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Customizable User Interfaces: Does Giving Individuals The Ability To Customize Information Organization Improve Decision Making ?

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CUSTOMIZABLE USER INTERFACES: DOES GIVING INDIVIDUALS THE ABILITY TO CUSTOMIZE INFORMATION ORGANIZATION IMPROVE DECISION MAKING?

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DEDICATION

To my wife and children, without whom I most assuredly would not have begun or finished this path in life.

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ABSTRACT

Recent technological innovations permit individuals to customize the way information they view is organized by incorporating personal themes, personal menu structures, personal reports, and custom dashboards. Relying on the theory of cognitive fit, I investigate the effects of one aspect of customization on decision making, information order. Through use of an online experiment with Amazon Mechanical Turk workers, I test the hypothesis that decision accuracy will increase for participants who use custom displays. However, I do not find support for the hypothesis using either the originally proposed measure of decision accuracy or two additional measures of decision accuracy. Furthermore, supplemental analysis finds no significant relations between customization and two other measures of decision quality. Analysis suggests the participants possess sufficient self-insight to reliably perform the task and provides initial statistical confirmation that people organize information on a list from top to bottom based on the relative importance of the information to the decision maker.

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LIST OF ABBREVIATIONS

AAPL..... Apple Inc.'s Company Identification on NASDAQ

ACCURACY .....Correlation between reported and actual case rank

ANCOVA .....Analysis of Covariance

BETADIFF ..... Absolute difference between estimated and environmental beta values

CONTROL.....Study condition including ranking but not organizing or using

CONSISTANT.....Coefficient of determination for a decision model

COUNT ..... Number of significant cues used in a decision model

CUSTCORR .....Correlation between initial and reported cue ranks

CUSTOM..... Study condition including ranking, organizing, and using

CW .....Participant's Estimated Cue Weight using Lens Model

EPS .....Earnings per Share

HIT ..... Human Intelligence Task

MTurk..... Amazon Mechanical Turk

NASDAQ.....National Association of Securities Dealers Automated Quotations

RANKCORR ..... Correlation between initial and reported company ranks

RKDIFF ..... Number of cases ranked within one position of the actual rank

RW ..... Participant's Self-Reported Cue Weight

SUPP ..... Study condition including ranking and organizing but not using

POSITION ..... Relative position of cue during organizing activity

WEIGHT..... Sum of the absolute beta coefficient weights for a cue

CHAPTER 1

INTRODUCTION

Advances in information systems significantly increased the quantity of accounting information available for a large number of tasks including investment, audit, tax, and management tasks. One example is the amount of company specific information available to investors. Consider the National Association of Securities Dealers Automated Quotations (NASDAQ) (2014b) website. Accessing the website and typing in a company symbol (e.g., AAPL for Apple Inc.) takes the individual to the company's "Real-Time Quote" page which displays thirty-one information items related to volume, price (opening, closing, high, low, and current), and recent trades. In addition, an intraday trading chart is shown which includes links to view ten additional charts. The "Real-Time Quote" page represents just one of the twenty-nine menu items available. The menu items are divided into seven categories which include "Company News," "Fundamentals," and "Stock Analysis." Accounting information in various forms appears throughout. By any objective standard, the amount of information available in today's connected world is immense. While making more financial and non-financial information available to individuals is often intended to improve decision quality, the quantity of information challenges human cognitive processing limits associated with decision making.

At an individual decision making level, increasing information quantity has been shown to increase cognitive load, leading to dysfunctional effects. This is especially true

when complex decision models are used, as is frequent in tasks using accounting information (e.g., Benbasat and Taylor 1982; Bonner 1994; Coller and Tuttle 2002; Hitt and Barr 1989; Hooper and Trotman 1996; Leung and Trotman 2005; Maletta and Kida 1993; Tam et al. 2006). In addition to mental effects including stress, confusion, and anxiety (Jacoby et al. 1974; Malhotra 1982; Mayer and Moreno 1998), high cognitive load leads decision makers to simplify decision models as a cognitive coping mechanism which reduces the inclusion of otherwise useful information (Bawden and Robinson 2009; Payne et al. 1988). That is, cognitive coping mechanisms may help reduce cognitive load but could have substantial negative impacts on decisions. The objective of my study is to explore the potential effects of allowing individuals faced with high cognitive load to customize information organization to examine the effect of customization on decision quality.

Customizing information organization may be an effective way to reduce the dysfunctional effects due to high cognitive load. Bonner (1994) identifies input clarity, including presentation format, as a key component of audit task complexity. From Bonner's discussion, two methods to reduce task complexity are (1) to format the display to fit the individual's memory or mental model or (2) to keep the display and reformat individual memory. Cognitive fit theory suggests improving cognitive fit between the display and the individual's memory or mental model may improve decision making (Kelton et al. 2010; Speier 2006; Vessey 1991; Vessey and Galleta 1991). Combining Bonner's discussion of task complexity with the theory of cognitive fit suggests decision making may be improved by display customization.

Customizing displays to improve fit between information organization and individual decision models may avoid the need to reformat memory. Stated in other terms, research finds decision models are individual and task specific (Blom 2000; Oppermann 1994; Pinsker et al. 2009). By allowing individuals to customize how information is displayed, individuals may reorganize information to better reflect their decision models. Customized displays may be particularly helpful because system designers cannot anticipate every individual's decision model or every task to be performed.

To better understand the impact of custom displays on individual decisions, I administered an experiment through online software. The ability to customize how information is displayed is the independent measure of interest and is manipulated between participants. In one condition, participants used a predefined information display. In a second condition, participants submitted preferences which were then used to create a custom display for each participant. Participants viewed accounting information which reflected changes in performance from the prior year to the current year for real companies. While viewing this information, participants completed the primary task of ranking firm performance by ordering companies from the greatest increase in stock price to the greatest decrease in stock price. I measure participant decision quality by comparing participant reported ranks for each company to the actual ranks for each company.

The hypothesis predicts participants who use customized displays make better decisions than participants who do not use customized displays. Decision quality, as measured by the prediction achievement index (Libby 1975), was not statistically

different between conditions. Supplemental analysis included four additional measures of decision quality, none of which were significantly different between customization conditions. Results of this study do not provide evidence of an effect due to customization on decision making performance. Potential reasons for not finding an effect are explored.

Nevertheless, my research contributes to existing theory by allowing the individuals' decision models to affect information organization. Existing studies identify effects from non-customized lists that vary in information quantity, content, structure, format, and representation on information credibility, source credibility, decision quality, and decision models (e.g., Bonner 1994; Boritz 1985; Cuccia and McGill 2000, Hirst et al. 2007; Kelton et al. 2010; Miller 1956; Speier et al. 2003; Swink and Speier 1999; Vessey 1991). However, none of this literature investigates individuals' preferences for information organization and the effect on decision quality of allowing individuals to freely self-organize information. This study specifically allows individuals to exercise information preference by customizing information organization and finds the effect of custom information organization on decision making is insignificant.

Although the hypothesis is not supported, there are several findings of note in this study. First, this study provides evidence that allowing information users to control displays influences their perception of task difficulty. Second, through analysis of several weighting measures, this study supports prior literature demonstrating significant self-insight on the part of information users. And finally, while anecdotal evidence suggests people organize information by placing more important cues at the top of lists, this study provides empirical evidence by finding a direct, significant relation between the position

of a cue on a list and the importance of the cue as measured by the perception of the user and the user's estimated decision model.

The remainder of this paper is structured as follows. Chapter 2 presents relevant theory and formally states the hypothesis. Chapter 3 describes the proposed method. Chapter 4 presents the analytical results. Chapter 5 includes a discussion that concludes this dissertation.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 CONTEXT

A necessary conditions for customization to influence individuals' decisions is for each individual to prefer some information over other information. A complete novice is expected to lack sufficient knowledge of information importance and therefore exhibit no preference for information. On the other hand, individuals with expertise in a task have been shown to use directed search strategies which implies a significant preference for specific information (e.g., Anderson 1988; Bouwman et al. 1987). Prior literature finds experienced individuals have substantial insights into their decision models and can accurately describe the information that receives greater weight than other information (Mear and Firth 1987; Wright 1977).

Individuals have different decision models because the process of cognitively acquiring and organizing information is unique to each individual based on a lifetime accumulation of knowledge (Driver and Mock 1975). When learning to use accounting information, individuals build knowledge structures which include relevant information and relational links between information items (Bentz 1975; Newell and Simon 1972). The linking is evident through physical measurement of brain activity (by electroencephalography) which shows a difference in brain activity level when viewing related information items versus unrelated information items (Morton et al. 2013). As

learning continues, individuals develop a preference for specific information and information organization (Abelson and Black 1986; Fiske et al. 1983). While one may expect experts to share a common decision model, evidence suggests the opposite by showing decision models of experts are quite diverse (Ashton 1990; Coller and Tuttle 2002; Einhorn 1974; Einhorn and Hogarth 1975; Larcker and Lessig 1983; Todd and Benbasat 1991, 1992). Because experts exhibit different decision models, it is unlikely that a single presentation will satisfy all individuals. However, a single static presentation is exactly what legacy information systems provided in the past.

To illustrate the diversity of decision models for a common task using financial information, consider a decision making tool provided through the NASDAQ website. Individuals selecting the "Guru Analysis" link see a display showing a company's evaluation by different gurus (NASDAQ 2014a). Each guru evaluation focuses on an investing methodology such as value, growth, or momentum investing. By selecting a guru analysis, the criteria used in evaluating the company is depicted as a list of evaluation items with "pass" or "fail" values. In addition, information below the list defines the criteria and provides support for the values. When exploring this site, it soon becomes apparent that gurus have very different strategies and that even gurus with the same investing methodology incorporate different information into their evaluations. While the NASDAQ presentation supports multiple evaluation models, it is unlikely to support every model, and it is possible that no guru model matches a specific individual's decision model. By allowing customization, individuals may build personal investment displays founded on personal information preference to facilitate decision making. From

this point forward, I assume individuals have sufficient knowledge to express preference for information and are in a condition of high cognitive load.

2.2 Cognitive Fit

Cognitive fit theory predicts cognitive fit between mental models and information presentations is positively correlated with improved decision making (Vessey 1991). Cognitive fit refers to the relation between task types and information formats. Vessey (1991, 1994) and Vessey and Galleta (1991) review conflicting results in the information presentation literature and find that the inconsistent results are explained by the fit between how information is presented and the type of tasks performed. Individuals tend to perform better on spatial tasks when using graphical presentations and better on symbolic tasks when using tabular presentations. Based on this observation, Vessey develops and tests a theory of cognitive fit suggesting that information that is presented in a way that fits the task will result in better task performance. Cognitive fit theory provides a foundation for understanding the source of many dysfunctional effects associated with information presentation.

