EXAMINING COGNITIVE PROCESSES OF UNSTRUCTURED DECISION MAKING

by

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B.S. Kansas State University, 1990
M.S. Kansas State University, 2000

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Abstract

Unstructured decision making is a dynamic process where an individual must create an alternative because one is not available or provided. In this type of a decision, an individual may not have formed preferences or may not know the path to arrive at a solution. As opposed to selecting from existing alternatives, little research examines when decision makers create an alternative. Electronic commerce websites allow individuals to create a product by customizing it. A web-based simulation called Interactive Choice was developed for the investigation. It is an interactive naturalistic decision space permitting experimental controls such as random placement of participants into conditions and random display of stimuli. Participants customized three products (pizza, cell phones, shoes). Building on theoretical foundations of unfolding model and Image Theory, a model asserts the presentation of the information and preparation of the decision maker influences a decision maker. A phased examination explores decision makers' cognitive processes by measuring participants' evaluations of the product created and the process to create it.

In the first phase, three experiments find, contrary to previous independent investigations, participants rarely retain a pre-selected default value. Logistic regression reveals that the odds ratio of predicting default retention is dependent on product type. In the second phase, results identify that problem solving instructions influence decision making. Analyses of multidimensional scaling and cluster analysis reveal patterns for default retention and problem solving instructions that define an electronic decision aid called Choice Builder. The dissertation suggests that when an individual creates a product, he or she has more control over the process that subsequently reduces the influence of the default. A new theoretical foundation is proposed identifying that for unstructured decisions individuals construct both decision strategies and preferences while creating an alternative. With an active process of acquiring and evaluating information, an individual forms a decision strategy and updates preferences to achieve an ideal outcome. This dissertation makes four contributions that include 1) a research

tool, Interactive Choice, for exploration, 2) the identification of cognitive processes involved, 3) a proposal of a new theoretical approach, and 4) an electronic decision aid, Choice Builder.

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Dedication

I dedicate this work to my husband, Michael Crow. He is my guide, support, and partner in this journey.

CHAPTER 1 - OVERVIEW OF UNSTRUCTURED DECISION MAKING AND LITERATURE REVIEW

Sarah stops by a new coffee shop on her way to work. She orders a cup of coffee and must answer a barrage of questions--short or tall, light or dark, caf or decaf, lofat or nofat. Then she proceeds to meet with a consultant to design her office with modular furniture. Sarah must decide what panels, countertops, overhead bins, and drawers to assemble into an office. Sarah's day is just beginning as she is planning an upcoming conference. She must decide what activities, where to hold them, who to invite, and how to advertise the conference.

When an individual organizes a conference, creates a software program, customizes a sofa, or even orders a cup of coffee, this style of decision making is unstructured. “Unstructured refers to decision processes that have not been encountered in quite the same form and for which no predetermined and explicit set of ordered responses exists” (Mintzberg, Raisinghani & Theoret, 1976, p. 246).

The challenge for unstructured decision making is that the decision maker may not know what he or she values. In new or novel situations, an individual may not have considered the various aspects of the decision. Decisions are more straightforward for situations that are familiar, simple, and directly experienced (Fischhoff, Slovic, & Lichtenstein, 1980).

Svenson (1990) asserts a decision falls into one of four levels. The first level consists of an automatic or unconscious decision. The second level is a choice between equally desirable alternatives. The third level involves decisions where tradeoffs between alternatives exist. The fourth level of decisions is when the alternative is not defined and nor are the attributes. In this case, the decision maker must generate an alternative. This fourth level of decision making is called an “unstructured decision.”

Most decision making research focuses on level two and level three-type decisions (Svenson, 1990; Payne, Bettman, & Johnson, 1993; to name a few). The nature of the investigations uses a “researcher-defined” decision space. By this, the researcher defines the alternatives or attributes for a decision maker to evaluate. When creating an alternative however, we do not know what the space would look like (Crow, Shanteau, & Casey, 2003). More importantly, with a restricted defined decision space, we may limit what we discover about decision processes. As Fischhoff (1996) suggest, “there may be value to studying how the nature of outcome spaces affects people's thinking (p. 241).” To date investigative tools such as MouseLab (Payne, Bettman, & Johnson, 1993) examine choices between fixed alternatives. However, interactive tools and the Internet allow participants to create their own alternative set.

Prior work on unstructured decision making has focused on organizational decision making processes (Mintzberg, et al., 1976; Gettys, Pliske, Manning & Casey, 1987; Keller & Ho, 1988). In another line of research, “ill-structured” decisions making have alternatives are available, just not in an organized manner (e.g., Sinnott, 1989). “Ill-structured” decisions are not to be confused with “unstructured” decisions where an alternative is not available.

Missing from current decision making research is how an individual arrives at a decision when he or she creates an alternative. Some have argued decision theories inadequately describe the complex process by which decision makers create alternatives (Maier, 1960). Slovic (1995) identifies that models must address changing preferences. “Describing and explaining failures of invariance will require choice models of far greater complexity than the traditional models” (Slovic, 1995, p. 364). Described herein is a model to explain and a method to explore unstructured decision making. Building on existing theory, the following outlines the development of a theory of unstructured decision making.

Theoretical Background

As stated earlier, unstructured decision making is when an alternative is not available and the decision maker must create an option, presumably close to his or her ideal. Theoretical approaches to unstructured decision making are limited. Introduced more than 30 years ago, Coombs' (1975) Unfolding Theory that recognizes an individual’s preference is an ideal point within a multidimensional space. The ideal point reflects a single-peaked preference function where preferences unfold around the ideal point. As the name implies, the single peaked point is the ideal and any point away from the ideal is less satisfactory.

Beach's Image Theory (1990) assumes that a decision maker maps his or her image onto an outcome. To find an ideal option, a compatibility test “is designed to evaluate the fit between the features of a particular option and the decision maker's standards” (Beach, 1993). Both Unfolding Theory and Image Theory recognize an individual’s ideal point in an outcome space.

These approaches suggest that to obtain an ideal point, an individual must identify his or her goals. There are multiple uses for considering goals in decision making. For researchers, identifying decision makers' goals can determine their strategy (Schneider & Burns, 2003). For the decision maker, concentrating on goals can aid the decision process (Keeney, 1992). "Realization of goals, in turn, realizes the decision maker's principles–how things should be and how people ought to behave–which is the driving force behind the entire process" (Beach & Mitchell, 1998, p. 13).

However, Svenson (1999) argue a decision maker may be uncertain about how different aspects of the decision relate to his or her goal. In addition, preferences, especially in ambiguous situations, can be labile (Fischhoff, Slovic, & Lichtenstein, 1980). That is, preferences are likely to change or be unstable based on the context or novelty of the issue. Image Theory identifies the difficulty in applying values: "It is difficult to know exactly what features of the goal are and, therefore, what image constituents are relevant when considering their adoption" (Beach & Mitchell, 1998, p. 12).

