analytics* simply as the subset of *data analytics* dealing with the business community. The business literature we cite often uses these terms interchangeably.

[2] A limitation of this study is that we do not test decision-making quality directly, not only the decision weight placed on unfamiliar non-financial data. However, research has shown that when accountants incorporate non-financial data, if relevant, into their decision-making, their decision-making quality improves (Trompeter and Wright 2010; Brazel et al. 2009). Accordingly, we believe that our study addresses FASB's requirement for "unbiased" decision-making.

effects of data familiarity and graphical presentations on undergraduate accounting students' judgments and decisions in an audit task?

Using information literacy (IL) theory from education literature and the proximity compatibility principle (PCP) from information systems research, we investigate the research questions in two experiments. Experiment 1 uses a 2 x 2 between participants design using a computerized dashboard with 77 undergraduate accounting students performing an audit task. In the dashboard, we manipulate: (1) whether the data (which are inputs to the dashboard) are familiar (financial) or unfamiliar (non-financial); and (2) whether the BA dashboard graphical presentations of the data are aggregated (two lines on one graph) or disaggregated (two graphs with one line on each). Results from experiment 1 indicate interaction effects when the graphical presentation is disaggregated versus aggregated, participants increase the weight placed on the unfamiliar data, but do not increase the reaction to or the weight of the familiar data. Another factor which influences how well they make use of the information is participants' ability to visually search and identify differences between similar but separate graphical representations. Experiment 1 finds that when determining the weight placed on the data, participants utilize more comparative visual searching ability when receiving unfamiliar data than when receiving familiar data.

To further investigate participants' utilization of familiar versus unfamiliar data, we conduct experiment 2 with 44 undergraduate accounting students. Experiment 2 is the same as experiment 1 except that all of the participants in experiment 2 received a combination of familiar and unfamiliar data in the dashboard (hereafter: mixed data). The graphical presentation of the data is still manipulated between disaggregated and aggregated. Results from experiment 2 demonstrate that participants tend to incorporate more familiar data than unfamiliar data regardless of graphical presentation. Interestingly, when participants increase their percentage of incorporation of unfamiliar data, their reaction to the information in the dashboard is enhanced, which indirectly increases their weight on the importance of the mixed data.

Our research contributes to the AIS education literature in several ways. First, our results indicate that accounting educators need to be aware of accounting students' familiarity with data being used in their lessons on BA. Second, our findings suggest that accounting students need to be aware of their biased reactions to familiar and unfamiliar data so that they can debias the reactions in their own use of the data. Additionally, as future accountants, they can assist clients in debiasing their perceptions of familiar and unfamiliar data. Third, as a result of the first two contributions, our study contributes to meeting FASB's (2010) requirement that financial reporting be made in an unbiased manner. Fourth, by using a measure of comparative visual searching ability, not previously used in AIS education research, we find that undergraduate accounting students are able to utilize this ability to help process unfamiliar data. Fifth, the study suggests a solution to a research question from Messier et al. (2013) on investigating additional mechanisms to stimulate accountant's use of unfamiliar non-financial data. We find that presenting accounting students with disaggregated graphs can help them put more weight on the importance of unfamiliar non-financial data. This solution indicates that it can be beneficial to present unfamiliar data to accountants as multiple graphs on a dashboard. Sixth, our study adds to the growing accounting education research using information literacy theory. Specifically, our study indicates how to improve the information literacy of undergraduate accounting students in regard to non-financial information using BA dashboards.

The rest of this paper is organized into five sections. The next section develops the hypotheses. Section III presents the design of experiment 1. Section IV reports the results of experiment 1. Section V discusses experiment 2. And Section VI concludes the paper.

Background and Hypotheses

The Importance of Big Data in Accounting and Accounting Education

Big Data elements (i.e., the "4 Vs": volume, velocity, variety, and veracity) (IBM, 2012) and BA have been applied to multiple dimensions in both accounting education, research and practice (Moffitt and Vasarhelyi, 2013). In education and research, for example, the Resources, Events, Agents (REA) model, a standard pedagogical model in AIS education, has been extended to include Big Data elements (Murthy, 2016). In practice, Big Data analytics have been applied to the tax practice. Tax accountants and data scientists are collaborating to generate new ways to understand the data and new visualization mechanisms of the data to increase the deduction amount for the tax payers (Cragun, 2016). In auditing practice, auditors process various data sources from financial (e.g., salary expenses) to non-financial (e.g., employee turnover ratio) to improve their understanding of the client. Auditors utilize non-financial reports (e.g., Corporate Social Responsibility Reports) from the client (Srivastava et al., 2013) and collect non-financial data from unstructured platforms such as email and social media (Brown-Liburd et al., 2015).

The Importance of Unfamiliar Non-Financial Data in Accounting

Degree of familiarity with data is a critical determinant of how data is processed and how well tasks are performed. For example, studies show that unfamiliar non-financial data can be as important as or more important than the more familiar financial data for many accounting tasks, but both accounting students and professionals often ignore the importance of the unfamiliar non-financial data for many accounting tasks. Cohen et al. (2008) conducted a case study to test accounting students' perceptions of the importance of non-financial data in audit planning processes. Their results indicate that students over-rely on familiar (financial) data and under-rely on unfamiliar (non-financial) data. Jans et al. (2014) examined the use of meta-data (i.e., data about data), a specific type of non-financial data, to assist auditors' data analysis during audit analytical procedures. Their results indicate that with unfamiliar meta-data analysis, auditors can find hidden Overall, unfamiliar meta-data can provide auditors additional data sources with more detailed information about the nature, timing, and scope of business transactions and has the potential to enhance the efficiency and effectiveness of audit detection (Jans et al,. 2013).

Further, as discussed above, FASB (2010) requires that financial reporting "faithfully represent" the information being presented. In defining, "faithful representation" FASB includes the requirement that such information is to be "unbiased." Accordingly, any financial and non-financial in the financial statements (e.g., in MD&A) must be free of bias. As our study shows, the degree of familiarity with information affects how familiar/financial information and unfamiliar/non-financial information are perceived and used.

Information Literacy Theory and Proximity Compatibility Principle

One of the primary theories in education is the information literacy (IL) theory (Fiegen, 2011). According to the Association of College and Research Libraries (ACRL), information literacy consists of six components: (1) recognize when information is needed; (2) access the information; (3) critically evaluate the information; (4) incorporate the information into one's knowledge base; (5) use the information effectively and efficiently; and (6) understand economic, legal, social, and ethical implications of use of the information (ACRL, 2000, 2-3). Accounting, which is one of the primary providers of business information, requires its students and practitioners to possess a high level of IL in regards to business information, especially familiar financial and unfamiliar non-financial information (AACSB, 2019; PwC, 2015).

Several papers have used IL theory for accounting education research (see Fiegen, 2011 for a literature review). Cunningham and Anderson (2005) note "the perceived 'crisis' in accounting education at the university level" (p.4) and develop a financial accounting course using IL principles. They test this course against one without IL and find that the IL-based course students performed significantly better. Similar successful applications of IL theory to accounting courses are reported by Jackson and Durkee (2008), Kelly et al. (2010; 2011), and Joseph et al. (2015). Central to these studies is the importance of teaching students to recognize what information is needed for a particular problem, and then to quickly find, evaluate, and apply the information—abilities investigated in our experiments. An equally significant finding is that the role of instructor must shift from presentation information to facilitating students in finding and using information for themselves. None of these prior studies applied IL to AIS education; yet AIS courses are ideal for incorporating IL principles (recognize, locate, evaluate, and use) because AIS courses typically involve a significant amount of interactive hands-on work with various IT software. As suggested by our study, such IT-oriented AIS courses can be designed to emphasize IL principles and information processing in all of its stages.