The reason cognitive fit is important is that individuals alter how they process information when information presentation does not fit their preferred decision models (Arunachalam and Daley 1996; Silver 1991). Individuals have been found to change decision models based on information content, structure, and order (Bettman et al. 1993; Camerer and Hogarth 1999; Diamond and Lerch 1992; Hoffman et al. 2003; Kelton et al. 2010; Kida and Smith 1995; Luft 2010; Payne et al. 1993; Pennington and Tuttle 2009; Slovic 1972; Umanath and Vessey 1994). In addition, individuals alter how they seek information and determine relevance based on how information is presented (Arnold et

al. 2012; Ditto et al. 1998; Erdem and Swait 1998; Frey 1981; Hodge et al. 2004; Tang et al. 2014; Thayer 2011). Cognitive fit theory suggests (1) a high mental cost is associated with a lack of fit between individual decision models and information presentation and (2) individuals exert effort to change decision processes in response to information presentation.

With regard to cognitive fit, consider the difficulty of using information that is not organized the way you like it. Imagine you are planning to invest in the stock market and are evaluating public companies based on financial information. Further, assume you are somewhat familiar with investing and already have a preferred information set for evaluating individual company performance relative to market price. Picture in your mind how you would organize the information on a computer screen if given a choice. Would you put more important information at the top, or would you randomly mix it with less important information? Using technology to create a custom information display could ease the workload of your evaluations by allowing you to create fit. That is, fit is improved by putting the information you consider to be important where it is easy to find. When the display matches your picture of how you would prefer to see the information, you experience high cognitive fit. High cognitive fit is especially beneficial for repeated tasks because the mental effort required to complete the task is reduced multiplied by the times the task is repeated.

Customization provides individuals a tool to improve cognitive fit on an individual basis. Improving cognitive fit eases cognitive load, making more cognitive resources available for other aspects of decision making. Hence, individuals can process information more effectively, leading to better decisions. Because individual perceptions

of information change based on information structure, format, and content (e.g., Bonner 1994; Hirst et al. 2007; Kelton et al. 2010; Speier et al. 2003; Swink and Speier 1999; Vessey 1991), individuals may avoid dysfunctional effects associated with a lack of cognitive fit by customizing their information screens to reflect their decision models. To the extent that information presentation matching decision models leads to improved cognitive fit, more cognitive resources are available for decision making, leading to better performance. I propose the following hypothesis.

Hypothesis: Individuals who use custom displays make better decisions than individuals who do not use custom displays.

CHAPTER 3

RESEARCH DESIGN

3.1 BASIC TASK

Participants are asked to rank 20 companies based on five financial measures (cues). The five cues are projected industry sales growth (%), percent change in debt to total assets, percent change in asset turnover, percent change in profit margin, and dollar change in earnings per share (EPS). Participants are told the cue values accurately reflect company performance and market conditions for a company with stock traded in a public exchange in the United States. The task of ranking companies creates a high cognitive load condition because it requires participants to simultaneously process five cues each for 20 companies (100 pieces of information). Even if participants choose to compare two companies at a time, the participants will need to process ten values for the two companies and repeat the process for each two-company combination. All participants complete the task using a computer.

3.2 INDEPENDENT VARIABLES

The design of this study is best characterized as 20 cases x 2 conditions where cases are varied within participant and conditions are varied between participants.[1] All company information for this study is from Coller and Tuttle (2002) where participants

[1] Testing the hypothesis only requires two conditions which are the focus of discussion in this section. A third condition is included to facilitate supplemental analysis and is discussed in Chapter 4.

estimated stock prices based on financial information (Table 3.1). The cues were chosen by the authors through review of textbooks and articles on financial analysis and include firm specific and macroeconomic cues. Coller and Tuttle limit their information to five cues and select companies so that intercue correlations are insignificant in order to facilitate statistical analysis of results after data collection. The cue values have inter-cue correlations ranging from -0.227 to +0.418 which are statistically insignificant ($p > 0.05$; $N = 20$). All firms were from SIC 3500 to 3699 for years 1988 or 1992.

Conditions are controlled by randomly assigning participants to one of two study conditions. In the CONTROL condition, cues are presented on task screens in alphabetical order (initial order) and remain in the initial order for the remainder of the study. In the CUSTOM condition, cues are presented to participants in alphabetical order on a customization screen. Participants then customize the cue order using the new customized order for the remainder of the study. In order to ensure information symmetry between conditions, all participants see all cues for all cases regardless of condition.

3.3 Dependent Variable

Libby (1975) states the goal of providing information to information users is to enhance decision making and that the most important measure of decision quality is the prediction achievement index. The *prediction achievement index* is the correlation between the known environmental state being predicted and the predictive responses of individuals. This measure is labeled ACCURACY for the remainder of this study and is calculated as the correlation between two ranked lists: actual company rankings and participant reported company rankings (Coller and Tuttle 2002; Libby 1975).

3.4 PARTICIPANTS

3.4.1 PARTICIPANT RECRUITMENT

Participants were recruited from Amazon Mechanical Turk (MTurk) to participate in this study. MTurk participants self-selected by both enrolling to become MTurk workers and by choosing to participate in specific tasks called Human Intelligence Tasks (HITs). Appropriate wording was used in the HIT posting to encourage participation by knowledgeable workers. I restrict which MTurk workers are allowed to view the HIT to workers who have a 95% or higher HIT approval rating to obtain participants who have a history of properly completing HITs. I also restrict access to participants located in the United States or Canada to increase the potential for participants to be familiar with United States financial markets.

There can be significant differences in participant information usage based on domain knowledge (Libby 1976) and experience (Tubbs 1992). Participants unfamiliar with an information set are less able to consider the importance of information items or the relations between information items. Hence, I use preliminary questions to identify MTurk workers as either high-expertise or low-expertise based on their answers. Each participant is then randomly assigned to one study condition. Each condition of the study is limited to 68 total participants, 34 high-expertise participants and 34 low-expertise participants, using a quota option in Qualtrics. While this option does not guarantee equal cell sizes due to participants not completing the entire study, the option helps cells be of approximately equal sizes.

Expertise was determined using three preliminary questions in Qualtrics. Workers answered these three total questions, which included an attention check imbedded within

one of the questions, prior to gaining access to the full study. The attention check was one of five statements randomly presented to workers in the first question and read "I am a human and not an automated response program." Workers not selecting this item for question one were directed to an end of study notification and are not considered study participants. The first preliminary question related to personal experience in investing. I specifically asked participants to select each of the following statements (in random order) that applied: "I personally select company stocks for personal investments."; "I invest in one or more common stock mutual funds."; "I am currently or have been employed in a finance position."; and "I am currently or have been employed as a stock analyst." Some participants indicated no personal experience in investing which resulted in their being classified as a low-expertise participant.

The second question requests a true or false response to the statement "Net revenues and net profits mean the same thing." The third question is a multiple choice question which reads "In general, an increase in earnings results in ____." Potential answers include "an increase in the company's stock price", "a decrease in the company's net profit margin", "an increase in the company's working capital", and "a decrease in the company's asset turnover" presented to participants in a random order. Only participants who selected at least one of the four answers from the investing experience question and answered both the second and third questions correctly were identified as high expertise.

3.4.2 Participant Compensation

Each participant received a fixed payment of $1 for completion of the study. In addition, each participant was paid $0.25 for each company rank that was within one position of the correct rank. Each participant was notified of both the fixed and

performance based payment system prior to accessing the study and again at the beginning of the study. The fixed payment was made through MTurk within three days of the participant completing the study. Payments based on performance were made three days after the last participant completed the study. Total compensation for the study ranged from $1.00 to $3.50 with an average of $2.06 paid to each participant. Based on the average time to complete the study of 10.85 minutes, the effective hourly wage was $11.39.

3.5 Procedures

3.5.1 Participant Recruitment and Screening

As shown in Figure 3.1, the study begins with MTurk workers accessing a HIT posted on the MTurk website. MTurk workers who selected the HIT saw a post that included information related to the study as well as a link to participate in the study (Figure 3.2). Workers who chose to click on the survey link were directed to a Qualtrics survey. In Qualtrics, each worker was presented with preliminary questions to determine expertise classification (Figure 3.3) and to determine whether the quota of participants had been reached within the different expertise conditions.

After completing the preliminary questions, participants were provided information about the study including the primary task, compensation, and participant rights (Figure 3.4). Participants next saw the instruction screen which provided information about the ranking task (Figure 3.5). All participants saw the same instructions prior to random assignment to study conditions. Random assignment was accomplished through a randomization procedure in the Qualtrics survey. Participants in

the CUSTOM condition next completed the customization task followed by the ranking task. Participants in the CONTROL condition proceeded directly to the ranking task.

3.5.2 Customization Task

The customization task asked participants to choose the order in which they would prefer to see cues. The customization screen included a brief instruction and a vertical list of the cues that participants use during the study (Figure 3.6). Instructions were located at the top of the customization screen, and notes describing cue interpretation were located at the bottom of the customization screen. All cues were initially listed in alphabetical order for all participants. The customization screen provided participants a tool to change the order of cues. Participants changed the order of cues using drag-and-drop functionality. After completing the customization task, participants proceeded to the ranking task.

3.5.3 Ranking Task

The ranking task asked participants to organize companies by the change in stock price from the prior year to the current year, highest to lowest, given the values of five cues. Before beginning the ranking task, participants were given brief instructions (Figure 3.7). Cues for the 20 cases were then presented to participants in a table on a single screen (Figure 3.8). The screen also included instructions at the top of the screen and notes describing cue interpretation at the bottom of the screen.

The order of cases was determined by randomly assigning participants to one of two random orders created prior to the study (Table 3.1). Each order was created by generating a random number for each case using software. The cases were then ordered based on the random number from least to greatest. Company names were created by

joining four randomly generated letters together. Regardless of case order, participants all saw the same company name order. This means the first company name was the same for all participants even though the company data would be based on case order.

3.5.4 Post-Experiment Survey

3.5.4.1 Self-Reported Cue Weights

After completing all study cases, participants were asked to self-report the relative weight of each cue based on how important the cue was in their decision. Based on the process used in Tuttle and Stocks (1997), participants were asked to indicate the importance of each cue by allocating 100 points among the cues (Figure 3.9). Participants were instructed to assign the points based on decision importance with a value of zero for cues not used to make a decision. The program forced the total points assigned to equal exactly 100 before allowing the participant to continue.