Traditional decision making research ties uncertainty to known probabilities and ambiguity to unknown probabilities. In contrast, Mintzberg, et al. (1976) relates uncertainty and ambiguity to structured and unstructured decision making. He explains uncertainty is having an alternative, but not knowing the consequences of the decision. This is characteristic of structured decision making. According to Mintzberg ambiguity is not having an alternative given as well, as not knowing the consequences. This describes unstructured decision making.

The challenge to decision making in general but more specifically to unstructured decision making is that "life does not always provide an ordered set of options" (Fischhoff, 1996, p. 240). *<u>Ambiguity</u> defines the crux of the problem. An individual must make a decision where no alternatives exist <u>and</u> he or she may not have existing preferences.* While some researchers identify ambiguity in relationship to a goal (Keeney, 1992), others explain ambiguity as an unclear path to decision making (Fischhoff, 1996). Unstructured decision making is ambiguity both about the goal and about the path to take.

Research has yet to explain when the decision maker is ambiguous about both the goal as well as the path to decision making. Image Theory is the closest in conceptualization to dealing with this dual ambiguity. Beach explains, "I often have regretted that the theory was named Image Theory, if only because the description of the images is its least well-developed feature"

(Beach, 1998, p. 263). He goes on to say, “Future work must expand upon the role that images play in guiding behavior” (Beach & Mitchell, 1998, p. 13). Using the theoretical background as a guide, the following is a process model explaining the reduction of ambiguity in unstructured decision making.

A Model to Explain and Method to Investigate Unstructured Decisions

A two-component model is proposed describing the process for unstructured decisions. The first component is identification of a decision maker's values. The second component is application of these values. Values are whatever the decision maker identifies as important. As well, values are how an individual seeks his or her ideal option.

Decision makers' values or goals are central to finding the ideal option. This may seem straightforward. However, decision makers may not understand their values in relationship to the decision (Fischhoff, 1996; Svenson, 1999) or may even have difficulty identifying these values (Keeney, 1992). Problem solving strategies may help decision makers identify values. Problem solving is transforming a given situation into a desired solution or goal (Hayes, 1989). There is a connection between problem solving strategies and decision making: “Strategies for decision making are but a subset of strategies for problem solving in general” (Christensen-Szalanski, 1998).

The application of values is the second component of the model. Like the first component, applying values in decision making may seem obvious. However, past research reveals that presentation of information will influence a decision and perhaps interfere or influence the goals of a decision maker. For example, framing (Levin & Gaeth, 1988), anchoring and adjustment (Tversky & Kahneman, 1974) are well-known effects that influence decision outcomes. As well, the presentation of risk information in different formats results in different decisions (Edwards, 1954). Thus, to apply values one must consider these context factors.

Product Customization: An Approach to Study Unstructured Decisions

How does one study unstructured decision making when an individual must create an alternative built on an unstated preferences? This is what has puzzled researchers since the publication of Mintzberg's, et al. (1976) seminal paper defining unstructured decision making. Technology and the Internet are crucial to answering this question. Specifically, the Internet gives researchers more methodological options, especially useful for studying unstructured decision making (Crow, Shanteau, & Casey, 2003). As a result, researchers can go beyond traditional research methods, protocols, and subject pools.

Product customization incorporates the unique characteristics of unstructured decision making. When an individual customizes a product, the exact specifications of the product are not set in advance. The alternatives may not even exist in the mind of the individual. The decision maker may only have a vague idea of the end product and may be unsure of how to proceed.

Merging product customization and technology to study unstructured decision making becomes possible because of the Internet. Many websites offer individuals the ability to customize products ranging from engagement rings (www.bluenile.com), and blue jeans (www.mejeans.com) to athletic shoes (www.NikeID.com), to name a few. At one Web site (www.wilsonboots.com), Internet shoppers can create boots by choosing from six leathers, with 15 dies, seven stitching colors, and three styles of toe shapes and four heel styles; thus, the number of boots an individual could potentially create is 7,560.

One could imagine how challenging it must be to combine these attributes to create an ideal pair of boots. How does an individual know what or how to choose the right attributes to create an ideal product? This research began with prior investigations of the factors influencing product customization (Crow, 2000; Crow, 2004). The following summarizes this earlier work.

Product Customization – Empirical Investigations

In an initial study, Crow (2000) examined factors influencing the customization process. Participants generated products on a website modeled after electronic commerce sites. They customized three products by selecting product attributes for pizza, personal digital assistant (PDA), and athletic shoes.

The study identified factors that influence product customization. The most interesting result related to the presence of default values. In one condition, participants received a default or starting value for each attribute. Participants could choose that value or pick another from a drop-down box revealing more selections. In another condition, the drop down box included instructions to “Select one.”

In general, options with default values were preferred. Specifically, the presence of default values made the process of customizing a product less difficult. This supports previous research indicating reliance on default values (Tversky & Shafir, 1992), especially in online environments (Reips, 2002).

However, the question remains as to when or why people are likely to rely on default values (Johnson, 2005). This is of particular interest when individuals create their own products. One of the aims of this present investigation is to explore the presence of defaults on decision making, especially as it relates to the identification and application of personal values.

EuroShoe Project

In the EuroShoe Project, a consortium of 35 partners from the footwear industry in Europe, examined consumer preferences for customizing shoes (Piller, 2002). What was noteworthy was not what individuals would prefer to customize (e.g., color material, sole, etc.), but how participants reacted to customizing shoes. Results indicated participants would likely customize a pair of shoes. However, when faced with new questions or questions never previously considered such as design issues, participants revealed they were reluctant to consider new options.

Several reasons may account for these results. The findings might be due to data collection methods (e.g., focus groups and questionnaires). In contrast, when individuals customized shoes in a simulation (Crow, 2000), they did so with little difficulty. Another reason may be the nature of unstructured decision making; individuals may have had a difficult time addressing new issues, “If an issue does not arise naturally, then people may do particularly poorly when asked to address it” (Fischhoff, 1996, p. 239). Customization of products typically purchased off-the-shelf is not a natural situation. The EuroShoe Project study illustrates when individuals customized products, they encounter the difficulties of unstructured decision making.

In summary, prior empirical studies show that individuals are willing to customize products. However, it also appears individuals may only have a vague idea as to their ideal product or the process to set to their ideal.

Exploring Unstructured Decisions – *Interactive Choice*

It is the intent of this investigation to explore unstructured decisions in an environment that mimics a decision of this type while allowing experimental control over the investigation. A web-based program created for this project called Interactive Choice simulates customizing a product. Interactive Choice implements experimental controls over the investigation.