From the information systems literature, we use the proximity compatibility principle (PCP) to operationalize IL in our experiments (Wickens and Carswell, 1995; Carswell and Wickens, 1996). Specifically, our experiments implement the first five components of IL listed above: recognition, access, evaluation, incorporation, and effective use (but does not address the socio-ethical implications of use). PCP proposes that, when sources of information are closely related to each other, the presentation of the sources need to be close to each other in order to increase the efficiency of information processing. PCP defines two types of proximity: display proximity and processing proximity. The former represents the degree of similarity in the presentation of information sources (e.g., the closeness, color, or shape in a display design). The latter represents the task requirement on the level of integration of the sources. For example, if a task requires high integrative processing of the sources, the processing proximity is high. PCP also proposes possible matches between information processing types and processing proximity levels such as: integrative processing on high processing proximity and non-integrative processing on similar sources of lower processing proximity.[3] When applying PCP to display design, the principle suggests that the level of display proximity should align with the requirement of processing proximity. As a result, information processing costs increase as the inconsistency between processing and display proximity increases. Thus, PCP helps us understand why the relationships among multiple graphical displays impact the graphical design for decision makers.

The Aggregated and Disaggregated Graphical Presentations

As indicated in PCP, spatial proximity is a type of display proximity which represents the physical distance among displayed items (Wickens and Carswell, 1995). In a decision aid (e.g., dashboard) with graphical presentations, spatial proximity can be manipulated as either aggregating (i.e., high display proximity) or disaggregating (i.e., low display proximity) the presented elements, holding control over other factors of the graphical design such as color, shape, and type. A practical example of a disaggregated presentation in widespread current use is the BA dashboard (e.g., Power BI and Tableau used in many AIS courses). According to Yigitbasioglu and Velcu (2012), dashboards can reduce decision makers' cognitive load by presenting several graphs simultaneously and allowing users to focus on and manipulate each graph individually. In our study, the cognitive benefits of dashboard presentations are operationalized by disaggregating the graphical presentation: breaking a single graph with multiple variables into two or more separate graphs. We predict that disaggregating the graphical presentation reduces the likelihood of undergraduate accounting students to make mistakes by correlating variables that should be analyzed separately and forming conclusions that deviate from the intended use of the dashboard.

PCP predicts various forms of interactions between processing proximity and display proximity on performance efficiency (Wickens and Boles, 1983). In our study, the predicted interaction effect is shown in Figure 2, based on Wickens and Boles (1983; p. 12 Figure 2b). The pattern of the interaction effect shows that: When processing proximity is high, matching display proximity to processing proximity has little effect on performance efficiency; when processing proximity is low, matching the display proximity to processing proximity has a strong effect on performance efficiency.

Based on the predicted interaction effect in PCP, we predict that disaggregating the graphical presentations will have a stronger effect when undergraduate accounting students receive unfamiliar data (e.g., non-financial data) than when they receive familiar data (e.g., financial data). Kida and Smith (1995) and Kida et al. (1998) demonstrate that accountants have a tendency to analyze numerical data in an integrative manner and to reconstruct the presented information using memory schema instead of processing the data directly without reconstruction (Kida et al. 1998). However, these two papers examined only familiar (financial) numerical data and did not discuss the unfamiliar (non-financial) counterpart. Based on the IL theory and the PCP, the processing proximity is high when undergraduate accounting students receive financial data because it is the type of data that they are familiar with, and they have been trained to apply calculations and comparisons on financial data. In contrast, since undergraduate accounting students are usually not familiar with how to analyze non-financial data, their processing proximity of non-financial data is low, and they are less likely to conduct integrative processing on this type of data. When presenting data using dashboards by varying the display proximity, we expect that processing proximity dominates

[3]Based on PCP (Wickens and Boles 1983), *integrative processing* in our study refers to information processing involving the combination of items (e.g., by calculation), whereas *non-integrative processing* refers to information processing in which items are compared but left separate and not combined (e.g., by pattern recognition or visual comparison).

display proximity when the data is financial, and display proximity dominates processing proximity when the data is non-financial.

Therefore, we predict that: disaggregating the graphical presentations of the data will impact the weights undergraduate accounting students place on unfamiliar data; but such disaggregation will have no effect on the weights placed on familiar data. We hypothesize the following interaction:

> **H1**: Type of data (unfamiliar, familiar) and degree of graphical aggregation (aggregated, disaggregated) will interact such that undergraduate accounting students increase the weight on the data more (less) when unfamiliar (familiar) data is presented in disaggregated versus aggregated graphs on a BA dashboard.

Reactions to the Graphs and Their Comparative Visual Searching Ability

It is unclear from prior research whether undergraduate accounting students' reactions to the information in a graphical presentation (i.e., awareness and sensitivity to the risk embedded in the graphical presentation) are stronger when the data is familiar versus unfamiliar regardless of how that data is presented (aggregated or disaggregated). The integrative approach of analyzing familiar data (Kida and Smith, 1995; Kida et al., 1998) may increase the impact of useless comparisons and potentially impair undergraduate accounting students' reaction to the information in graphs; whereas the tendency to underweight the importance of unfamiliar data (Brazel et al. 2014) may reduce undergraduate accounting students' reaction to graphical presentations. Accordingly, we hypothesize:

> **H2a**: Undergraduate accounting students' reaction to the graphical information is different when the underlying data is familiar versus unfamiliar, regardless of the display proximity of the graphical components (aggregated or disaggregated).

Consequently, undergraduate accounting students' reaction to the dashboard can influence their weight on the importance of the data (Rest, 1979). Accordingly, we predict that this reaction to the information type mediates the weight undergraduate accounting students place on the importance of the information. Thus, we hypothesize:

> **H2b**: The effect of data type (familiar or unfamiliar) on undergraduate accounting students' weighting of the importance of the data is mediated by their reaction to the graphical information.

Receiving different types of data may either activate or deactivate undergraduate accounting students' comparative visual searching ability, a form of pattern recognition (Atkins et al., 2006) that can affect their interpretation of graphical presentations (Underwood et al., 2008). On one hand, since undergraduate accounting students are more familiar with financial data than with non-financial data, they might undervalue the information presented in non-financial data and be reluctant to visually search for important information embedded in the presentations. On the other hand, when a task does not require comparative processing of numerical data, conducting calculations and comparisons on familiar financial data may attenuate undergraduate accounting students' awareness of abnormal changes (Kida et al., 1998); whereas, lack of familiarity with non-financial data might serve as an external shock to activate their comparative visual searching abilities. As a result of these opposing predictions, we hypothesize:

> **H3**: Undergraduate accounting students utilize their comparative visual searching ability differently when the data is familiar versus unfamiliar.

Design of Experiment 1

Participants

The 77 volunteer participants in experiment 1 were undergraduate accounting students who had completed or were in the process of completing their first auditing course at a public university in the southeastern United States. Table 1 presents demographic data for the participants.

Materials and Experimental Procedure

Participants in the experiment were provided with a case that places them in the role of a staff auditor of a hypothetical audit engagement of a publicly traded retail company. The case scenario was similar to that in Brazel and Agoglia (2007) and Brazel et al. (2014); however, the selection of unfamiliar non-financial data and design of the dashboard, along with numerous other details, were different in our study.