3.5.4.2 Individual Attitude

Individual attitude toward an information system is a determinant of intent to use an information systems as well as its subsequent actual use, and could therefore possibly affect subjects' reactions to customization features (e.g. Ajzen 1991). Attitude related information was gathered to understand the impact of customization on individual attitudes toward the ranking task using the information system provided. I specifically collected participants' attitudes toward the ranking task because with the exception of cue order, the ranking task was identical for all participants, so any difference in attitudes toward the ranking task can be attributed to the process of customizing information.

Following the rating system developed by Ajzen and Fishbein (1980), I measure attitude by asking participants to respond to five statements. The scales all begin with

"All things considered, I believe the company ranking task was:." Responses were gathered using 7-point scales labeled on opposite ends with Good/Bad; Wise/Foolish; Favorable/Unfavorable; Beneficial/Harmful; and Positive/Negative (Figure 3.10). Because prior literature finds attitude as a significant factor related to system use, the attitude measures allow assessment of how customization influences attitude toward the system.

3.5.4.3 Perceived Ease of Use

In an effort to measure ease of use, participants were asked to answer questions based on Mathieson and Keil (1998). Similar to attitude, the ease of use measures allow analysis of the effect of this form of customization on participants' perceptions of ease of use. Both attitude and ease of use have the potential to be influenced by participants' assigned experimental conditions. Each participant was presented with three statements and asked his or her agreement with each statement (Figure 3.11). The statements were focused on column organization and read as follows: "The columns of information were in an order that made it easy to complete this task."; "The columns of information were in an order that made it easy to compare companies."; and "The task would require less effort if the columns were in a different order." Responses were on a seven-point scale with the numbers "1" through "7" appearing from left to right above the response selections. In addition, the left endpoint was labeled "Completely Disagree" while the right endpoint was labeled "Completely Agree."

3.5.4.4 Confidence

Research provides evidence that confidence is an important factor in decision making (Barber and Odean 1998; Bloomfield et al. 1996). Lee and Moray (1994)

demonstrated that participants with high confidence prefer control over tasks while participants with low confidence trust automated system to perform tasks. In order to understand how confidence relates to this task, I asked each participant to rate decision confidence on a seven-point scale (Figure 3.12). The prompt read "How confident are you that your rankings will match the actual rankings?" The left endpoint was labeled "Not at all Confident," and the right endpoint was labeled "Very Confident." In addition, each point on the scale was labeled from left to right beginning with "1" and ending with "7."

3.5.4.5 MOTIVATION

Psychological research suggests individuals with choice demonstrate greater motivation to perform a task than individuals without choice (e.g., DeCharms 1968; Rotter 1966). Because some participants chose and used a preferred order of cue presentation, these participants may have been more motivated to perform the task (Becker 1997; Gagné and Deci 2005; Kernan et al. 1991). I asked each participant to rate their motivation on a seven-point scale. The prompt read "Please rate how motivated you were to correctly match your company rankings to the actual company rakings." The left endpoint was labeled "Not Motivated" and the right endpoint was labeled "Highly Motivated." Each point on the scale was also labeled with numbers beginning with "1" on the far left selection and ending "7" on the far right selection.

3.5.4.6 DEMOGRAPHICS

Demographic information was collected (1) to evaluate whether random assignment was successful and (2) to assess whether the participants were appropriate for

the task. Demographic information included age, gender, and educational information as well as a self-assessment of knowledge of accounting and finance.

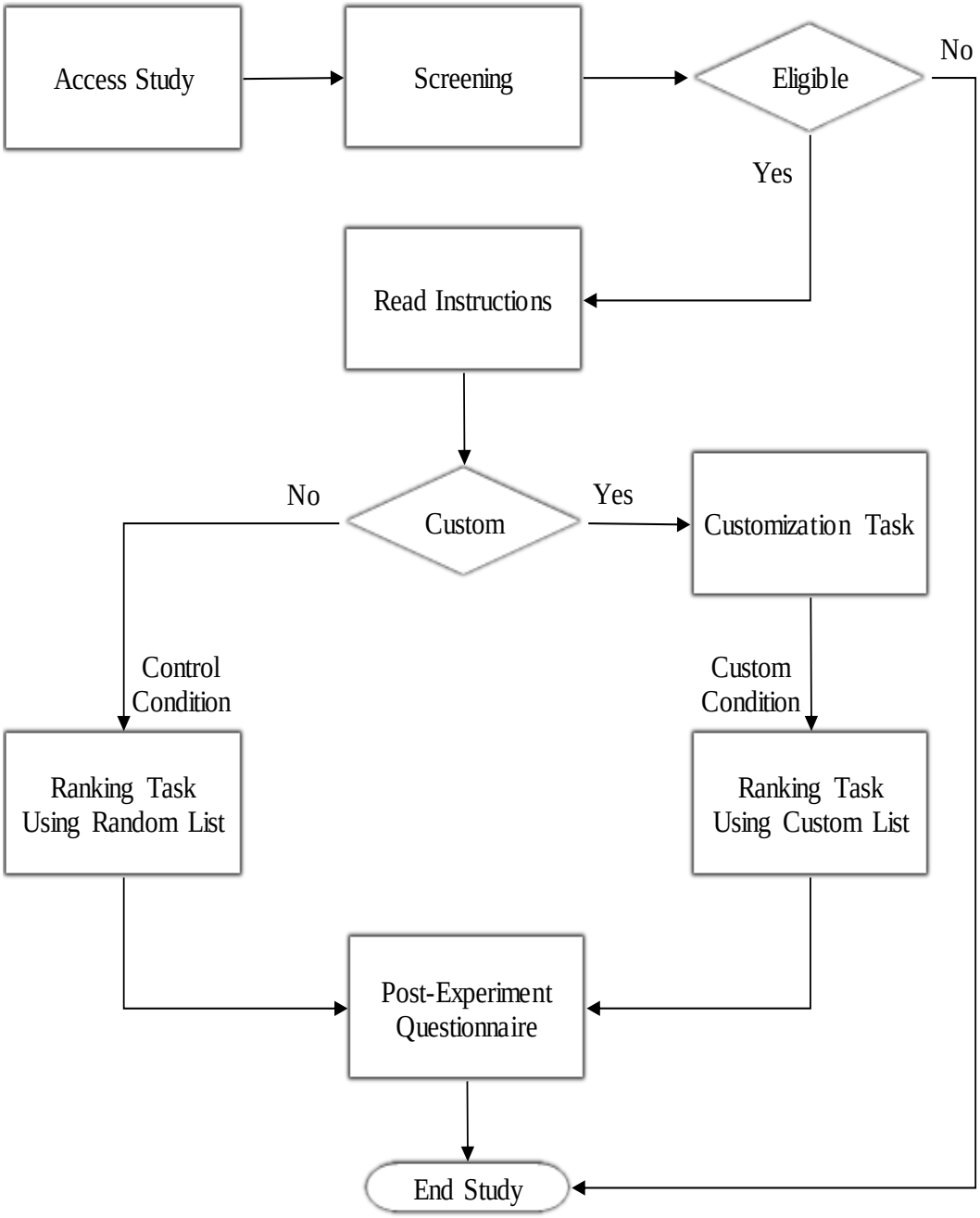


FIGURE 3.1: PROCEDURAL FLOW

Instructions

The purpose of this study is to better understand individual choice and decision making. To complete this study, you are asked to read instructions carefully, complete all tasks, and complete a survey.

Target workers have prior investing experience. Participants are asked to rank publicly traded companies in order of the change in stock price from the prior year based on the information provided.

You will be required to answer screening questions prior to participating in this study. Only workers who complete the entire study will be compensated.

This study is expected to take no more than 30 minutes. Payment for completing the study includes a $1.00 fixed amount paid within 3 days of completing the study. In addition, you will receive a bonus payment of $0.25 for each company you rank within one position of the company's actual rank based on the change in stock price. This payment will be made at the end of the study. Maximum compensation for this study is $6.00.

Make sure to leave this window open as you complete the survey. When you are finished, you will return to this page to paste the code into the box.

Survey link: http://www.linktosurvey.com

Provide the survey code here: _____

FIGURE 3.2: AMAZON MECHANICAL TURK HUMAN INTELLIGENCE TASK POST

1. Please select each item below that applies to you. (Check all that apply.)
   - □ I am currently or have been employed in a finance position.
   - □ I invest in one or more common stock mutual funds.
   - □ I personally select company stocks for personal investments.
   - □ I am currently or have been employed as a stock analyst.

2. Net revenue and net profit mean the same thing.
   - ○ True ○ False

3. In general, an increase in earnings results in _____.
   - ○ a decrease in the company's net profit margin.
   - ○ an increase in the company's stock price.
   - ○ an increase in the company's working capital.
   - ○ a decrease in the company's asset turnover.

- MTurk Workers who do not select "I am a human and not an automated response program." were directed to an end of study screen.
- The order of all five responses on question one were randomized for each worker.
- The order of all four responses on question two were randomized for each worker.
- Participants were classified as high expertise if they did all of the following:
  - Select at least one of the four investing related items in question one,
  - Select "False" for question two, and
  - Select "an increase in the company's stock price." for question three.
- All participants not classified as high expertise were classified as low expertise.

FIGURE 3.3: PRELIMINARY QUESTIONS

Introduction and Notices of Participants' Rights

The purpose of this study is to better understand individual choice and decision making. To complete this study, you are asked to read instructions carefully and complete all tasks. One of the tasks asks you to rank companies by the change in stock price. This ranking task is used to determine bonus compensation.

This study is expected to take no more than 30 minutes. Compensation for your participation is a non-negotiable transaction through Amazon Mechanical Turk. Payment for completing the study is $1.00. Participants completing all tasks will be paid this amount within three (3) days of completion. In addition, you will earn $0.25 of bonus compensation for each company you place within one position of the correct rank. The maximum bonus amount is $5.00. Bonus compensation will be paid at the conclusion of the study. Maximum compensation for this study is $6.00.

There are no known risks associated with this study. The researcher is committed to maintaining confidentiality. The only link between you and your responses is your personal identification code. The personal identification code is generated by Qualtrics and entered into Amazon Mechanical Turk by you. Your personal identification code is used to facilitate the payment process.