Specifically, the program 1) presents multiple stimuli in random order, 2) randomly assigns participants to conditions, 3) provides multiple response modes, and 4) incorporates repeated measure designs.

Notably, Interactive Choice tracks and records the activity of participants and presents the appropriate experimental stimuli based on previous activity of the participant. For example, if the experimental protocol requires a mixed design with a random order of experimental stimuli between subjects and random order of stimuli within subjects, Interactive Choice monitors participant activity to assure protocol procedures are accurately carried out.

The program has undergone extensive functionality and usability testing to create a natural decision environment with experimental controls. Interactive Choice is the outcome of a National Science Foundation sponsored workshop and its development was partially supported by a grant from the National Science Foundation.

Dissertation Outline

Contained in this dissertation are four "self-contained" chapters. This first chapter has been an overview and background literature of unstructured decision making. The next two chapters detail the investigation of the components of the model explaining unstructured decision making. Chapter 2 discusses the investigation of factors influencing an unstructured decision. Building from the findings in Chapter 2, Chapter 3 is an examination of identifying decision maker's values. Chapter 4 summarizes the investigation and lays the foundation for future directions while discussing limitations.

Note: Each chapter is self-contained with individualized introductions specific of the problem area and details related to that phase of the investigation. In addition, each chapter also includes its own discussion and reference section. The intent is to seek publication of these chapters.

Summary

This chapter identifies the background and direction for this dissertation. First, it explains the characteristics of unstructured decision making. Primarily, the features include ambiguity of the path to take and unclear preferences for an ideal outcome. The basis for understanding unstructured decision making comes from the theoretical background of Coomb's unfolding model (1975) and Beach's Image Theory (1990).

Consumer decision making typically explores choices between two or more existing alternatives. In these situations, the alternatives are available to the decision maker to evaluate. In unstructured decision making, the decision maker must create the alternative. Little exploration has been done on decision makers creating alternatives.

Creating alternatives is a complex, dynamic decision process where the selection of an item can influence another item. As such, the cognitive process of evaluating and considering option, as well as the presentation of information can influence the outcome. This dissertation explores a process model for the application and identification of values to solving an unstructured decision problem.

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CHAPTER 2 - PRESENTATION OF INFORMATION – DEFAULT VALUES

Imagine that while working late, you realize you hadn't taken the time to eat. You decide to order a sandwich online and have it delivered. The sandwich shop advertises "they will make any sandwich any way you like." At the website for convenience, each ingredient has a starting or default value. Research suggests you are likely to be influenced by the default (Johnson, Bellman & Lohse, 2002; Choi, Laibson, Madrian, & Metrick, 2003; Brown & Krishna, 2004). This is especially true when you are told you can have whatever you like (Crow, 2005a).

In online environments, it is possible to create an ideal alternative by customizing a product. An individual does not select from a set of existing products but must create one. The type of decision a consumer makes is "unstructured" (Mintzberg, Raisinghani & Theoret, 1976). The consumer may know the final product (i.e., a sandwich), but does not know what it will look like or how to specify the product. There is little known about consumer decision making when the decisions are unstructured. Moreover, decision theories do not adequately described the complex process of creating alternatives (Maier, 1960).

An important question for an unstructured decision is the presence of default values. Since prior research suggests default values influence choice, one would assume that in an unstructured decision the presence of default values would have a similar impact. This is especially true when preferences are liable. Typically, decision makers do not have an explicit ordered set of responses (Fischhoff, 1996). Clear preferences are likely for familiar, simple, or directly experienced decisions (Fischhoff, Slovic & Lichtenstein, 1980). When selecting between consumer options, preferences may be constructed (Bettman, Luce, & Payne, 1998).

In electronic commerce settings, defaults are common. A default is a starting value that remains until an individual makes a change. When a consumer customizes a product, many times companies provide a default. At the Blue Nile website (www.bluenile.com) for example, consumers create an engagement ring by selecting the shape of the diamond. Prior research (i.e., Johnson, et al., 2002) predicts that when the oval shape is pre-selected as a default, there is a greater likelihood the oval diamond will be selected.

A common assumption by consumers is that customizing a product leads to an additional fee. With advances in technologies however, manufacturers can assemble many products based on consumer specifications without increasing costs (Dewan, Jing & Seidmann, 2003). When upgrading an item, such as increasing the size of a computer's hard drive, it makes sense to pay more. For a fixed price, an individual can select the colors for a pair of shoes (www.nikeid.com) or the shape of a diamond (www.bluenile.com). We have a limited understanding of how consumers select price neutral attributes. Previous investigations have explored consumer's reaction to customizing price specific attributes (Park, Jun & McInnis, 2000; Liechty, Ramaswamy, & Cohen, 2001). The purpose of the investigation is to understand when and why individuals select default values in unstructured decisions. The present dissertation focuses on customized products with price neutral attributes.

Explanations of Default Effects

Prior research provides some understanding of the effects of defaults on consumer choice. Specifically, when presented with and without default values, participants rate the default options as "less difficult" (Crow, 2005b). Employees select retirement plans with defaults (Madrian & Shea, 2001) despite positive or negative wording of an offer (Johnson, et al, 2002). Thus, an obvious area of investigation is to understand when the "default effect" occurs and why (Johnson, 2005).

Brown and Krishna (2004) assert consumers interpret the default as a sign of marketer's ability to manipulate their choice. Defaults may reduce cognitive effort (Johnson et al, 2002) by providing an anchor (Park et al, 2000). An anchor influences individuals' initial impressions (Anderson, 1967). In addition, the default may serve as an adaptation level or psychological neutral point that exerts influence on how we judge objects (Helson, 1959). This phenomenon is similar to the anchoring and adjustment effect, whereby an individual's judgment centers on a reference point (Tversky & Kahneman, 1974).

The default may serve to maintain the status quo. As such, individuals may put a disproportional emphasis on the status quo option (Samuelson & Zeckhauser, 1988). In addition, the status quo (default) may be viewed as giving up or losing something and emphasis may be on the loss aversion (Kahneman & Tversky, 1984). As such, individuals may view switching from the default as a potential loss (Kahneman, Knetsch & Thaler, 1991).

Previous investigations have explored externally provided defaults. That is, the researcher supplies the defaults. However, these explorations have not examined mental defaults. Mental defaults are internal representations of consumer preferences. Brown and Krishna (2004) propose, "...defaults cause consumer choices to deviate from their true preferences" (p. 529). Hence, consumers may deviate from their mental defaults. Our investigation explores this issue.

There is little understanding of why individuals retain defaults. Building on previous research identifying that defaults provide information about the option, this dissertation proposes individuals view defaults in one of two ways. They may view defaults as a *convenient* option in which the default serves as a suggestion. It is offered as consideration for the consumer to choose or not. Others may view the default as a *necessary* option required for product satisfaction. Choosing something other that what the vendor suggests, will result in displeasure. In prior explorations, individuals draw implicit recommendations as to the default's purpose (Madrian & Shea, 2001; Brown & Krishna, 2004). This investigation focuses participants on the convenient or necessary aspects of the defaults by using explicit recommendations.