Based on prior literature (Ernst & Young, 1998[4]; Kaplan and Norton, 1996), we selected six non-financial data items and grouped them into three categories for use in the instrument: Net Sales Revenue, Cost of Goods Sold, and Operating Expenses. (1) The two items under Net Sales Revenue are "the company's market share" and "customer complaints as a percentage of total items sold"; (2) the two items under Cost of Goods Sold are "the percentage of defective units shipped" and "the percentage of long-term supply agreements utilized"; (3) the two items under Operating Expenses are "the average success rate of new products" and "the staff turnover ratio".

First, participants were informed that their senior auditors, based on previous year's audited results, budgeted a total of 500 audit hours for three income statement line items: 100 hours on Net Revenue, 100 hours on Cost of Goods Sold, 300 hours on Operating Expenses. Second, participants were told that senior auditors were expecting them to recommend changes to the allocated audit hours with the help of a BA dashboard. The dashboard presented the data and trends of two different variables across four years (2011-2014) for each income statement line item in the current audit and generated a report with three sections. Among the trend graphs in the dashboard, the graphs of the variables predicting Net Revenue and Cost of Goods Sold contained abnormal changes in the current year (huge spikes in the current year numbers, but flat in prior years) that should encourage participants to increase audit hours to these two income statement line items. In contrast, there were relatively flat lines across years in the graph(s) for Operating Expenses. In each section, participants indicated their predicted risks of misstatement for each income statement line item by selecting a value from a nine-point Likert scale (a higher value indicates a higher risk).

Third, participants saw the same graphical presentations of the BA dashboard again (on a long page); if any changes were needed, the participants' task was to determine how to reallocate the audit hours among the three income statement line items. Fourth, participants provided reasons for their finalized decisions by typing into a text-entry box. Fifth, they rated the dashboard by giving scores (0 to 10) on the degree to which the dashboard was easy to understand and had provided relevant information. Finally, they finished two manipulation check questions and a post-experiment questionnaire to complete the whole experiment. Figure 3 shows the steps in the experiment and variable(s) captured in each step (see Appendix A for detailed descriptions on the experiment).

Independent Variables

Type of Data

The type of data in the dashboard was manipulated between subjects at two levels: familiar (financial) data (*FAM*) and unfamiliar (non-financial) data (*UNF*). Under the familiar (unfamiliar) data level, for each income statement line item, participants received data on two client-specific familiar/financial (unfamiliar/non-financial) ratios.

Graphical Presentation Type

The presentation of the graphs was manipulated between subjects at two levels: disaggregated (*DIS*) and aggregated (*AGG*). Under the disaggregated condition, for each income statement line item, participants received two graphs with one line on each graph. Under the aggregated condition, for each income statement line item, participants received two lines on a single graph. According to PCP, the scale, the size, the color of the lines, and the type of graph were the same for each level to ensure that spatial proximity is the only variable that determines the graphical presentation of the data.

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[4] Ernst and Young identified and ranked 39 non-financial indicators based on their influence on companies' performance. In our study, the non-financial variables for Net Revenue, Cost of Goods Sold, and Operating Expenses are ranked top 15 among the 39 indicators.

Dependent Variables and Control Variables

There are two main dependent variable in this study. The first variable, which is both a mediator and dependent variable, is participants' degree of reaction to the information in the dashboard (*REACT*). It was measured by the sum of the predicted risk of misstatement indicated for Net Revenue and Cost of Goods Sold plus a reversed coding (nine minus the indicated score) in the predicted risk of misstatement indicated for Operating Expenses.[5] The second variable represents participants' weight on the importance of the variables in the dashboard (*WEIGHT)*. *WEIGHT* was measured by the sum of the audit hours that participants entered for Net Revenue and Cost of Goods Sold.[6] It is important to note that the two dependent variables are not measures of performance quality (e.g., accuracy), but only of the use of unfamiliar data. Regardless of whether such use affects performance quality, students must first address the issue of data use before investigating whether the data will improve task performance (Messier et al., 2013).

In addition, two covariates were captured on the post-experiment questionnaire (PEQ) based on participants' personal traits on the two manipulated factors. The first covariate (*FAM_UNF_DIFF*) was captured from a set of questions that asked participants to weight the importance of three (familiar) financial and three (unfamiliar) non-financial indicators regarding a decision to invest in a company's stock; the difference between their summed weight of familiar and unfamiliar indicators was the value of this covariate, which measured participants' inclination to over (under) weight the importance of financial (unfamiliar) measures. The second covariate (*CORRECT*) was captured from three "spot-the-differences" games which measured participants' comparative visual searching ability. Each game required participants to spot the differences between two similar photos. Within 120 seconds in each game, participants needed to identify four differences by left-clicking the photo on the left. Participants' average number of correct differences identified was the value of the covariate. See Appendix A for an example.

Manipulation Checks

Manipulation checks were conducted to ensure that participants understood the type of data and the degree of aggregation in the graphical presentation they received. Participants were asked to answer two manipulation check questions, each relating to one of the factors in the experiment. The first manipulation check question asked participants whether the data presented in the dashboard was two lines on one graph or two graphs with one line on each. Four (5.19%) participants failed this manipulation check. The second manipulation check question required participants to indicate whether the data in the dashboard was familiar data or unfamiliar data. Eight (10.39%) participants failed this manipulation check. There was one (1.30%) participant who failed both questions. Therefore, we dropped the participant from our sample and returned a sample size of 76.

Results of Experiment 1

Test of Hypotheses

Since H1 predicts a specific ordinal interaction based on PCP in which the increased weight from a disaggregated graphical presentation is greater for participants in the unfamiliar condition than in the familiar condition. As a result, the default ANOVA test is not a powerful test for the interaction effect (Buckless and Ravenscroft, 1990). Therefore, we conduct a planned contrast that more accurately tests our predicted mean pattern.[7]

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[5] A reversed measurement on participants' risk score on Operating Expenses was added because it demonstrates participants' correct reaction to the graph(s) with no dramatic changes.

[6] There were two other variables used in the experiment: participants' perceived ease of understanding the decision aid (*RATE_EASY*), and their perceived relevance of the data in the decision aid (*RATE_REL*). These variables are derived from the Technology Acceptance Model (TAM) (Venkatesh and Davis 2000). Results support the TAM but add no new insight and have no effect on our reported results. Therefore, we drop these two variables from further discussion in the paper.

[7] Although we use planned contrast to test H1, we present the conventional ANOVA results for completeness. However, we caution against drawing conclusions from the ANOVA results given our predicted ordinal interaction effect. Table 2, Panel A reports the means, standard deviations, and cell sizes by experimental conditions for our

Based on Buckless and Ravenscroft (1990) and Guggenmos et al. (2018), the weights of the main contrast that tests H1 are assigned as: - 1 for FAM/AGG, - 1 for FAM/DIS, - 1 for UNF/AGG, and +3 for UNF/DIS. Its two residual contrasts are: -1 for FAM/AGG, 2 for FAM/DIS, -1 for UNF/AGG, and 0 for UNF/DIS; +1 for FAM/AGG, 0 for FAM/DIS, -1 for UNF/AGG, and 0 for UNF/DIS.