Your participation in this study is strictly voluntary. You may refuse to participate in this study. You may cease participation at any time. The total number of participants is limited. If you receive a message stating the maximum number of participants has been reached, you will not be allowed to participate in this study and any information provided will not be used.

This study is conducted by Charles Boster under the direction of Dr. Brad Tuttle. For study related questions or comments or to obtain study results, please contact Charles Boster (charles.boster@moore.sc.edu). Results will not be released until the study is completed. Please contact the University of South Carolina Institutional Review Board office (803-777-7095) for questions about your rights as a participant.

Thank you for your support of this research study.

FIGURE 3.4: STUDY DISCLOSURE

General Instructions

You will be presented with information for 20 actual companies on a single screen. Not all companies are from the same industry. Each company was traded on an active exchange in the United States at the time data were collected. Each company's prior year stock price was adjusted to be exactly $10.00.

Based on the information provided in this study, you are asked to rank the 20 companies from greatest positive change in stock price to greatest negative change in stock price. Companies with negative change in stock price would be ranked lower than companies with positive growth in stock price. There are no ties allowed in the ranking task.

You will be provided with five company measures to use when making your decision. The measures are the only information available to you. Explanations for each of the measures are included at the bottom of the decision screen.

FIGURE 3.5: GENERAL INSTRUCTIONS

Measure Preference

Imagine you are going to compare companies and rank the companies based on the change in stock price from the prior year. When making your decision, you will see each company's performance for each of the measures listed below. If each of the measures was a column heading on a table, please indicate your preferred order (from left to right) of the columns. To do so, drag and drop the measures until they are in the order you prefer. Items you prefer further to the left should be higher on the list below (lower rank number).

To drag and drop, move your pointer to the measure you would like to move. Click and hold the left mouse button while moving the pointer up or down. Release the mouse button when the measure is in the position you would like.

Rank	Measure
1	Projected Industry Growth (%)
2	Net Profit Margin (Relative %)
3	Earnings per Share (Change)
4	Debt to Total Assets (Relative %)
5	Asset Turnover (Relative %)

Notes:

- **Asset Turnover (%)** relative to its industry is computed as Total Sales divided by Average Total Assets. The higher the ratio, the better a company is at using its assets to produce revenue. It measures the ability of a company to convert assets (such as buildings and inventory) into revenue and will be presented as a percentage above or below the industry average. Values provided are the percentage above (+) or below (-) industry averages.
- **Debt to Total Assets (%)** relative to its industry is computed as Total Debt divided by Total Assets. The lower the ratio, the less debt the company owes in relation to its assets. This ratio measures the company's risk for getting into trouble from debt and will be presented as a percentage above or below the industry average. Generally, lower debt to total assets is considered better. A higher than average ratio may indicate that the company has substantial levels of existing debt with few additional financing alternatives. A company with a lower than average ratio may have considerably more financing alternatives to help it avoid trouble. Values provided are the percentage above (+) or below (-) industry averages.
- **Earnings per Share (Change)** identifies an increase or a decrease (-) in the dollar amount of earnings on a per common share basis as compared to the prior year. Earnings per share is calculated by dividing net income by the number of common shares outstanding. "Increase" indicates the company had greater earnings per share in the current year than in the prior year while "Decrease" indicates the company did not have greater earnings per share in the current year than in the prior year. Earnings per share reflects the proportion of the 'Bottom Line' associated with each share of stock.
- **Net Profit Margin (%)** relative to its industry is computed as Net Income divided by Net Sales and will be presented as a percentage above or below the industry average. Generally, a higher net profit margin is better than a lower net profit margin. It shows how much of each dollar of sales is available (after expenses) for re-investment into the company and to pay stockholders dividends. Values provided are the percentage above (+) or below (-) industry means.
- **Projected Industry Growth (%)** (in Sales) is the percent sales growth expected in the industry in the coming year. This measure indicates the change in the total market in which the company operates and may or may not relate to sales growth for a specific company. Values presented indicate industry growth (+) or industry shrinkage (-).

FIGURE 3.6: CUSTOMIZATION TASK

Company Ranking Instructions

On the next screen you will see a list of 20 companies along with company information. You are to rank the companies by the change in stock price from the prior year.

The company with the greatest positive change in stock price should be ranked number "1" and be at the top of the list.
The company with the greatest negative change in stock price should be ranked number "20" and be at the bottom of the list.

Ranking the companies will be done by dragging and dropping the line for the company information up or down on the list. To drag and drop, move your pointer to the company you would like to move. Click and hold the left mouse button while moving the pointer up or down. Release the mouse button when the company is in the position you would like.

When you are ready to begin this task, please click on the ">>" button below.

FIGURE 3.7: COMPANY RANKING TASK INSTRUCTIONS

Company Ranking Screen

The table below includes information for each company. Based on the information provided, please rank the companies based on the change in stock price from the prior year. Companies with greater increases (lower decreases) should be ranked higher (lower rank number) than companies with lower increases (greater decreases).

Company	Asset Turnover (Relative %)	Debt to Total Assets (Relative %)	Earnings per Share (Change)	Net Profit Margin (Relative %)	Projected Industry Growth (%)	Rank
YMNH	-25	-40	Decrease	-41	+18	1
TDSD	+24	+26	Increase	+99	+21	2
NXHO	+44	+34	Decrease	-15	-7	3
IZYX	+0	+28	Decrease	-68	+21	4
IBRU	-18	-51	Increase	-79	+18	5
KUTH	+24	-43	Decrease	+157	+31	6
CHQI	-14	+30	Decrease	+129	-7	7
LSAT	+40	+34	Increase	-48	+21	8
ZMGM	+26	-41	Decrease	-86	-7	9
EJIO	+18	-38	Increase	-74	+18	10
YEJP	-24	+71	Decrease	-91	-7	11
UJUB	-42	-59	Increase	-92	+31	12
VXWV	+4	+48	Decrease	-58	+31	13
RZGB	+24	-74	Increase	+88	+21	14
HUCR	-29	-43	Increase	+49	+31	15
SYUS	-33	+35	Increase	-55	+18	16
RRKM	-54	+48	Decrease	+230	+18	17
XKDZ	-55	+30	Increase	+74	-7	18
QVSM	-34	-84	Decrease	+140	-7	19
MENI	+4	+48	Increase	-57	+31	20

Notes:

- **Asset Turnover (%)** relative to its industry is computed as Total Sales divided by Average Total Assets. The higher the ratio, the better a company is at using its assets to produce revenue. It measures the ability of a company to convert assets (such as buildings and inventory) into revenue and will be presented as a percentage above or below the industry average. Values provided are the percentage above (+) or below (-) industry averages.
- **Debt to Total Assets (%)** relative to its industry is computed as Total Debt divided by Total Assets. The lower the ratio, the less debt the company owes in relation to its assets. This ratio measures the company's risk for getting into trouble from debt and will be presented as a percentage above or below the industry average. Generally, lower debt to total assets is considered better. A higher than average ratio may indicate that the company has substantial levels of existing debt with few additional financing alternatives. A company with a lower than average ratio may have considerably more financing alternatives to help it avoid trouble. Values provided are the percentage above (+) or below (-) industry averages.
- **Earnings per Share (Change)** identifies an increase or a decrease (-) in the dollar amount of earnings on a per common share basis as compared to the prior year. Earnings per share is calculated by dividing net income by the number of common shares outstanding. "Increase" indicates the company had greater earnings per share in the current year than in the prior year while "Decrease" indicates the company did not have greater earnings per share in the current year than in the prior year. Earnings per share reflects the proportion of the "Bottom Line" associated with each share of stock.
- **Net Profit Margin (%)** relative to its industry is computed as Net Income divided by Net Sales and will be presented as a percentage above or below the industry average. Generally, a higher net profit margin is better than a lower net profit margin. It shows how much of each dollar of sales is available (after expenses) for re-investment into the company and to pay stockholders dividends. Values provided are the percentage above (+) or below (-) industry means.
- **Projected Industry Growth (%)** (in Sales) is the percent sales growth expected in the industry in the coming year. This measure indicates the change in the total market in which the company operates and may or may not relate to sales growth for a specific company. Values presented indicate industry growth (+) or industry shrinkage (-).

FIGURE 3.8: COMPANY RANKING TASK

My Strategy

Please use the spaces below to indicate the important each measure in your ranking decision.

You must assign 100 points among the measures. The more points you assign to a measure, the more important the measure is to you. Use a value of 0 for each measure that is not at all important to you.

Information

Asset Turnover (Relative %)	50
Debt to Total Assets (Relative %)	25
Earnings per Share ($ Change)	12
Net Profit Margin (Relative %)	7
Projected Industry Growth (%)	6
Total	100

FIGURE 3.9: SELF-REPORTED CUE WEIGHTS

During this study, you were asked to rank 20 companies based on your estimate of their change in stock price. When answering the following questions, please think about the company ranking task you performed.

All things considered, I believe the company ranking task was:

Bad						Good
1	2	3	4	5	6	7

All things considered, I believe the company ranking task was:

Wise						Foolish
1	2	3	4	5	6	7

All things considered, I believe the company ranking task was:

Unfavorable						Favorable
1	2	3	4	5	6	7

All things considered, I believe the company ranking task was:

Harmful						Beneficial
1	2	3	4	5	6	7

All things considered, I believe the company ranking task was:

Negative						Positive
1	2	3	4	5	6	7

FIGURE 3.10: SATISFACTION MEASURES

During this study, you were asked to rank 20 companies based on your estimate of their change in stock price. When answering the following questions, please think about the company ranking task you performed.

The columns of information were in an order that made it easy to complete this task.

Completely Disaggree 1	2	3	4	5	6	Completely Agree 7
○	○	○	○	○	○	○

The columns of information were in an order that made it easy to compare companies.

Completely Disaggree 1	2	3	4	5	6	Completely Agree 7
○	○	○	○	○	○	○

This task would require less effort if the columns were in a different order.

Completely Disaggree 1	2	3	4	5	6	Completely Agree 7
○	○	○	○	○	○	○

FIGURE 3.11: EASE OF USE MEASURES

Panel A: Confidence

How confident are you that your rankings will match the actual rankings?

Not at all Confident						Very Confident
1	2	3	4	5	6	7
○	○	○	○	○	○	○

Panel B: Motivation

Please rate how motivated you were to correctly match your company rankings to the actual company rankings.