Explicit recommendations are not out of the ordinary. Websites offer instructions and recommendations for consumers customizing products. For example, Blue Nile (www.bluenile.com) informs consumers of their "easy three-step process" to design the perfect diamond. Timbuk2 (www.timbuk2.com) identifies specific "Employee Pick" attributes that are "highly recommended" when customizing messenger bags.

The hypothesis is that with different levels of recommendations, participants will choose defaults more frequently in the necessary-default condition over a control or convenient-default condition. That is, when told satisfaction is not guaranteed, participants will retain the pre-selected default. In addition, it is expected default recommendations will result in differences in how participants view the product, as well as the process of customization.

Limitations of Investigation

Challenges in investigating and isolating the influence of default values limit our understanding of default values. This paper identifies three challenges. The first challenge is whether the default is a desired choice or a by-product of the influence of defaults. A highly desirable attribute level may be chosen despite the presence of a default. Thus, it would be hard to know if a consumer desired the attribute level. However, it is expected that if the influence of defaults are robust, the influence should appear with neutral attributes i.e., an attribute level that is neither the most or the least preferred.

The second challenge is the complexity of the decision a consumer makes. Previous investigations present defaults as a choice between two alternatives (Choi, et al, 2003) or two levels of an attribute (Johnson, et al. 2002; Brown & Krishna, 2004) with one containing a default. In these investigations, there was a 50-50 chance the default was a preferred choice and not the influence of the default.

In laboratory settings, experiments that counter-balance conditions revealed that defaults are retained (Brown & Krishna, 2004). However, in many real-world situations, especially when customizing a product, consumers create products with numerous attributes and attribute levels. For example, a consumer customizes nine attributes on a pair of Nike shoes (i.e., base color, swoosh color, etc.) by selecting from two to 16 levels (i.e., colors) for each attribute. The total number of possible combinations is 2.3 billion pairs of shoes. Existing research environments do not tap into the complexity confronting a consumer (Crow, Shanteau & Casey, 2003). As well, "there may be value to studying how the nature of outcome spaces affects people's thinking (Fischhoff, 1996, p. 241)."

The third challenge in exploring the default values is the type of alternative. In an examining factors influencing product customization, consumers view products differently when presenting defaults (Crow, 2005b). In a step in the right direction, Brown and Krishna (2004) explored the effects on three different products. However, their approach of using two attributes per product may not reflect the type of complex decision a consumer faces.

This project provides a three-step approach to explore the full effects of default values: (1) define defaults with neutral values that are not the most or least preferred attribute, (2) replicate a decision consumers are likely to face specifically, with a larger set of attributes and more attribute levels within a product, and (3) use more than one product to identify product effects. This approach minimizes the challenges in exploring the effects of defaults while reflecting realistic consumer choices. In addition, the methodology isolates the effects to identify where and when consumers will choose defaults.

By incorporating explicit recommendations, this research identifies when and why default values are retained. In restating the hypotheses, it is expected that with “stronger” recommendations, participants will retain defaults values. As well, participants will rate the process of creating a product and the product differently by recommendation conditions.

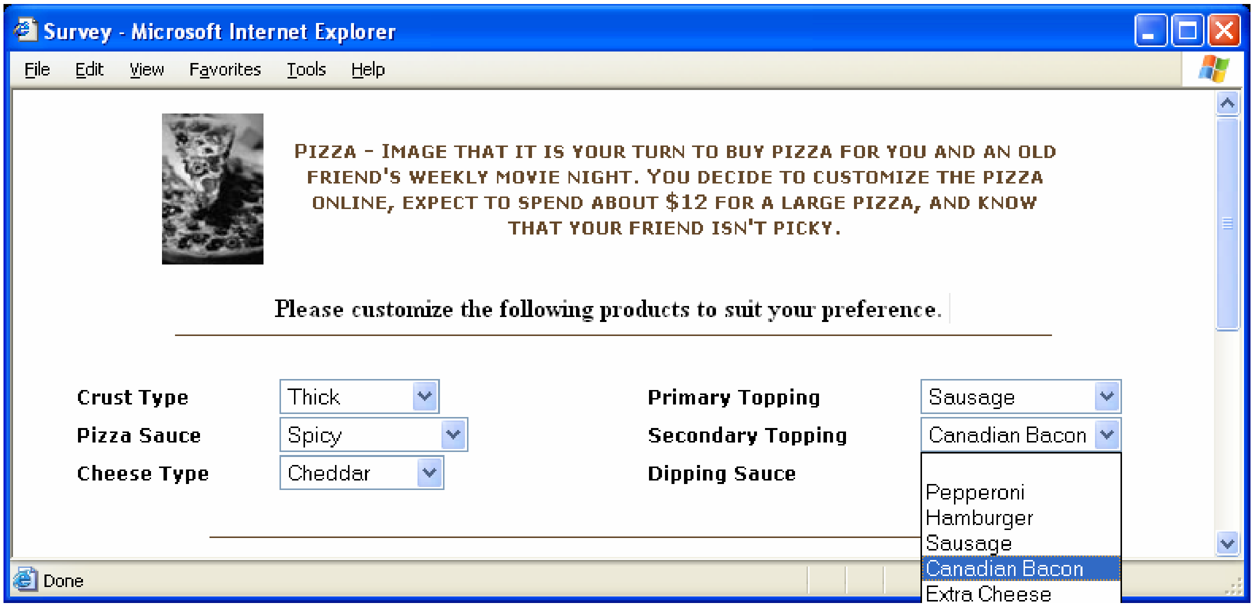
Chapter Outline

The investigation explores the effect of default values with three experiments. The first two experiments examine the effect of default values with three recommendation conditions (control, convenient-default, necessary-default). In these experiments, the two default conditions are compared to a control condition as in previous investigations (e.g., Brown & Krishna, 2004). In the experiments, participants are given different incentives to encourage participation (Experiment 1, pizza coupon; Experiment 2, a request for help). The incentives are compared as part of Experiment 2. The purpose of the third experiment is to explore the effect of default retention across recommendation conditions where all of the conditions contain default values.

Experiment 1

To broaden our understanding of the influence of default values, the first experiment used a decision space consisting of six attributes per condition and attribute levels ranging from four to six. The total number of possible product combinations a participant could create was 76,800. In other investigations, participants could create at most 12 alternatives (e.g., Brown & Krishna, 2004). In this experiment, the attributes and attribute levels were identical and in the same order for all conditions. The attributes were presented as a drop down list as shown in Figure 2.1. The figure illustrates for pizza toppings that Canadian Bacon is the default. It appears in the box on the lower right and in the middle of the drop down list.