To test H1, we follow the three-part testing approach provided by Guggenmos et al. (2018). Figure 4 graphically depicts the mean of *WEIGHT* by experimental conditions, and a visual evaluation of the mean pattern indicates that our planned contrast fits the mean pattern. Contrast testing results are shown in Table 2, Panel C. The main contrast (contrast 1) is significant (t = 2.91, p = 0.003, one-tailed), and its residual contrasts (contrasts 2 and 3) are insignificant (p-values > 0.1). The q^2 value of the main contrast is 0.039, indicating that approximately only 3.9% of the systematic variance is not explained by the main contrast. In summary, results from the three-part contrast testing strongly support H1.

To further understand participants' reactions to the dashboard and utilization of comparative visual searching ability in the task, we conduct a path analysis to test H2a, H2b, and H3. Table 3 presents the correlation matrix of the path model.

Figure 5 presents the results of the path model. Following Hair et al. (1998), we investigate several model fit indices to test whether our path model has a good fit. First, the Chi-square test of model fit is insignificant (χ^2 = 0.68, degree of freedom = 2, p = 0.714), indicating that the path model is a strong fit for the data. Second, the comparative fit index (CFI) of 1.00 exceeds the cut-off point of 0.90 (Hu and Bentler 1999). Third, the root-mean-square error of approximation (RMSEA) is < 0.001, and the standardized root-mean-square residual (SRMR) is 0.016, representing a good fit (Browne and Cudeck 1993). Thus, these indices all indicate that our path model has a good fit.

H2a posits that participants react to the information in the dashboard differently when the data is familiar versus unfamiliar. Accordingly, the path from data type (*UNF*) to information reaction (*REACT*) is significant (Path Coefficient = 1.95, p = 0.022), indicating that participants who received unfamiliar data reacted to the information in the dashboard in a greater degree than those who received familiar data. Therefore, H2a is supported.

H2b predicts that participants' reaction to the information in the dashboard mediates the effect from data type to participants' weight of the data. In the path model, the effect from *REACT* to *WEIGHT* is significant (Path Coefficient = 9.41, p < 0.001), which creates a significant indirect effect from *UNF* to *WEIGHT* (Path Coefficient = 18.32, p = 0.039) through the mediator: *REACT*. Therefore, H2b is supported. Interestingly, the direct effect from *UNF* to *WEIGHT* (Path Coefficient = - 73.55, p = 0.067) is marginally significant, which yields an insignificant total effect from *UNF* to *WEIGHT* (Path Coefficient = - 55.24, p = 0.173). Therefore, we conclude that when the mediation effect of reaction is removed, participants underweighted the importance of unfamiliar data. However, through reacting to the unfamiliar data in a greater degree, participants also increased their weight on its importance. This mediation effect (a type of inconsistent mediation effect)[8] demonstrates that the negative direct effect (i.e., underweighting the unfamiliar data) and the positive indirect effect (i.e., increasing the weighting of unfamiliar data through reaction) are cancelled out and produce an insignificant total effect.

H3 further proposes that participants utilize their comparative visual searching ability differently when they receive familiar versus unfamiliar data. Although the main effect of the comparative visual searching ability variable (*CORRECT*) on *WEIGHT* is insignificant (Path Coefficient = - 10.15, p = 0.437), the interaction effect (*UNF*CORRECT*) on *WEIGHT* is significant (Path Coefficient = 39.00, p = 0.044). The significant interaction

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main dependent variable of interest – participants' weight on the importance of data (WEIGHT). Table 2, Panel B presents the results of the ANOVA model.

[8] MacKinnon et al. (2000) define an inconsistent mediation effect as a mediation effect that the mediator acts as a suppressor variable. In this situation, it is possible that both the direct effect and indirect effect are significant but have opposite signs. Therefore, the total effect is likely to be insignificant because the direct and indirect effects are opposite to each other.

effect shows that comparative visual searching ability helped participants increase the weight only when they received unfamiliar data. Therefore, H3 is supported.

Experiment 2

Overview

Experiment 1 is based on the condition that participants receive either familiar data or unfamiliar data in the dashboard. Experiment 2 is designed to complement experiment 1 by specifically investigating the situation where participants receive mixed data, i.e., both familiar and unfamiliar on the same BA dashboard.

The Experiment 2 has two objectives. First, since this study applies the guidance from Ernst and Young (1998) to select unfamiliar non-financial variables in the dashboard, the diagnostic power of the unfamiliar variables in our study may be stronger than those selected in Brazel et al. (2014). Therefore, it is worth investigating whether participants in our study still incorporate more familiar data into their decisions than unfamiliar data. Second, results in experiment 2 should complement instead of contradict to the results in experiment 1 since the condition of mixed data is essentially a mid-point between the conditions of familiar data and unfamiliar data. In experiment 2, we expect the degree of incorporating diagnostic unfamiliar variables to be positively relate to participants' weight on the importance of the mixed data; this correlation is also mediated by participants' reaction to the information in the dashboard.

Method

Except as noted, the method used in experiments 2 and 1 is the same.

Participants

Participants were 44 graduate students from a public university in the southeastern United States. The recruiting requirements in experiment 2 and 1 were the same.

Design

Experiment 2 used a 1 x 2 between-participants design manipulating the graphical presentation as either disaggregated or aggregated. All participants were given mixed data.[9]

Materials, Experimental Procedure, and Variables

Experiment 2 had one additional procedure that was not presented in experiment 1. In experiment 2, participants were told to assign percentages to the two variables in the mixed data according to their impact on participants' predicted risk of misstatement in each income statement line item. The sum of the percentages must be 100%.

The sum of the percentages allocated to unfamiliar (non-financial) data for the three income statement line items is the value of this additional variable (*UNFINCORP)* in experiment 2, which represents participants' degree of incorporating unfamiliar data into their decisions.

[9] In order to utilize all the financial and non-financial variables in experiment 1, experiment 2 had two versions where version 1 presented financial data in solid lines and non-financial data in dashed lines, and version 2 flipped the line types of the presentations.

Manipulation Checks

Two participants (4.55%) failed both manipulation check questions regarding to the type of data and graphical presentations. One participant indicated 100% incorporation of unfamiliar data and 0% incorporation of familiar data for all income statement line items. This participant was also removed from further analyses as a significant outlier. Therefore, the sample size of experiment 2 was 41.

Results

To investigate whether participants incorporate familiar data more than unfamiliar data, we conduct a one sample t-test on the mean difference between participants' percentage of incorporating familiar and unfamiliar data. The results are consistent with our predictions (Mean Difference = 43.40, $t = 6.97$, $p < 0.001$), and are not dependent upon the version of the experiment ($F = 0.004$, $p = 0.947$) or the type of graphical presentation ($F = 0.25$, $p = 0.619$). A further analysis on the difference on each income statement account demonstrates the mean differences for Net Revenue (Mean Difference = 16.42, $t = 7.01$, $p < 0.001$), Cost of Goods Sold (Mean Difference = 12.32, $t = 3.86$, $p < 0.001$), and Operating Expenses (Mean Difference = 14.66, $t = 4.46$, $p < 0.001$) are all significant. Therefore, we conclude that participants have the tendency to incorporate more familiar data than unfamiliar data even though they are both diagnostic. This finding is consistent with the related conclusion in Brazel et al. (2014).

Figure 6 presents the results of the path model. Model fit indices[10] indicate a good model fit. We find positive direct effects from *UNFINCORP* to *REACT* (Path Coefficient = 0.033, $p = 0.012$) and from *REACT* to *WEIGHT* (Path Coefficient = 8.95, $p < 0.001$). Additionally, the indirect effect from *UNFINCORP* to *WEIGHT* is positive and significant (Path Coefficient = 0.30, $p = 0.039$).[11] Collectively, the results suggest that when participants incorporate more unfamiliar data into their decision, they place more weight on the mixed data through their reaction to the information in the dashboard.