Not Motivated						Highly Motivated
1	2	3	4	5	6	7
○	○	○	○	○	○	◉

FIGURE 3.12: CONFIDENCE AND MOTIVATION MEASURES

TABLE 3.1: COMPANY INFORMATION

Case	Projected Industry Growth (%)	Debt to Total Assets (%)	Asset Turnover (%)	Net Profit Margin (%)	Change in Earnings per Share ($)	Adjusted Share Price Current Year ($)	Order 1	Order 2
A	31	(43)	24	157	Decrease	20.93	7	6
B	21	(74)	24	88	Increase	17.13	2	14
C	18	48	(54)	230	Decrease	6.53	3	17
D	(7)	30	(14)	129	Decrease	10.71	14	7
E	21	28	0	(68)	Decrease	10.25	8	4
F	21	34	40	(48)	Increase	15.81	1	8
G	18	35	(33)	(55)	Increase	9.17	20	16
H	21	26	24	99	Increase	16.67	5	2
I	(7)	(84)	(34)	140	Decrease	8.73	17	19
J	31	(43)	(29)	49	Increase	58.19	9	15
K	18	(40)	(25)	(41)	Decrease	11.71	12	1
L	18	(51)	(18)	(79)	Increase	10.58	10	5
M	31	48	4	(58)	Decrease	6.38	19	13
N	(7)	30	(55)	74	Increase	14.23	15	18
O	18	(38)	18	(74)	Increase	13.00	11	10
P	(7)	71	(24)	(91)	Decrease	5.23	6	11
Q	(7)	34	44	(15)	Decrease	7.04	4	3
R	31	48	4	(57)	Increase	23.08	13	20
S	31	(59)	(42)	(92)	Increase	15.24	18	12
T	(7)	(41)	26	(86)	Decrease	12.05	16	9

- Payments were based on participant responses compared to "Adjusted Share Price Current Year ($)" sorted in descending order.
- All company information is based upon Coller and Tuttle (2002).
- Each participant saw cases listed in either Order 1 or Order 2.
- Asset turnover measures the ability of a company to convert assets into revenue. This measure is relative to same industry companies.
- Debt to total assets measures the company's risk for getting into trouble from debt. This measure is relative to same industry companies.
- Earnings per share is calculated by dividing net income by the number of common shares outstanding. This measure reflects an increase or decrease of earnings per share as compared to the prior year.
- Net profit margin is computed as net income divided by net sales and represents the percent of each dollar of sales available for reinvestment. This measure is relative to same industry companies.
- Projected industry growth is the percent sales growth expected in the industry in the coming year.

CHAPTER 4

RESULTS

4.1 INTRODUCTION

This chapter presents the analytical findings. First, general information is presented reconciling the total number of MTurk workers accessing the Qualtrics website to the number of participants included in the study. Second, general statistics are presented including demographic information by condition. Then, the hypothesis test results are presented. Following the hypothesis test, I conduct several supplemental investigations.

4.2 PARTICIPANT SELECTION

Participants were recruited through a posting on Amazon's Mechanical Turk and completed the experiment through Qualtrics, an online survey engine. A total of 1,128 MTurk workers followed the link to Qualtrics (Table 4.1). Of the total workers following the link, 882 workers completed the preliminary questions only. Workers who completed only the preliminary questions included 131 workers who were excluded for not identifying themselves as human on an attention check embedded in the first preliminary question and 751 who were directed to an end of survey screen due to quota limitations. All 751 workers would have been classified as low-expertise participants. An additional 37 workers quit the study after viewing the instructions on Qualtrics and

prior to ranking the companies. Fifteen workers did not complete the demographic survey at the end of the study and are excluded from analysis. A total of 194 usable responses were obtained resulting in a usable response rate of 17.2% of total workers. The term participant, for the remainder of the study, refers only to the 194 workers who provided usable responses.

Of the 194 usable responses, two participants did not change the position of any cases during the ranking task. Although this suggests the task was not completed, the participants may have decided the companies were correctly ranked and chose to leave them in the order presented. Because there is no way to measure participant intent, the two participants are included in the results of this study. Interpretation of the results of this study do not change when including or excluding these two participants. Individual effort level for participants will be investigated as part of the supplemental analysis section.

The participant group was 40.2% female (Table 4.2). The participants average 34.6 years old with an age range from 18 to 67 years. Self-reported knowledge of accounting and finance shows an average rating of 44.5 and 44.8 respectively on a 100 point scale. On average, participants completed the entire study in 10.85 minutes with a range from 2.1 to 43.9 minutes. None of these demographic measures is statistically different by condition.

Overall, 85.6% of participants reported having at least one post-secondary degree. There were significantly more participants with at least one post-secondary degree randomly assigned to the control condition than to the customization conditions (χ^2 = 6.58, p = 0.0373). While 93.8% of participants in the control condition hold a degree,

only 85.1% of the customization group and 77.8% of the supplemental group reported holding a degree.

4.3 Test of the Hypothesis

The hypothesis predicts participants who use the custom ordered list (CUSTOM) will outperform participants who do not use a custom ordered list (CONTROL). The dependent measure is the correlation between participants' rankings of company performance and actual rankings of company performance (ACCURACY). To test for statistical significance, ACCURACY for participants in the CONTROL condition is compared to ACCURACY for participants in the CUSTOM condition.

Analysis of ACCURACY is completed using analysis of covariance (ANCOVA) with CUSTOM v. CONTROL condition as the independent variable of interest and three covariates. The covariates include case sequence, expertise, and holding at least one post-secondary degree. Participants were randomly assigned to one of two case sequences. To control for case sequence, a dichotomous variable coded zero and one identifies the sequence of cases initially presented to participants. With regard to expertise, prior literature found task specific knowledge influences task performance (Libby 1976). To control for task knowledge, level of expertise is included as a dichotomous variable set to zero (low expertise) or one (high-expertise). A further measure of task knowledge is a dichotomous variable indicating if a participant did or did not complete a post-secondary degree. For participants who reported the completion of at least one post-secondary degree, the variable was set to one. For all other participants, the variable was set to zero.

Analysis of covariance results do not provide support for the hypothesis although the model is moderately, statistically significant ($F=2.10$, $p=0.0850$). With regard to the

hypothesis, the difference in ACCURACY between the CUSTOM and CONTROL conditions is 0.003 (Table 4.3) and is not statistically significant (F=0.08, p=0.7814) (Table 4.4) between study conditions.[2] Evaluation of the covariates in the ANCOVA yielded only one significant factor. Participants with degrees outperformed participants who did not have degrees (F=3.98, p=0.0483). ACCURACY for participants who hold at least one degree (mean=0.358, standard deviation=0.246) is significantly higher than ACCURACY for participants who do not hold at least one degree (mean=0.199, standard=deviation 0.303). This result provides limited evidence that the task was of suitable cognitive difficulty to require participant expertise and attention to case related information.

4.4 Supplemental Analysis

4.4.1 Ranking Companies Based on Compensation Measure

Two additional measures of decision accuracy are developed for use in this study as potential checks for robustness of findings. One of the two measures is directly related to the compensation system communicated to participants and used to determine participant compensation. Participants received bonus compensation for each company ranked within one position of the actual rank. A count by participant of the number of cases meeting this threshold is used as the participants' difference score (RKDIFF). RKDIFF is analyzed using the same procedures that are used to test the hypothesis.

This alternate measure of accuracy shows that the effect of study condition is not statistically significant (F=0.35, p=0.5562) (Table 4.4). Of the covariates, only level of

[2] The analysis was also conducted using a z-transformation of accuracy. The interpretation of statistical significance for the model, the primary independent variable, and the covariates are the same when using the z-transformation. The z-transformed results are not reported or discussed.

expertise is a significant predictor of RKDIFF (F=4.38, p=0.0384) with high-expertise participants (mean=4.5, standard deviation=2.0) outperforming low-expertise participants (mean=3.8, standard deviation=1.6). This result provides evidence that the level of expertise (as determined by the preliminary questions) is directly related to the compensation received by participants. Any conclusions based on this finding should also consider the overall model's lack of statistical significance (F=1.34, p=0.2580).

4.4.2 Accurately Predicting Cue Importance

Developed by Egon Brunswik (1952, 1956), the Lens Model provides a method to evaluate the relations between environmental factors (cues) and behaviors of actors (observers) (Figure 4.1). Observers weight cues (Cue_i) based on personal preferences when making decisions. The importance of each cue in a specific individual's decision model is the correlation (r_{is}) between the cue values and the response values (Y_s).[3] The r_{is}s are then used to calculate predicted individual responses ($\hat{Y}_s$) for each set of cues. I separately estimate each participant's decision model using the lens model (Brunswik 1952, 1956; Libby 1975) by regressing the participant's reported ranks on the cue values and two-factor cue interactions. The regression technique is stepwise regressions with a modified forward selection process following the approach of Coller and Tuttle (2002) (Neter et al. 1989).

A separate analysis using the same cues but including the known environmental state (Y_e) in place of observers' responses yields an additional set of correlation values (r_{ie}). By standardizing the correlation values and making a direct comparisons between the r_{is}s and r_{ie}s, I create a final measure of accuracy. BETADIFF is the sum of the

[3] Multi-factor interactions are excluded from Figure 11 for simplicity.

absolute value of the differences between the standardized beta weights from the participant's estimated model and the best fit model for all main effects and two-factor effects. BETADIFF is analyzed using the same procedures that are used to test the hypothesis. As is found with the other measures of accuracy, the effect of condition is not statistically significant in the model (F=0.39, p=0.5310) (Table 4.5). The only statistically significant factor in the model is the sequence of cases (F=5.11, p=0.0254). While the reason for sequence of cases appearing as a significant factor is not clear, this result may be driven by participants' effort levels during the ranking task. As is found with RKDIFF, the overall model lacked statistical significance (F=1.45, p=0.2219).

4.4.3 Additional Measures of Decision Quality

In addition to measures of accuracy, prior research has shown presentation format may impact other measures of decision quality (Speier and Morris 2003). The two measures are the count of signification cue correlations and the consistency of decisions. Both of the measures are based on results from estimating individual responses to cues using the Lens Model. When all of the cues provided to decision makers are relevant, decision quality improves as decision makers incorporate more of the cues into their decisions. (Chewning and Harrell 1990; Trotman et al. 1983). The total number of statistically significant cues from each participant's estimated decision model is a measure of information use by each participant (COUNT). For this analysis, a cue is counted as used if the cue is statistically significant as a main effect or as part of a statistically significant two-factor interaction effect in a participant's estimated decision model. In other words, COUNT is the number of cue correlations (r_{is}) that are significant for each participant based on estimated decision models. In addition, if the correlation

value r_{ijs} is significant, both cue i and cue j are counted as significant cues for that participant. While COUNT includes cues when significant as either a main effect or multi-factor interaction, no cue is included more than once for any participant regardless of the number of times it appears in an estimated decision model. So, if a cue is part of a main effect and part of three two-factor interactions, that cue is counted once as being present in the participant's decision model.