Figure 2.1 Stimulus page for pizza in the convenient-default recommendation condition



It is possible that when an individual selects a default, he or she will prefer the pre-defined default. To understand if the choice was a preferred choice or the influence of the default, two methods were employed. The first is to validate in an experimental condition where the default is a neutral attribute. The second is an approach by Brown and Krishna (2004) that used a control condition as a comparison. In the control condition, everything was identical without pre-set defaults. Instead, the attribute was left blank and participants were asked to select for the same list of attribute levels (e.g., color of shoes). Pretests identified products used by the test subjects, product attributes, and attribute levels (e.g., shoe colors, type of material, etc.). A pilot experiment tested recruiting procedures, instructions, and the functionality of the web-based program to refine the experimental protocols.

Independent Variables

The first independent variable was type of recommendations as shown in Table 2.1. The control condition explains to the participant to customize the product to suit his or her preference. The convenient default recommendation condition identified that a pre-selected default was a "convenient" option. Figure 2.1 shows the convenient recommendations. The final condition was the necessary-default condition indicating that the pre-selected default is provided but choosing other than the pre-select, may not guarantee satisfaction. A participant was randomly placed in one of the three recommendation conditions.

Table 2.1 Recommendations per condition

Control	Please customize the following products to suit your preference.
Convenient Default	Please design the following products by indicating your preference for each feature. For each feature, one option has been pre-selected; however, this selection is simply for your convenience and is not intended to be viewed as the correct choice. Please feel free to choose whatever is the best option for you.
Necessary Default	Please customize the following products by indicating your preference for each feature. For each feature, the recommended choice has been pre-selected. While you may choose a different option, if you do so, your satisfaction with the product is not guaranteed.

The second independent variable was the type of product participants customized. Three products were identified from pretests. One criterion was that the products are used by the subject pool, college students. The products selected were cell phones, athletic shoes, and pizza.

An objective of the experiment was to explore price-neutral attribute levels. That is, selecting an attribute does not affect the overall price of the product. Participants were told the fixed prices of the products ($250 cell phone, $90 shoes, $12 pizza).

In addition, the products range in the degree of customization. Typically, pizza is a customizable product when an individual selects pizza toppings. Shoes are not commonly thought of as customizable. However, at Nike’s website consumers can customize a pair of shoes. Currently, cell phones are not customizable. Participants were told the products were popular brands but that the names were withheld for confidentiality purposes.

Dependent Variables

Three dependent variables were used. The first two are consumer ratings of the product and process. Participants rated on a scale from 0 to 99 the likelihood of purchasing the product. Participants also evaluated difficulty to customize with 0 being less difficult to 99 more difficult. The third dependent variable was the selection of the default. It identified whether a participant retained a default value or selects another attribute level.

Method

An email message was sent to 56 college students of a Midwest university directing them to a website specifically designed for this project that simulates customizing a product. The message included the website address, information about the experiment, and the length of time to complete it. Once at the website, participants were assigned randomly to one of three recommendation conditions. Following the instructions and informed consent, the recommendations appeared on a separate page. The recommendations also appeared on each product page as shown in Figure 2.1. As an incentive, a pizza coupon was offered to those completing the experiment.

Research Tool: *Interactive Choice*

Interactive Choice is a web-based program created to test unstructured decisions. When participants accessed the program via an email message, they are in a familiar setting, i.e., a "natural" decision environment. Still, *Interactive Choice* maintains experimental control over the investigation. Procedures and methodologies, such as checking for multiple submissions, preserve data quality (Birnbaum, 2000, 2001; Reips & Bosnjak, 2001). In addition, *Interactive Choice* presents multiple stimuli in random order to counter-balance order effects.

Participants customized each product by selecting the attribute level from a drop down box. After customizing each product, participants were asked questions about the product and the process. A participant could include optional comments in the open textbox provided. Next, the participant advanced to another product page. To counter-balancing order effects, all product pages were presented in random order. After participants customized three products, the same three products were presented in a different random order. At the conclusion, participants were asked to fill out a short form assessing their product experience and answering brief open-ended questions about defaults. The experiment took on average of 9.9 minutes to complete with a range of 5 to 22 minutes.

Results

A 3 x 3 repeated measures mixed design was used. The conditions were type of recommendations (control, convenient-default, necessary-default) and product type (cell phones, pizza, athletic shoes). The analysis of the recommendations was between subjects and the products were within subjects. Nineteen undergraduates volunteered to participate in the experiment. The mean age was 23. The number of participants per condition were divided fairly equally (7 control, 6 convenient-default, 6 necessary-default).

An ANOVA was conducted and is summarized in Table 2.2. The table shows the F statistic, mean squared error, partial eta squared, and power. The power statistic identifies the sensitivity of the test (Keppel, 1991). The following describes the results for all products combined. With 19 participants each customizing 3 products twice, the data set includes 114 observations (control = 42, convenient-default = 36, necessary default = 36).

Significant differences were found for the type of recommendations (control, convenient-default, or necessary-default) and the dependent variable of the likelihood to purchase, F (2, 111) = 4.64, $\eta_p^2 = 0.08$, power = 0.77. Significant results were also found on the type of recommendation and the difficulty to customize, F (2, 111) = 4.23, $\eta_p^2 = 0.07$, power = 0.73. No significant interactions were identified between the recommendations and product type, F (4, 105) = 1.91 for the likelihood to purchase or the difficulty to customize, F (4, 105) = 0.70. These results suggest the recommendations influenced participants' interpretation of the product and process.

Table 2.2 Influence of recommendations on dependent variables for all products combined, Experiment 1

Dependent Variable	F	MSe	η_p^2	Power
Likelihood to Purchase	4.64*	687.68	0.08	0.77
Difficulty to Customize	4.23*	418.83	0.07	0.73
Retain Default Values	2.34	0.42	0.01	0.47

* significant at $p < 0.05$

Central to this experiment is retention of default values. This was examined in three phases. The first phase explored the effects of recommendations on retaining defaults for all product categories combined. The second phase analyzed retaining defaults for individual products. The final phase of the investigation focused on the influence of the recommendations for the individual attribute levels.

As expected, defaults were retained slightly more in the necessary-default than in the convenient-default condition for all products combined. Participants retained defaults 20% in the control condition, 23% in the convenient-default condition and 28% in the necessary-default condition. Contrary to the hypothesis, there were no significant differences between recommendation conditions F (2, 681) = 2.34. When examining individual products, no significant differences were identified for retaining the defaults (cell phones F (2, 225) = 1.55; pizza F (2, 225) = 0.87; shoes F (2, 225) = 3.00).