Summary and Conclusion

This study examines whether and why disaggregating the graphical presentation of the data can help undergraduate accounting students put more weight on the importance of unfamiliar data, e.g., non-financial information displayed in a business analytics dashboard. Results from experiment 1 support the prediction that when participants receive unfamiliar data in disaggregated versus aggregated graphs, they propose more changes to the task than those who receive only familiar data. Moreover, the path model shows that: (1) participants who received unfamiliar data had a stronger reaction to the information in the BA dashboard, which stimulated them to increase the weight on the importance of the unfamiliar data; and (2) participants' comparative visual searching ability in playing the "spot-the-difference" game was associated with their weight on the importance of the data only when they receive unfamiliar data. Additionally, results from experiment 2 are consistent with the findings from Brazel et al. (2014) that participants tend to not incorporate unfamiliar data in the same degree as that of familiar data in their decisions. Further, experiment 2 also shows that participants' weight on the importance of the mixed data increases as they perceive unfamiliar data as more important.

Like all research, this study is subject to limitations. First, the visualization in our BA dashboard is restricted to graphical presentations. Future research can investigate other styles of visualizations used with dashboards. Second, since this experiment is a single-period experiment, it does not investigate participants' learning and feedback across different periods. Future research can extend this experiment in a multi-period setting. Third, the familiar and unfamiliar data in this study is all quantifiable financial and non-financial data; future studies can investigate the

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[10] $\chi^2 = 0.490$, degree of freedom = 1, $p = 0.484$; CFI = 1.000; RMSEA < 0.001; SRMR = 0.029

[11] The direct effect from *DIS* to *UNFINCORP* is not significant (Path Coefficient = - 3.98, $p = 0.800$), and the direct effect from *UNFINCORP* to *WEIGHT* is not significant (Path Coefficient = - 0.10, $p = 0.481$). Therefore, those two links are excluded from our path model in Figure 6.

diagnostic power of other types of data, e.g., qualitative non-accounting data. Fourth, our study looked only at having participants increase the weight placed on unfamiliar data and did not examine how to use unfamiliar data to improve performance. However, research by Trompeter and Wright (2010) and Brazel et al. (2009) shows that by incorporating non-financial information into their decision-making, when relevant, accountants significantly improve decision-making. This suggests that our study does, at least indirectly, address the issue of decision-making, e.g., as stressed in FASB (2010). Future research can investigate the performance quality. Finally, the abnormal changes presented in the graphical presentations of this study represent extreme deviations from prior years (about a 20% change from a total of 50%). Future research can further investigate undergraduate accounting students' reaction and task performance with the exposure of less salient changes. Finally, the generalizations of the findings in the research are restricted by our use of undergraduate accounting students acting as novice auditors.

Our study contributes to the AIS education literature in several ways. First, we find that undergraduate accounting students increase their weight on the importance of unfamiliar data when they increase their reaction to the information in the BA dashboard. Thus, accounting educators need to be aware of the degree of familiarity of the data being used in their lessons on BA. Second, our results are potentially helpful to accounting students and accountants by making them aware of their own biases when using data with varying degrees of familiarity. Such self-insight can enable them in debiasing their own use of this information and can assist them in presenting information to clients so that clients too can avoid biased decision-making based on the information. Third, we contribute to FASB's (2010) requirement that financial reporting be "faithfully" presented in an "unbiased" manner. Those promulgating and those using financial statements would benefit from an increased awareness of any latent biases in their perception of different types of information. Fourth, our results answers the call by Messier et al. (2013) to examine additional mechanisms to stimulate accountant's use of unfamiliar non-financial data. We find that presenting accounting students with disaggregated graphs can help increase the weight they place unfamiliar non-financial data. This result indicates that it can be beneficial to present unfamiliar data on dashboards for accounting tasks when the dashboards use certain types of display. Fifth, we use a measure of comparative visual searching ability not previously used in accounting education research. Results indicate that undergraduate accounting students are able to utilize this visual search ability to help process unfamiliar data. The correlation between participants' comparative visual searching ability in the "spot-the-difference" games and interpreting the visualizations exists only when participants receive unfamiliar data; accounting educators can use thus finding to gamify their training content to enhance undergraduate accounting students' ability in those tasks that require comparative visual searching skills. Finally, our study adds to the growing but still small accounting education literature using information literacy theory. Our research indicates how the information literacy skills of undergraduate accounting students in regard to non-financial information can be enhanced by means of the graphical display design of BA dashboards.

Table 1
Demographics of Sample (n=77)[a]

		Familiar/Combined		Familiar/Separated		Unfamiliar/Combined		Unfamiliar/Separated	
		n=20		n=18		n=20		n=19	
		Mean	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Audit Experience in Months		1.10	1.65	0.72	1.13	1.15	1.63	0.89	1.76
		Number	**Percentage of Total Cell Size**	**Number**	**Percentage of Total Cell Size**	**Number**	**Percentage of Total Cell Size**	**Number**	**Percentage of Total Cell Size**
Gender:	**Male**	7	35%	8	44%	11	55%	5	26%
	Female	13	65%	10	56%	9	45%	14	74%
Education:	**Junior**	1	5%	1	6%	0	0%	1	5%
	Senior	17	85%	16	89%	19	95%	16	84%
	Fifth Year	2	10%	1	6%	1	5%	2	11%
Grade:	**A**	5	25%	5	28%	4	20%	3	16%
	B	9	45%	8	44%	8	40%	10	53%
	C	6	30%	2	11%	8	40%	5	26%
	D	0	0%	3	17%	0	0%	0	0%
	F	0	0%	0	0%	0	0%	1	5%

Definition of Variables:
Audit Experience in Months: Participants' number of months of audit-related work experience
Grade: Participants' grade in their first audit class or the grade on their most recent exam on the class
[a] Pearson Chi-Square tests indicate no significant difference in the frequencies across treatments for gender ($\chi^2 = 3.70$, $p = 0.295$) and education ($\chi^2 = 1.85$, $p = 0.933$). ANOVA tests indicate no significant differences in treatment means for auditing I grade ($F = 0.20$, $p = 0.894$), and audit experience in months ($F = 0.30$, $p = 0.827$). These testing results show that randomization is effective in the experiment.