The final measure of decision quality is the correlation between individual rankings (Y_s) and expected responses for the individual ($\hat{Y}_s$) (CONSISTANT). Specifically, the adjusted-R^2 from each individual's estimated decision model is used as CONSISTANT (Chewning and Harrell 1990; Trotman et al. 1983). Because participant decision models are expected to have a different number of significant cues and cue interactions, adjusted-R^2 provides a better measure than unadjusted R^2 of the predicted decision model's explanatory power while taking into account differences in the number of cues. Higher values of CONSISTANT indicate that participants are using well defined strategies while completing the task. For each participant, both COUNT and CONSISTANT are determined based on the same regression model used to calculate BETADIFF.

Both COUNT and CONSISTANT are analyzed using the same procedures that are used to test the hypothesis. Neither the model for COUNT (F=0.55, p=0.6981) nor the model for CONSISTANT (F=0.31, p=0.8723) are statistically significant. That stated, condition is found to be a statistically insignificant estimator of both COUNT (F=0.08, p=0.7779) and CONSISTANT (F=0.01, p=0.9254) (Table 4.6). In fact, there are no significant factors in the model. Through the analysis of multiple dependent variables,

results suggest there is no change in decision quality related to customization for this task.

4.4.4 Individual Perceptions

As part of the post-experiment questionnaire, several questions were asked to collect information about individual perceptions related to this study. Ease of use was measured by asking participant to rate their agreement with three statements on a seven-point scale. When reporting agreement related to the order of columns making the task easier, responses from participants in the CUSTOM condition were significantly greater than responses from participants in the CONTROL condition (t=2.40, p=0.0177) (Table 4.7). However, when reporting agreement related to the order of columns making comparison of companies easier, responses were not statistically different (t=1.31, p=0.1941). This combination of results suggests participants believed the order of columns helped with the task of ranking but did not help with comparing individual companies.

The last measure of ease of use evaluates whether participants believe the task requires less effort if the columns were in a different order. Results suggest a moderately significant difference between conditions. Participants in the CONTROL condition believed changing the order of columns would reduce the effort required to complete the task more than participants in the CUSTOM condition (t=1.95, p=0.0536). However, response averages of 3.56 and 3.03 for CONTROL and CUSTOM respectively are below the middle value of the scale indicating participants in both groups believe changing the order of columns is unlikely to reduce the effort required to complete the task.

Participants also responded to satisfaction measures related to the task. The five measures assessed participants' perceptions of the task as good, wise, favorable, beneficial, and positive. The difference in measures between the CONTROL and CUSTOM conditions range from 0.06 to 0.37 on a seven-point scale, but none of the differences were statistically significant. Interpretation of this result must be considered with caution. The lack of significance may be related to the fact that this is the first interaction with the specific task. It is possible that either customization does not improve satisfaction perceptions for a new task, or the participants were unable to relate the questions to the task.

Participants also reported their confidence that their reported rankings would match the actual rankings and their motivation to correctly rank companies. Overall confidence averaged 3.5 on a seven-point scale. This does not signify an overly confident participant base. While participants in the CUSTOM condition reported more confidence than participants in the CONTROL condition, the results were not significantly different ($t=1.31$, $p=0.1912$). Confidence is significantly correlated with level of expertise ($F=9.93$, $p=0.0020$). Participants in the high-expertise category reported confidence levels 0.73 points higher than participants in the low-expertise category ($t=3.15$, $p=0.0020$).

Self-reported motivation averaged 5.9 on a seven-point scale. Although participants in the CUSTOM condition reported more motivation to correctly rank companies, the differences was 0.11 and lacked statistical significance ($t=0.55$, $p=0.5824$). While high motivation is an indicator that participants may have exerted high effort when completing the task, additional analysis is needed to support this observation.

4.4.5 Analysis of Participant Effort on Customization and Ranking Tasks

Several observations related to participant responses and analysis suggests effort levels could play a role in the results of this study. While self-reported perceptions of effort were gathered as a part of the post-experimental survey, an analysis of the differences between starting and ending positions for the cues in the customization task and the cases in the ranking task provide additional insight into the effort spent by participants during the customization and ranking tasks. With respect to effort during the ranking task, for each participant, the correlation between the originally assigned sequence of cases and the final sequence of cases as ranked by the participant is calculated (RANKCORR). With respect to the customization task, for participants who customize the display, the correlation between the original sequence of cues and the final sequence of cues as ordered by the participant is calculated (CUSTCORR). For each measure, a higher correlation value indicates less task related effort for the participant.[4] In this case, perfect correlation (e.g., 1.0) between the original list provided to the participants and the list after the participant either customized the cue order or ranked the companies for performance suggests that no effort was expended during the customization and/or ranking tasks. Accordingly, CUSTCORR and RANKCORR are tested against the null hypothesis that the correlation is one yielding significant p-values of less than 0.0001 in both cases. This indicates that participants took both tasks seriously by exerting significant effort to re-arrange the cue information and to rank the companies by performance.

[4] Effort reflects both motivation on the task and the distance between the original sequence of cases or order of cues and the desired sequence/order.

The average CUSTCORR values of -0.116 and -0.121 for the SUPP and CUSTOM conditions respectively are not statistically different (t=0.09, p=0.9311). Results from the ranking task show moderate statistical differences between conditions. The average RANKCORR values are 0.261, 0.273, and 0.159 for CONTROL, SUPP, and CUSTOM conditions respectively. While CONTROL and SUPP are not statistically different (t=0.23, p=0.8148), CUSTOM is moderately statistically different than CONTROL (t=1.95, p=0.0531) and statistically different than SUPP (t=2.18, p=0.0308). This finding suggests that participants in the CUSTOM condition may have exerted more effort when completing the ranking task than participants in the other two conditions.

4.4.6 Participants Interacting with Information

McCaffery and Baron (2003) show individuals increase focus and reliance on information after simply interacting with information. The process of creating a custom list requires individuals to consider information relative to all other available information. This is likely to increase salience of both the information and their decision models. In addition, prior literature suggests customization may introduce affective responses related to the information (e.g. Elliot et al. 2012; Rose et al. 2004). Because both increased salience and affective response may influence decision makers, I conduct additional analysis to investigate potential differences between creating and using a custom list versus simply creating a custom list.

While the primary analysis for this study focused on only two conditions, a third condition is included in in the study (Figure 4.2). The third condition (SUPP) is necessary for supplemental analysis addressing the differences between participants interacting with information and participants using customized displays. Participants in the SUPP

condition perform the same customization task as participants in the CUSTOM condition. However, participants in the SUPP condition perform the company ranking task using cues in alphabetical order just as participants in the CONTROL condition. Therefore, inclusion of the SUPP condition allows testing of changes due to interacting with the information by comparing CONTROL to SUPP and changes due to using a customized display by comparing CUSTOM to SUPP.

To evaluate the impact of participants' interaction with information on decision quality, two sets of analysis, similar to that completed to test the hypothesis, are conducted for the three measures of accuracy and the two alternate measures of decision quality. The average values for each measure of decision quality by condition are included as Table 4.3. The first analysis set investigates the effect of participants interacting with information. When considering participants who interacted with information (SUPP) compared to participants who did not interact with information (CONTROL), there were no significant differences between initial test of the hypothesis and the supplemental analysis as shown in Table 4.5. In fact, there were no significant differences related to study conditions for ACCURACY ($t=0.12$, $p=0.9043$), RKDIFF ($t=0.31$, $p=0.7543$), BETADIFF ($t=0.14$, $p=0.8862$), CONSISTANT ($t=0.96$, $p=0.3358$), or COUNT ($t=0.31$, $p=0.7563$). These results suggest interacting with the information does not improve decision quality.

Next, I conduct analysis to evaluate the effect of using a preferred order versus not using a preferred order. Comparing the performance of participants who indicate and use a preferred order (CUSTOM) to the performance of participants who indicate a preferred order but use alphabetical order (SUPP) yields no significant differences related

to the primary independent variable. Using custom information does not appear to improve ACCURACY ($t<0.01$, $p=0.9969$), RKDIFF ($t=0.96$, $p=0.3400$), BETADIFF ($t=0.54$, $p=0.5889$), CONSISTANT ($t=1.15$, $p=0.2508$), or COUNT ($t=0.67$, $p=0.5029$) on this task. The study conditions, which control interaction with information and use of a customized display, have no significant influence on decision quality as measured with three measures of accuracy, one measure of consistency, and one measure of information use.

4.4.7 SELF-INSIGHT

Additional participant information was collected to measure self-insight. I use correlation analysis to investigate participants' self-insight into their decision models following a process similar to Tuttle and Stocks (1997). In order to evaluate self-insight, I capture each participant's reported cue weight (RW) using a self-reporting task. RW is a numeric weight assigned to each cue from a post-experiment questionnaire. In addition, I calculate relative cue weights (CW) for each participant based on the standardized beta weights of his or her estimated decision model (Luckett and Hirst 1989; Tuttle and Stocks 1997; Zedeck and Kafry 1977). The correlation between RW and CW provides a measure of participants' self-insights.