The attributes chosen in the non-default (control) condition were compared to the default conditions (convenient and necessary conditions). No significant differences were identified between the recommendation conditions and retaining the default for all products combined (F (1, 430) = 1.76) and individual products (cell phones F (1, 142) = 2.97; pizza F (1, 142) = 0.70; shoes F (1, 142) = 0.03). This comparison show the default is in fact neutral.

The final phase of the analysis focuses on whether the recommendations influenced individual attribute levels. For example, did the recommendations influence retaining the defaults more often for pizza crust than for pizza toppings? The results indicate no significant differences between the convenient-default and necessary-default recommendations for all 18 individual product attributes.

Discussion

The results revealed that recommendations influenced the likelihood to purchase and the difficulty to customize. Prior research predicted participants would retain defaults (Brown & Krishna, 2004; Choi, et al, 2003; Johnson, et al, 2002). This investigation identified despite focusing individuals on the purpose of defaults, participants retained defaults 20% to 28%. These findings are counter to previous research suggesting defaults cause individuals to deviate from their true preferences (e.g., Brown & Krishna, 2004). Instead, individuals appeared to rely on their own mental defaults. These mental defaults are their own personal status quo. It is what individuals carry with them as they construct preferences.

To explore when participants were likely retain a default, we examined product experience. Participants rated their frequency of purchasing products. Purchase frequency for pizza had a moderate affect. If an individual purchased pizza within the past week, he or she did not retain a default F (1, 226) = 4.90, η_p^2 = 0.02, power = 0.60. Other product experiences as well as other individual difference variables did not influence retaining defaults.

A couple of comments may clarify why defaults influenced only the pizza choice. Pizza was the least expensive item compared to shoes or a cell phone ($12 v. $90 or $250). In addition, it was purchased more frequently than the other products, χ^2 (2, N = 19) = 24.56, $p < 0.05$. It is possible individuals may retain "product specific" defaults for pizza. When primed by a recent experience, an external default may have less of an influence. In addition, using a pizza coupon as an incentive to recruit volunteers may remind individuals of their "product specific" mental defaults. Experiment 2 tests this question.

Experiment 2

Experiment 2 explores the possibility that the incentive to recruit volunteers might prime product specific experiences. This experiment addressed this question by offering a different type of incentive. As before, it is expected individuals will be influenced by the recommendations in the ratings of product and process and selection of default values. In this experiment, the same procedure was used as in Experiment 1. The only difference in this experiment was the method to recruit participants. In this experiment an encouraging message (e.g., "Please help me…") was used instead of a pizza coupon.

Results

Fourteen participants completed the experiment. The mean age was 23. The number of participants per condition was three for the control, eight for the convenient-default, and three for the necessary-default recommendation conditions. The purpose of this experiment was to investigate the type of incentive offered. In a comparison between Experiments 1 and 2, no differences were found for the likelihood to purchase, F (1, 196) = 3.43, or difficulty to customize, F (1, 196) = 1.77. As well, no differences were identified for retaining defaults, F (1, 1114) = 2.48.

To explain the results specific to Experiment 2, with 14 participants each customizing 3 products twice, the data set includes 83 observations. The results in Table 2.3 indicate a significant difference for recommendations for the likelihood to purchase, F (2, 81) = 4.15, η_p^2 = 0.09, power = 0.72, and difficulty to customize, F (2, 81) = 5.23, η_p^2 = 0.11, power = 0.82. No significant interactions were identified between the recommendations and the type of product, F

(4, 75) = 0.99 for the likelihood to purchase or the difficulty to customize, *F* (4, 75) = 0.22.

No significant results were found for retaining the default value. Defaults were retained 23% for the convenient-default condition and 25% for the necessary-default condition. The non-significance of default retention was consistent for all products combined *F* (1, 394) = 0.19, as well as for individual products (cell phones *F* (1, 129) = 0.04; pizza *F* (1, 130) = 1.27; shoes *F* (1, 130) = 0.02). The analysis compares the attribute levels most commonly chosen in the non-default (control) condition to the default conditions. As with Experiment 1, the recommendations did not influence retaining the defaults for the 18 individual product attributes.

Table 2.3 Effect of recommendations on the dependent variables for all products combined, Experiment 2

Dependent Variable	F	MSe	η_p^2	Power
Likelihood to Purchase	4.15*	410.36	0.09	0.72
Difficulty to Customize	5.23*	596.20	0.11	0.82
Retain Default Values	0.19	0.03	0.00	0.07

* significant at $p < 0.05$

Pizza Results

A purpose of this experiment was to identify whether offering a pizza coupon influences the outcome. For results specific to pizza, when comparing the results obtained in Experiment 1 to Experiment 2 no significant differences were identified between experiments for the likelihood to purchase *F* (2, 63) = 0.80, difficulty to customize *F* (2, 63) = 2.15, or retaining defaults *F* (2, 393) = 1.89.

In Experiment 2, the pizza results indicate no significant differences between recommendation conditions and the likelihood to purchase, *F* (2, 25) = 0.73, or difficulty to customize *F* (2, 25) = 2.07. In addition, there were no significant differences between recommendation conditions and retaining defaults for pizza, *F* (2, 165) = 1.15. When examining pizza purchase experience, there were no significant differences with pizza experience and retaining defaults *F* (3, 164) = 0.08. This result is counter to the previous experiment. However, the overall effect of non-retention of default values is consistent.

Discussion

In this experiment addressing whether an incentive to recruit participants influences the results, finds for all products combined no differences for the likelihood to purchase or difficulty to customize between Experiment 1 and Experiment 2. More importantly as with Experiment 1, no significant results were identified for retaining defaults.

To understand the influence of the pizza coupon, we examined pizza experience where differences were identified in Experiment 1. Specifically, when an individual recently purchased a pizza they were less likely to retain a default. This result was not replicated in Experiment 2. When *not* offering a pizza coupon, the effects of recommendations on customizing a pizza revealed no significant differences regardless of purchase experience. Thus, these results may be explained by that fact that in the first experiment, the pizza coupon reminds individuals of a recent experience, prompting them to be less influenced by the presence of defaults.

This investigation uses an approach similar as in previous investigations (i.e., Brown & Krishna, 2004) that compares a default condition to control condition that does not contain defaults. The control condition serves as a benchmark to measure the effects of defaults. The next phase of the investigation extends previous examinations by including three default conditions. In Experiment 3, defaults are added to the control condition to discover the effect of default values on a neutral recommendation condition.

Experiment 3

Experiment 3 explores the effect of default retention across all three recommendation conditions. As a reminder, the control condition instructs participants to customize products to suit their preference. These recommendations are neutral and similar to instructions in electronic commerce websites. Experiment 3's methods and procedures were similar to the previous two experiments. The only difference is that default values are predefined for all recommendation conditions. For convenience, the conditions are relabeled as control, convenient and necessary.