Table 2
The Effect of Data Type and Graphical Presentation on Participants' Weight of the Data
Dependent Variable = *WEIGHT*

Panel A: Means by Condition:

Type of Data	Graphical Presentation: AGG	Graphical Presentation: DIS	Row Means
Familiar	325.00	334.17	329.34
	(84.68)	(81.61)	(82.24)
	n=20	n=18	38.00
Unfamiliar	320.50	383.33	350.26
	(73.23)	(38.35)	(66.64)
	n=20	n=18	38.00
Column Means	322.75	358.75	
	(78.18)	(67.61)	
	n=40	n=36	

Panel B: ANOVA

Source	Type III Sum of Squares	Df	MS	F	p-value
UNF	9450.53	1	9450.53	1.81	0.183
DIS	24555.79	1	24555.79	4.70	0.034**
UNF * DIS	13642.63	1	13642.63	2.61	0.111
Error	376357.50	72	5227.19		
Total	9198275.00	76			

Panel C: Planned Contrast Results

Contrast	Value	Std.Err	t	df	p-value (one-tailed)
1. UNF/DIS > Other	170.33	58.54	2.91	72	0.003***
2. FAM/DIS > ALLAGG	22.83	41.04	0.56	72	0.290
3. FAM/AGG>UNF/AGG	4.50	22.86	0.20	72	0.423

* Significant at .1 level, ** significant at .05 level, *** significant at .01 level
UNF = 1 if the data in the dashboard is unfamiliar data; 0 if the dashboard has only familiar data.
DIS = 1 if the graphical presentation of the data in the dashboard has two graphs with one line in each graph; 0 if the graphical presentation of the data has two lines on a graph.
UNF*DIS =1 if the graphical presentation of the data in the dashboard has two graphs with one line in each graph showing unfamiliar data; 0 otherwise

Contrast 1 (main) = -1 for FAM/AGG, -1 for FAM/DIS, -1 for UNF/AGG, and +3 for UNF/DIS;
Contrast 2 (residual) = -1 for FAM/AGG, 2 for FAM/DIS, -1 for UNF/AGG, and 0 for UNF/DIS;
Contrast 3 (residual) = +1 for FAM/AGG, 0 for FAM/DIS, -1 for UNF/AGG, and 0 for UNF/DIS;

Table 3
Correlation Matrix

Variable	*UNF*	*CORRECT*	*UNF*CORRECT*	*WEIGHT*	*REACT*
UNF	—				
CORRECT	0.18	—			
*UNF*CORRECT*	0.89***	0.46***	—		
WEIGHT	0.14	0.13	0.21*	—	
REACT	0.25**	0.11	0.22*	0.48***	—
M	0.50	1.89	1.01	339.80	17.03
SD	0.50	0.77	1.14	75.09	3.87

* Significant at .1 level, ** significant at .05 level, *** significant at .01 level
UNF = 1 if the data in the dashboard is unfamiliar data; 0 if the dashboard has only familiar data.
CORRECT = Participants' average differences identified in the "spot-the-differences" game
*UNF*CORRECT* = Participants' average number of correct differences identified in the "spot-the-differences" game when they receive unfamiliar data
REACT = The sum of participants' predicted risk of misstatement for Net Revenue and Cost of Goods Sold plus a reversed risk score on Operating Expenses
WEIGHT = The sum of participants' allocated audit hours for Net Revenue and Cost of Goods Sold

Figure 1

Example of Business Analytics Dashboard using MS Excel

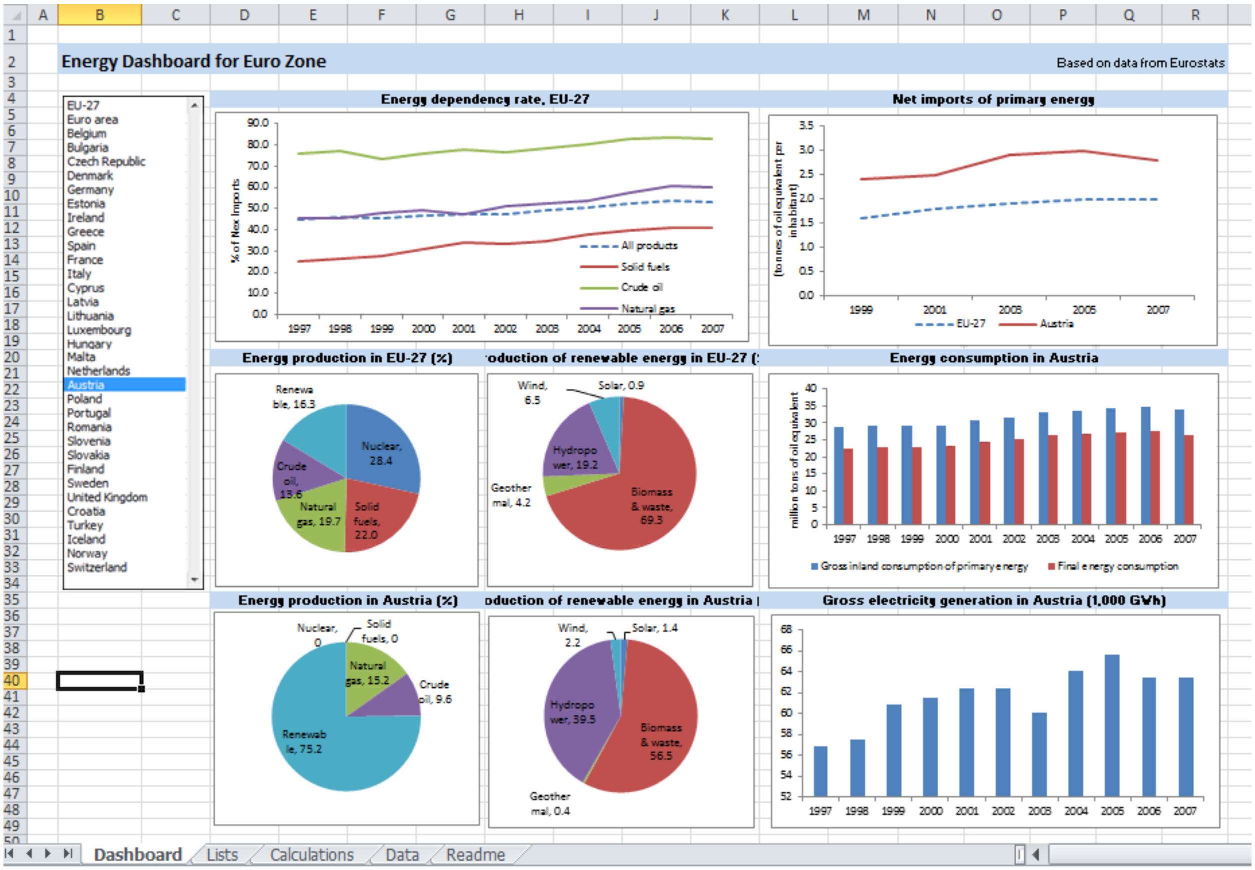
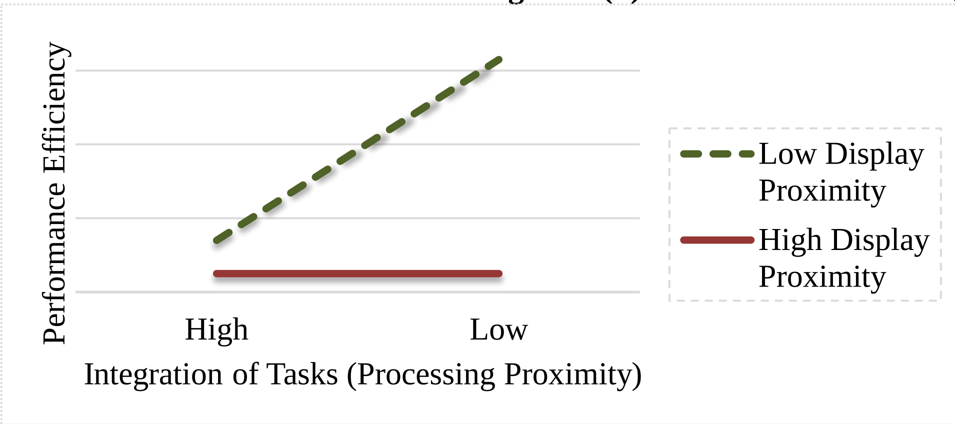


Figure 2
The Predicted Interaction Effect from Figure 2 (b) in Wickens and Boles (1983)