I investigate if participants in this study have self-insight related to the importance of cues when making decisions. High self-insight suggests participants possess sufficient domain knowledge and are well suited for the customization task. CW are based on the same estimated decision models used to calculate the measures of decision quality. Similar to BETADIFF, CW is based on significant values of both the main effect of a cue and any two-factor interactions with the cue as one of the two factors. Because the self-

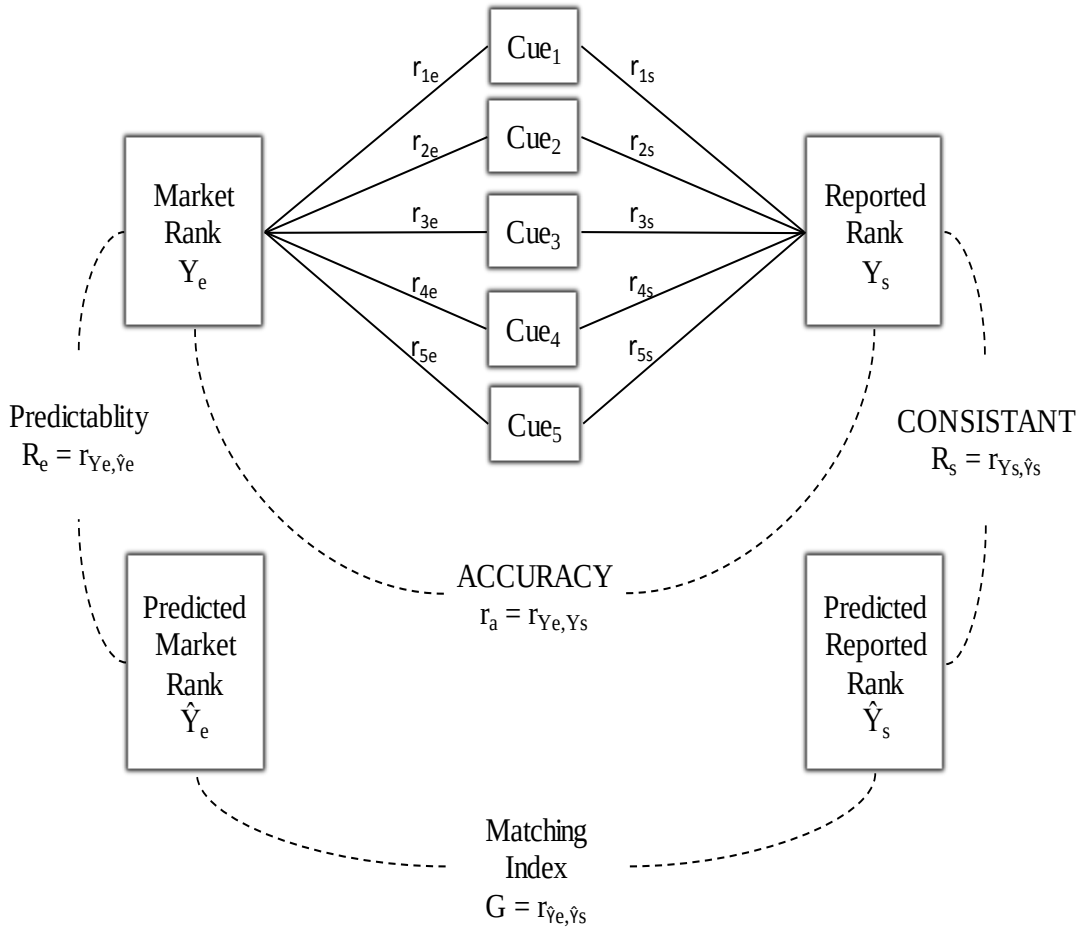
reporting task accepts only positive numbers, I correlate the absolute value of CW with RW for analytical purposes. The two measures are significantly, positively correlated with a correlation coefficient of 0.521 ($p<0.0001$). While correlation values increase from CONTROL to SUPP to CUSTOM, only the difference in correlation between CONTROL and CUSTOM is statistically significant ($Z=2.03$, $p=0.0424$). The trend coupled with a significant difference between CONTROL and CUSTOM provides limited evidence that customization may enhance self-insight.

4.4.8 INFORMATION ORGANIZATION

I test an assumption that individuals organize information based on the relative importance of the information in the individuals' decision models.[5] Pretests of the instruments used in this study in a pencil and paper format provided evidence that individuals prefer more important information to be higher on a list and more to the left than less important information. To formally test this assumption, I created individual importance measures for each cue for each individual and correlate the resulting importance measure with the position on the individual's custom list. Using the estimated decision model for each individual, the standardized beta weight for each cue is added to the standardized beta weights for two-factor interactions that include the cue ($WEIGHT_i = r_{is} + \Sigma\, r_{ijs}$ for $i \neq j$). The result represent the importance of each cue in each individual's decision model. POSITION is the order of cues in the customized list created

[5] Marewski et al. (2010) identify several reasons why individuals view some information as more important than other information. Generally, individuals assess their knowledge of the information with regard to recognition, fluency, and dominance. Based on this assessment, individuals make decisions on how and when information is used. In this study, I make no assertion about the process of determining relative importance of information by individuals. Also, I do not investigate if the information is more valued or if the individual only believes the information is more value.

by participants using the customization tool. Testing is completed by calculating the correlation between POSITION and WEIGHT. When calculating the correlations, I expect and find a statistically significant negative coefficient of correlation ($r=-0.357$, $p<0.0001$) for participants who completed the customization task. The result of this test provides support for the assumption by showing a significant correlation between the list location of a piece of information specified by an individual and the relative importance of that piece of information in the individual's decision model.



Notes:

ACCURACY is also known as prediction achievement index.

CONSISTANT is also known as response linearity.

COUNT is the number of cues appearing in at least one significant main effect or two-factor interaction in estimated decision models.

FIGURE 4.1: LENS MODEL

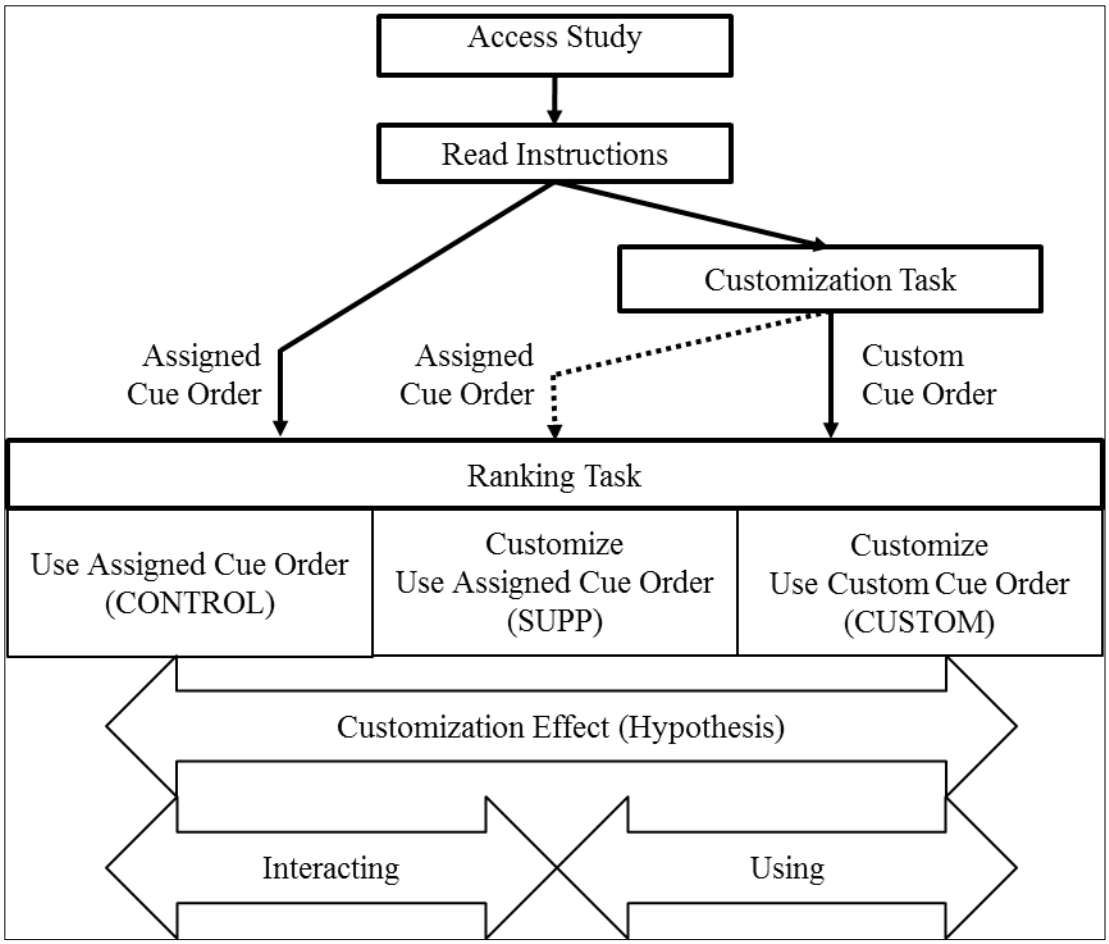


FIGURE 4.2: CUSTOMIZATION CONDITIONS

TABLE 4.1: AMAZON MECHANICAL TURK WORKER TRAFFIC

	Number of Workers	% of Workers
Failed attention check	131	11.6
Unable to continue due to quota limitation	751	66.6
Quit study prior to ranking task	37	3.3
Did not complete post-experiment questionnaire	15	1.3
Included as participant in study	194	17.2
Total accessing Qualtrics website using the link	1,128	100.0

Notes:

- The attention check is an imbedded response item in the first preliminary question.
- The quota was set at 34 high-expertise and 34 low-expertise participants within each condition. The total participant count was limited to 204.

TABLE 4.2: DEMOGRAPHIC INFORMATION BY CONDITION

Panel A: Demographic Measures (Participant Reported)

Measure	CONTROL	SUPP	CUSTOM	Total
Sample Size	64	63	67	194
Gender	39.1%	42.9%	38.8%	40.2%
Has a Degree	93.8%	77.8%	85.1%	85.6%
Age	36.1 (10.9)	33.7 (10.5)	34.1 (9.4)	34.6 (10.3)
Knowledge of Accounting	41.9 (26.5)	44.9 (24.3)	46.5 (26.0)	44.5 (25.6)
Knowledge of Finance	43.8 (24.0)	45.7 (23.8)	45.0 (24.0)	44.8 (23.8)
Time to Complete (Min)	10.39 (6.12)	10.84 (6.69)	11.30 (7.42)	10.85 (6.75)

Panel B: Tests for significant differences by condition for dichotomous measures

Measure	Degrees of Freedom	Chi-Square	p-Value
Gender	2	0.27	0.8721
Has a Degree	2	6.58	0.0373

Panel C: Tests for significant differences by condition for continuous measures

	Degrees of Freedom			
Measure	Numerator	Denominator	F-Value	p-Value
Age	2	191	1.08	0.3417
Knowledge of Accounting	2	191	0.53	0.5899
Knowledge of Finance	2	191	0.10	0.9032
Time to Complete (Min)	2	191	0.30	0.7416