Results

Twenty students completed the experiment with eight participants in the control, five in the convenient condition, and seven in the necessary condition. Data collected included individual difference variables of age, gender, and product related experience. As with previous experiments the analysis described here is for all products combined. There were no significant differences for defaults retained per recommendation conditions, F (2, 717) = 2.02. Defaults were retained 22% in the control condition, 19% in the convenient condition, and 27% in the necessary condition. These results are consistent with previous experiments and contrary to the initial hypothesis that individuals would rely on default values.

The behavioral response of default retention is a discrete choice. A default is retained or it is not. Other variables (i.e., likelihood to purchase, gender, etc.) are a combination of continuous and dichotomous variables. Logistic regression can predict a discrete outcome from a mixture of continuous and dichotomous variables (Tabachnick & Fidell, 2000). In addition, logistic regression models the odds of an event outcome (default retention) while estimating the effects of covariates on those odds (O'Connell, 2006).

A forward logistic regression was conducted to determine which variables (product, recommendations, likelihood to purchase, difficulty to customize, age, gender, and purchase experience) were predictors of retaining defaults. The logistic regression indicated the overall model with two predictors (product type and likelihood to purchase) was statistically reliable in distinguishing default retention (-2Log Likelihood = 753.33, χ^2 (2, N = 720) = 26.99, $p < 0.000$). The model correctly classified 76.4% of the cases. Although these results were significant, the variance accounted for was low, Nagelkerke $R^2 = 0.06$.

Regression coefficients, Wald statistics, and odds ratios for each of the two predictors are shown in Table 2.4. The Wald statistic indicates that the type of product and the likelihood to purchase are predictors for default retention. The probability of an outcome (retaining defaults) increases with odds ratios that are greater than one (Tabachnick & Fidell, 2000). Thus, the likelihood of retaining defaults is related to the type of product (odds ratio=1.45).

Table 2.4 Results of logistic regression analysis, Experiment 3

Predictor Variable	*B*	Wald Test	Odds Ratio	95% Confidence Interval Odds Ratio *Lower*	*Upper*
Product	0.37	11.20**	1.45	1.17	1.80
Likelihood to Purchase	-0.14	12.98**	0.99	0.98	0.99
Constant	-0.92	5.20*			

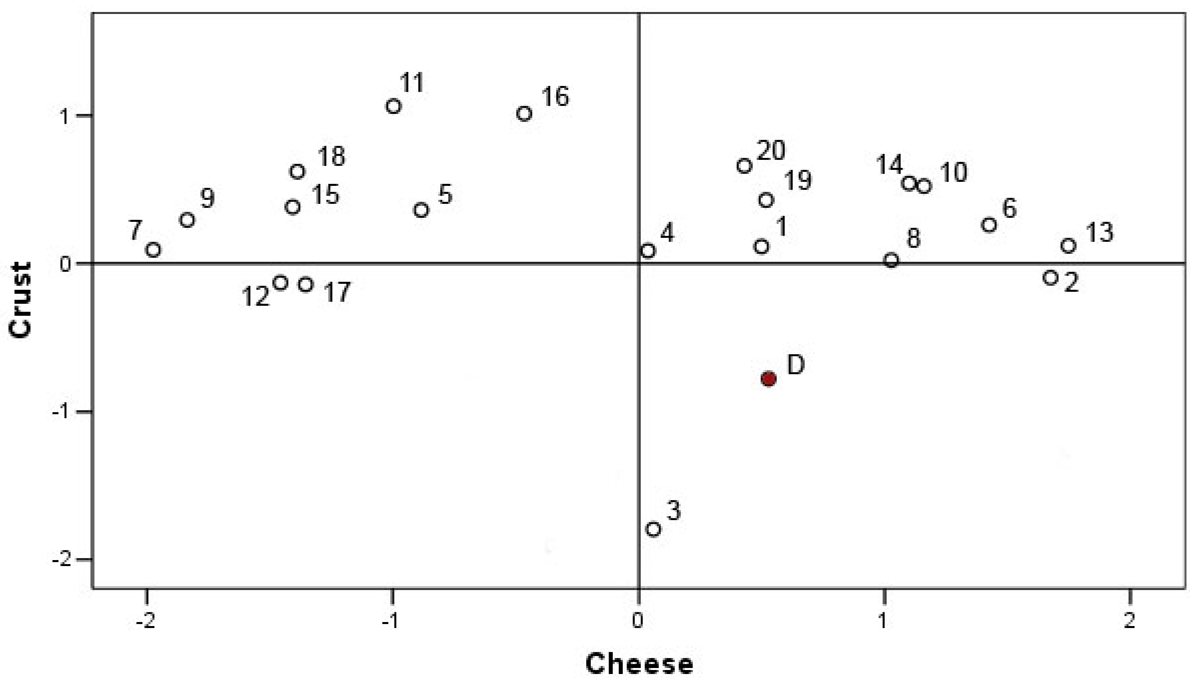
*$p \leq 0.05$, **$p \leq 0.00$

Product Creation

The next step in the analysis is to explore default retention for individual products. Products are a combination of attributes that consumers create products by selecting attributes. The analysis here explores whether the combined attributes selected by participants (products created) were similar to the combined attributes defined as “defaults” (default product) with a multidimensional scaling (MDS) approach. MDS reveals similarities and dissimilarities of a participant’s selection in a product space. The combined attribute coordinates map on to the product space. The results across three products were similar therefore, to simplify discussion the analysis focuses on one product, pizza. The MDS analysis was conducted using SPSS’s Alscal program.

The MDS for pizza revealed Kruskal stress value of 0.27 and squared multiple correlation (R^2) value of 0.93. These values are an indication of the degree of goodness of fit identified by the low stress and high R^2 values (Norusis, 2004). Figure 2.2 displays the Euclidean distance model. Each data point is the derived stimulus configuration. The data point refers to the participant number. In the upper left quadrant of Figure 2.2, there were seven participants’ products and nine in the upper right. The lower quadrants have two participants’ products in the lower left and two in the lower right.

Figure 2.2 Multidimensional scaling of product selection for pizza, Euclidean distance model



Note: The data point D is the default product configuration.

After obtaining the configurations of the products participants' created, the default configuration was added to the multi-dimensional scaling. The default configuration is the combined attributes pre-defined as defaults. The data point D in Figure 2.2 identifies the default configuration. It is located in the lower right quadrant at position 0.5276 and -0.7772. Of special interest is the degree of dissimilarity between the predefined default and the products participants' created. Only two products appear in the same quadrant as the default product. They are the products for participant #2 at position 1.6752 and -0.0959 and participant #3 at position 0.0588 and -1.7948. However, it is interesting that the location of these products is closer to the adjacent quadrants to than the default configuration.