The Predicted Interaction Effect from Figure 2 (b) in Wickens and Boles (1983)

Figure 3
Experimental Procedures

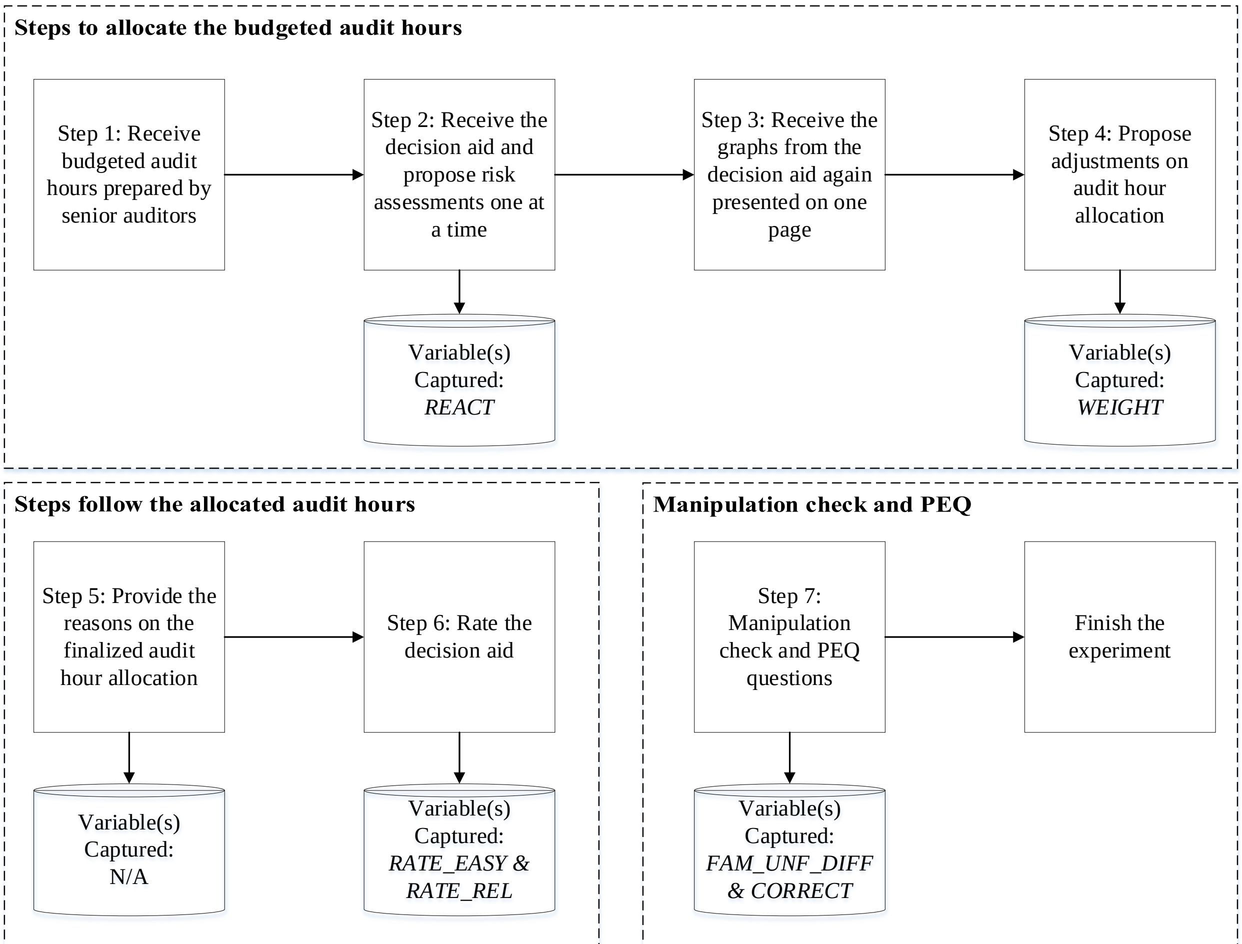
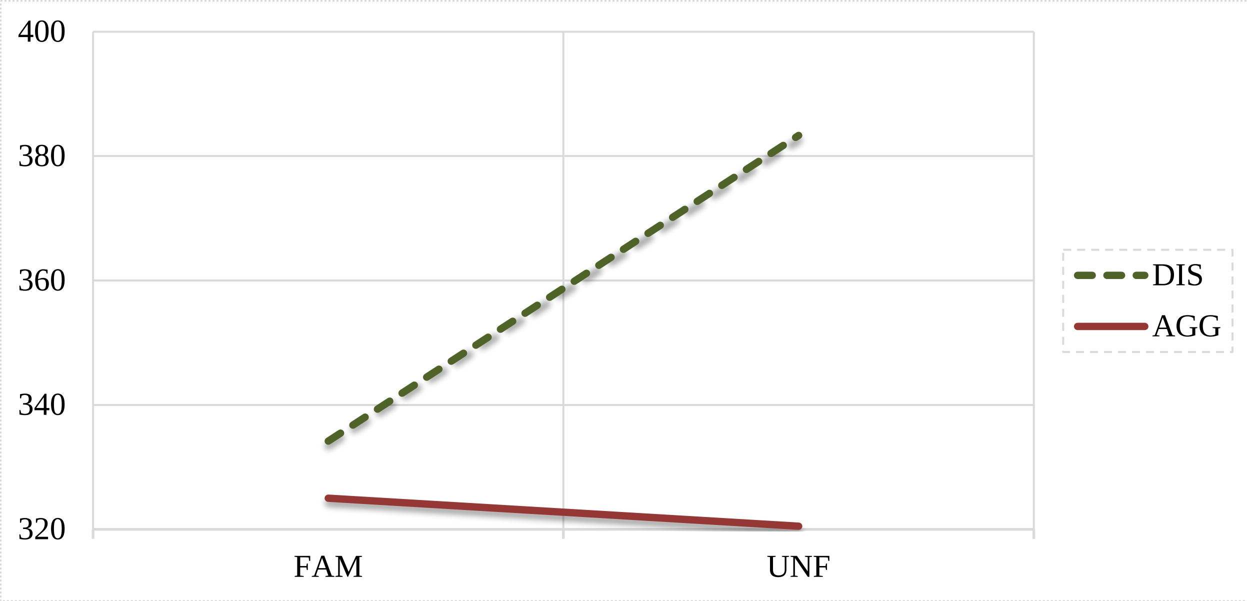
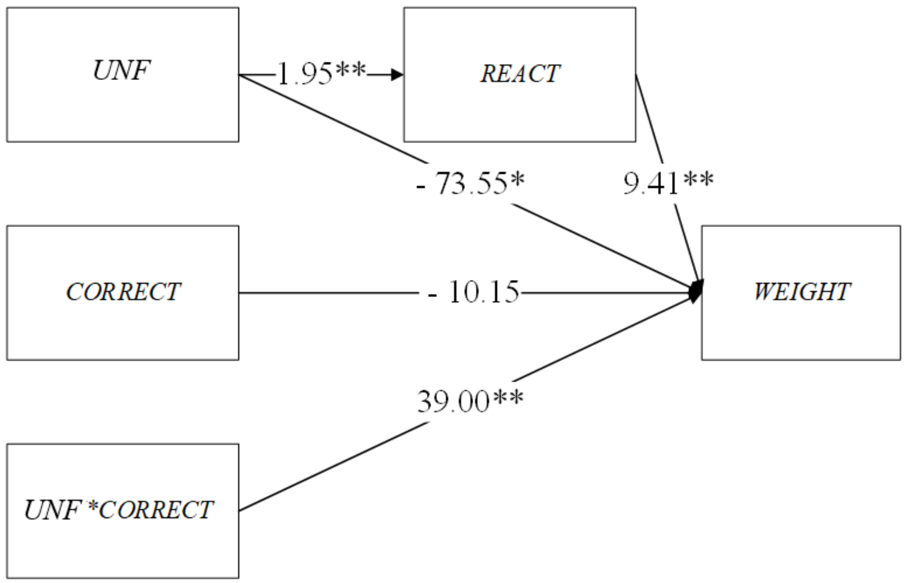