TABLE 4.3: AVERAGE VALUES OF DECISION QUALITY MEASURES BY CONDITION

Measure	CONTROL	SUPP	CUSTOM	All
ACCURATE: Prediction achievement index				
(Potential range from -1.000 and 1.000)				
Average	0.340	0.347	0.343	0.343
Std Dev	0.242	0.231	0.270	0.248
Minimum	-0.310	-0.152	-0.565	-0.565
Maximum	0.705	0.783	0.725	0.783
RKDIFF: Number of reported ranks within one of actual rank				
(Potential range from 0 to 20)				
Average	4.281	4.460	4.119	4.284
Std Dev	1.786	1.803	1.903	1.829
Minimum	1	0	1	0
Maximum	8	9	10	10
BETADIFF: Sum of absolute difference between estimated beta weights from decision model and estimated betas weights from environmental model				
(Potential minimum value of 0)				
Average	13.239	13.164	12.954	13.116
Std Dev	4.180	4.037	3.732	3.964
Minimum	3.214	4.720	5.352	3.214
Maximum	28.274	22.182	21.062	28.274
CONSISTENCY: Adjusted-R^2 of estimated decision model				
(Potential range from 0.000 to 1.000)				
Average	0.744	0.785	0.740	0.756
Std Dev	0.212	0.181	0.266	0.223
Minimum	0.160	0.202	0.001	0.001
Maximum	0.975	0.984	0.993	0.993
COUNT: Number of significant cues in estimated decision model				
(Potential range from 0 to 5)				
Average	3.016	3.063	2.925	3.000
Std Dev	1.291	1.378	1.374	1.343
Minimum	1	1	0	0
Maximum	5	5	5	5

TABLE 4.4: ANCOVA ON ACCURACY (HYPOTHESIS TEST)

Panel A: Model Results

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	4	0.531	0.133	2.10	0.0850
Error	126	7.979	0.063		
Corrected Total	130	8.510			

Panel B: Type III Sum of Squares

	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	1	0.008	0.13	0.7152
Sequence	1	0.152	2.40	0.1239
Expertise	1	0.054	0.85	0.3582
Has Degree	1	0.252	3.98	0.0483

Panel C: Model Results for Supplemental Analysis

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	5	0.351	0.070	1.15	0.3353
Error	188	11.480	0.061		
Corrected Total	193	11.831			

Panel D: Type III Sum of Squares for Supplemental Analysis

	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	2	0.001	0.01	0.9905
Sequence	1	0.194	3.17	0.0765
Expertise	1	0.130	2.12	0.1467
Has Degree	1	0.020	0.33	0.5678

- Condition is the experimental condition assigned to each participant.
- Sequence is a dichotomous variable indicating the initial sequence of cases presented to participants.
- Expertise is a dichotomous variable indicating low-expertise or high-expertise.
- Has Degree is a dichotomous variable indicating that a participant does or does not have a post-secondary degree.

TABLE 4.5: ANCOVA ON ALTERNATE MEASURES OF DECISION ACCURACY

Panel A: Model Results for RKDIFF

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	4	18.016	4.504	1.34	0.2580
Error	126	422.824	3.556		
Corrected Total	130	440.840			

Panel B: Type III Sum of Squares for RKDIFF

Source	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	1	1.168	0.35	0.5562
Sequence	1	0.134	0.04	0.8419
Expertise	1	14.690	4.38	0.0384
Has Degree	1	0.568	0.17	0.6815

Panel C: Model Results for BETADIFF

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	4	88.925	22.231	1.45	0.2219
Error	126	1933.483	15.345		
Corrected Total	130	2022.407			

Panel D: Type III Sum of Squares for BETADIFF

Source	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	1	6.055	0.39	0.5310
Sequence	1	78.486	5.11	0.0254
Expertise	1	4.682	0.31	0.5817
Has Degree	1	3.068	0.20	0.6555

- Condition is the experimental condition assigned to each participant.
- Sequence is a dichotomous variable indicating the initial sequence of cases presented to participants.
- Expertise is a dichotomous variable indicating low-expertise or high-expertise.
- Has Degree is a dichotomous variable indicating that a participant does or does not have a post-secondary degree.

TABLE 4.6: ANCOVA ON ALTERNATE MEASURES OF DECISION QUALITY

Panel A: ANCOVA model analysis for CONSISTANT

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	4	0.073	0.018	0.31	0.8723
Error	126	7.423	0.059		
Corrected Total	130	7.496			

Panel B: ANCOVA Results with Type III Sum of Squares for CONSISTANT

Source	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	1	0.001	0.01	0.9254
Sequence	1	0.011	0.19	0.6615
Expertise	1	0.033	0.56	0.4542
Has Degree	1	0.017	0.28	0.5951

Panel C: ANCOVA model analysis for COUNT

	Degrees of Freedom	Sum of Squares	Mean Squares	F-Value	p-Value
Model	4	3.957	0.989	0.55	0.6981
Error	126	225.921	1.793		
Corrected Total	130	229.878			

Panel B: ANCOVA Results with Type III Sum of Squares for COUNT

Source	Degrees of Freedom	Sum of Squares	F-Value	p-Value
Condition	1	0.143	0.08	0.7779
Sequence	1	1.290	0.72	0.3979
Expertise	1	0.088	0.05	0.8248
Has Degree	1	2.157	1.20	0.2748

- Condition is the experimental condition assigned to each participant.
- Sequence is a dichotomous variable indicating the initial sequence of cases presented to participants.
- Expertise is a dichotomous variable indicating low-expertise or high-expertise.
- Has Degree is a dichotomous variable indicating that a participant does or does not have a post-secondary degree.

TABLE 4.7: CUSTOMIZATION EFFECT ON INDIVIDUAL PERCEPTIONS

Panel A: Ease of Use

Measure	CONTROL	CUSTOM	t-Value	p-Value
The columns of information were in an order that made it easy to complete the task.	4.83 (1.63)	5.43 (1.23)	2.40	0.0177
The columns of information were in an order that made it easy to compare companies.	5.03 (1.63)	5.37 (1.36)	1.31	0.1941
This task would require less effort if the columns were in a different order.	3.56 (1.69)	3.03 (1.44)	1.95	0.0536

Panel B: Satisfaction

All things considered, I believe the ranking task was:	CONTROL	CUSTOM	t-Value	p-Value
Good / Bad	5.03 (1.51)	5.40 (1.22)	1.55	0.1230
Wise / Foolish (Reverse coded from study)	4.69 (1.54)	4.75 (1.17)	0.06	0.8059
Favorable / Unfavorable	5.11 (1.43)	5.19 (1.05)	0.15	0.6984
Beneficial / Harmful	5.36 (1.30)	5.19 (1.20)	0.57	0.4502
Positive / Negative	5.33 (1.40)	5.51 (1.01)	0.71	0.4005

Panel C: Confidence and Motivation

Measure	CONTROL	CUSTOM	t-Value	p-Value
Confidence	3.43 (1.42)	3.66 (1.31)	1.31	0.1912
Motivated	5.83 (1.23)	5.94 (1.10)	0.55	0.5824

CHAPTER 5

CONCLUSION

In today's connected world, people have access to more information than ever before, so the importance of understanding human-computer interaction continues to grow. Prior research documents that information presentation choices impact decisions due to cognitive fit (e.g. Kelton et al. 2010). Research also provides compelling evidence that individuals have substantially different decision models complicating the task of pre-specifying an optimal information display (e.g. Coller and Tuttle 2002). Leveraging current technological capabilities through customization may provide an avenue to improve the cognitive fit between information displays and individual decision models. In this study, I examined the effects of one aspect of customization on decision making in a stock ranking task. Based on cognitive fit theory, I hypothesized but did not find that individuals who use custom displays would exhibit better decision quality than individuals who do not use custom displays.

Through the planned test of the hypothesis and supplemental analysis, I analyzed a total of five measures of decision quality. In addition to measuring prediction achievement (Libby 1975) as specified for the hypothesis test, I created two additional measures of decision quality related to accuracy. The first measure is a count of reported ranks within one positon of actual ranks and is directly related to the compensation scheme communicated to participants. The second measure is the sum of the absolute difference between beta weights from estimated decision models for each participant and

a best fit decision model. Also, I included two measures of decision quality, consistency and amount of information used, as used by prior research (Chewning and Harrell 1990; Trotman et al. 1983). There were no statistically significant differences in any of the five measures of decision quality related to the study conditions. Therefore, the data from this study does not provide support for a claim that customization improves decision making.

Three potential reasons for not finding significant results apply to this study. First, the participants may lack sufficient knowledge of accounting and finance. The overall average for self-reported measures of knowledge of accounting (44.5/100) and knowledge of finance (44.8/100) suggest many participants lacked knowledge of the fundamental concepts applicable to the task.[6] In addition, findings from this study show decision quality improvements are correlated with the level of education. Future research should consider different participant groups with domain knowledge specific to the task.

Second, customization is expected to benefit participants by reducing the cognitive load of performing a task. It is possible the task may not have induced cognitive load because findings on ease of use measures show participants found the task relatively easy with an average rating of 5.15 out of seven. In light of participants reporting that the task was relatively easy, it is important to note that average performance was 4.2 out of twenty cases correctly ranked within one position of the actual rank, so performance was quite low. In addition, participants were limited to choosing the order of information which may not have provided sufficient customization options to improve mental processing. Further research is necessary to understand if alternate levels of cognitive

[6] Knowledge of accounting and knowledge of finance were used individually and simultaneously as potential alternate measures of expertise. Interpretation of results did not change when using these measures.

load or alternate customization options, such as choosing which information is and is not shown, benefits decision makers.

Finally, the hypothesis is based on cognitive fit theory which applies primarily to presentation representation as opposed to information organization (Vessey 1991, 1994; Vessey and Galleta 1991). Representation specifically addresses differences related to tabular versus graphical presentation. Cognitive fit theory may not be the appropriate basis for the hypothesis because all participants were presented the same information using the same representation.

This study is designed to investigate the role of individual preferences for information organization on decision making. Existing research predominately varies information presentation to determine the effects of presentation alternatives on individuals (e.g., Hirst et al. 2007; Speier et al. 2003; Swink and Speier 1999). This study provides an initial investigation into information presentation as an endogenous factor by allowing individuals some control over the information display. This design choice allows investigation of how information influences individuals absent researcher-dictated information displays. Specifically, this study evaluates decision makers' use of customization to improve the cognitive fit between information presentation and individual decision models.

In a natural setting, individuals have access to an abundance of information and extensive resources to explain how information may be used. Future research is needed to better understand the influence of personal information control through customization. Future research should consider which customization options are best for decision makers and under what conditions customization options are efficient. Allowing decision makers

complete control over customization could introduce dysfunctional effects which outweigh potential benefits.

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