Figure 4
Graph for the Significant Interaction Effect (DV: *WEIGHT*)



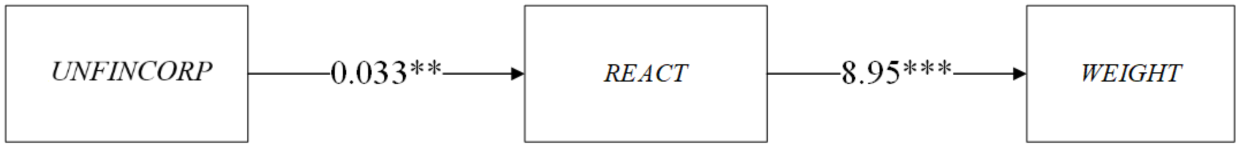
FAM = the data in the dashboard is familiar data
UNF = the data in the dashboard is unfamiliar data.
DIS = the graphical presentation of the data in the dashboard has two graphs with one line in each graph.
AGG = the graphical presentation of the data has two lines on a graph.

Figure 5
Path Analysis Results for Experiment 1



* Significant at .1 level, ** significant at .05 level, *** significant at .01 level
Model Fit Statistics: Chi-Square = 0.68, df = 2, p = 0.714; CFI = 1.000; RMSEA < 0.001; SRMR = 0.016
UNF = 1 if the data in the dashboard is unfamiliar data; 0 if the dashboard has only familiar data.
CORRECT = Participants' average differences identified in the "spot-the-differences" game
*UNF*CORRECT* = Participants' average number of correct differences identified in the "spot-the-differences" game when they receive unfamiliar data
REACT = The sum of participants' predicted risk of misstatement for Net Revenue and Cost of Goods Sold plus a reversed risk score on Operating Expenses
WEIGHT = The sum of participants' allocated audit hours for Net Revenue and Cost of Goods Sold

Figure 6
Path Analysis Results for Experiment 2



* Significant at .1 level, ** significant at .05 level, *** significant at .01 level
Model Fit Statistics: Chi-Square = 0.49, df = 1, p = 0.484; CFI = 1.000; RMSEA = 0.000; SRMR = 0.029
UNFINCORP = The sum of participants' percentage of unfamiliar data incorporated during their decision on predicting the risk of misstatement in the three income statement line items.
REACT = The sum of participants' predicted risk of misstatement for Net Revenue and Cost of Goods Sold plus a reversed risk score on Operating Expenses
WEIGHT = The sum of participants' allocated audit hours for Net Revenue and Cost of Goods Sold

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APPENDIX A

General Instructions

Experiment 1 Description

Please read the following carefully.

For this experiment you will assume the role of a staff auditor at Jones & Timothy, LLP, a large global audit firm based in Dallas that has more than 100 clients. In the current audit engagement, you and your audit team are engaged with DalMart, Inc., a retail company based in Dallas that sells a large selection of clothing, food, and electronics. The company is publicly traded on NASDAQ and has been listed for the past 10 years. This is your second year at Jones & Timothy, LLP, and the sixth year that Jones & Timothy, LLP is engaged with DalMart, Inc.

The current audit engagement with DalMart, Inc. is at the planning stage. The senior auditors (your superiors) on your team have budgeted 500 audit hours to three income statement line items (Net Revenue, Cost of Goods Sold, Operating Expenses). The senior auditors are expecting you to perform analytical review procedures, recommend changes to the allocation of budgeted hours based on the results of your review, and give the senior auditors reasons for your proposed changes. If you believe any changes are needed, your task is to determine how to reallocate the 500 budgeted audit hours for the three income statement line items. To assist you in making the decision, you have received your senior auditors' report (below) showing the allocation of budgeted audit hours based on the previous year's audited results:

Budgeted audit hours (500 hours in total) according to senior auditors' estimation based on the previous year's results:	
Net Revenue	100
Cost of Goods Sold	100
Operating Expenses	300
Total	500

In addition to the budgeted audit hours based on the previous year's audit, you have access to a report from a decision aid. The report has three sections containing additional information on each income statement line item. In each section, the decision aid presents the data and trends of two different variables across four years (2011-2014).

Financial Data Manipulation

The variables in this report are all <u>financial</u> variables.

Non-financial Data Manipulation

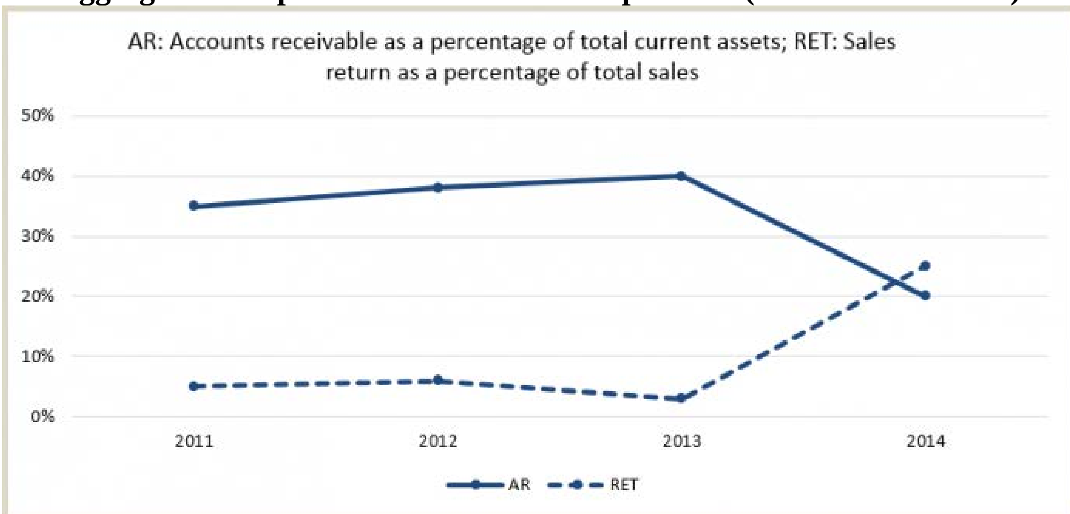
The variables in this report are all <u>non-financial</u> variables.

A data mining software was used to select the variables in the decision aid based on their importance to related income statement line items. Based on the graphical information in the decision aid, you will make your recommendations on the budgeted audit hours.

On the bottom of each section, you will indicate your predicted risk of misstatement in each income statement line item based on the information provided to you.

On the next page, you will see Section 1 of the decision aid: Income Statement Line Item #1: Net Revenue.

Aggregated Graphical Presentation Manipulation (with financial data)



Disaggregated Graphical Presentation Manipulation (with non-financial data)

An Example of the "Spot-the-Differences" Game

(Note: the four colored boxes that highlighted the differences were not shown to participants)