Labeling the dimensions of the Euclidean distance model is somewhat arbitrary. However, further analysis of the dimensions reveals an interesting pattern. When exploring pizzas created for Dimension 1, there were significant differences for individuals choosing the type of cheese, $F(1, 18) = 62.13$, $\eta_p^2 = 0.78$, power = 1.00, as well as the second topping, F (1,

18) = 26.74, η_p^2 = 0.60, power = 1.00. In the upper and lower right quadrants, which is the negative portion of Dimension 1, participants predominately choose “mixed cheese,” whereas in upper and lower left quadrants, the positive portion of Dimension 1, participants choose “mozzarella cheese.” Additionally, in the negative portion of Dimension 1, participants’ chose “extra cheese” as a second topping instead of a meat or vegetable topping, whereas in the positive portion of Dimension 1, participants choose pepperoni. In comparison, the default for cheese was “cheddar” and “sausage” for the second topping.

In Dimension 2 the results for pizza crust are significantly different, F (1, 18) = 10.63, η_p^2 = 0.37, power = 0.87. In the positive portion (upper right and left quadrants) of the MDS, participants created choose “pan” crust 50% of the time, whereas in the negative portion (lower right and left quadrants) of Dimension 2 participants choose “hand-tossed” or “thin” crust 40% of the time. The default for pizza crust was “thick.” From these analyses the labels for Dimension 1 is cheese and for Dimension 2 is crust.

Participant #3 may appear to be an outlier. However, reanalysis of the data without participant #3 finds similar results for Dimension 1 and Dimension 2. Specifically for Dimension 1 significant differences appear for the type of cheese, F (1, 17) = 57.05, η_p^2 = 0.77, power = 1.00 and the second topping, F (1, 17) = 47.92, η_p^2 = 0.74, power = 1.00. As well, for Dimension 2 significant differences appear for pizza crust, F (1, 17) = 21.48, η_p^2 = 0.56, power = 0.99. No other attributes were significant. Thus, these robust effects suggest in creating pizza participants favor cheese and crust.

Product Creation by Recommendation Conditions

A pertinent question is whether the type of recommendations influenced the products created. Using the multidimensional scaling configurations, Table 2.5 lists the number of products generated per recommendation condition relative to the quadrants of the MDS analysis. For example, in the upper left quadrant, four products were “created” using the control recommendation, one product was created using the convenient recommendation and two products were created using the necessary recommendation. In lower right quadrant where the default configuration lie, one product was created with the control recommendation and one product created with the convenient recommendation. Contrary to the hypotheses, no products created using the necessary recommendation condition fell in the default quadrant.

Table 2.5 Number of products created by recommendation condition

	Recommendation Conditions		
MDS Quadrants	Control	Convenient	Necessary
Upper left	4	1	2
Upper right	3	2	4
Lower left	0	1	1
Lower right*	1	1	0

* The lower right quadrant contains the default configuration.

When comparing recommendations, differences appear for Dimension 1, F (2, 17) = 3.57, η_p^2 = 0.30, power = 0.58 with specific differences for the control and necessary recommendations, F (1, 13) = 7.12, η_p^2 = 0.35, power = 0.69. When exploring Dimension 2 differences appear, F (2, 17) = 5.98, η_p^2 = 0.413, power = 0.81 in particular differences for the control and convenient recommendations, F (1, 11) = 6.04, η_p^2 = 0.35, power = 0.61, as well as the control and the necessary recommendations, F (1, 13) = 13.13, η_p^2 = 0.50, power = 0.92.

Discussion

As with previous experiments, when exploring retaining defaults for all products combined, the main effect does not reveal significant differences between recommendation conditions. These results were counter to the hypothesis that with stronger recommendations participants would retain defaults. As well, these results revealed contrary evidence to previous findings that individuals rely on default values (Johnson, et al 2002; Choi, et al 2003; Brown & Krishna, 2004).

In understanding when and where defaults are retained, logistic regression shows that the odds of predicting default retention were dependent on the type of product. In further exploration, multidimensional scaling identifies a Euclidean distance model that demonstrates the dissimilarity of the default configuration and products participants created. Most of the products spread out in quadrants away from the default configuration. Analysis of the dimensions of the Euclidean distance model identifies that when participants create products features of the product are a consideration. For pizza, individuals specifically focus on cheese and crust.

In this investigation, multidimensional scaling was used an exploratory technique to discover relationships between the default configuration and products participants created. In a curious overlap, Coombs' unfolding model (1964) provides a theoretical approach to understanding unstructured decision making and it is the forerunner to multidimensional scaling analysis (Young, 1987). Unfolding model explains that the preferences unfold around an ideal point and like multidimensional scaling, the closer a stimulus (i.e., default) is to the ideal the more it is preferred. While it was not the intent of this investigation to use the same theoretical construct and empirical tool, these approaches help illustrate the effects of default values on product creation.

In extending the theoretical approach to the observed results, this experiment reveals participants' ideal points reflected in the product configurations are dissimilar to the pre-defined default. These ideal points could be participants' mental defaults or their idealized preferences. The dissimilarity of the default and product configurations suggests that mental defaults are more persistent than external defaults. In other words, mental defaults are less resistant to change.

Conclusion

The purpose of these three experiments is to identify the purpose for retaining default values. Across all three experiments, results showed that the retention of default values is not automatic. This findings are counter to current thinking (Johnson, et al 2002; Choi, et al 2003; Brown & Krishna, 2004). Several key elements of this decision task can explain these results. One explanation may be the type of decision (i.e., unstructured). In an unstructured decision where an individual must create an alternative, he or she may not have considered various aspects of the decision. When creating a product, the decision maker may be unclear how to create it. However, through the process of creating the alternative, an individual may feel he or she has a "stake" in the outcome. Psychologically, this "stake" involves a vested or personal interest in the outcome. Perhaps the decision maker who is closely involved in getting the desired result may rely on his or her own preferences as opposed to external defaults. This personal interest and close involvement dilutes the effect of the default value thus, making the default less prominent.

A second explanation concerns the cognitive processes involved in creating products. It is believed that different processes are involved when comparing two or more alternatives than when creating an alternative. When comparing alternatives, an individual must discover or be alerted to differences in the products. Through the process of comparing alternatives, default values have been shown to have an influence (i.e., Johnson, et al, 2002). When an individual creates a product, he or she selects individual attribute levels. In this dynamic process, where choosing one attribute (i.e., outer shoe color) may influence the selection of another (i.e., accent color), additional cognitive processes may be involved.

A third explanation centers on the use of explicit recommendations for creating a product. The recommendations informed participants of the default's purpose (i.e., convenient or necessary). The investigation reveals that with varying levels of recommendations individuals' ratings and behavior was different with respect to default retention and product creation. Other investigations do not use explicit recommendations (i.e., Brown & Krishna, 2004).

The recommendations were intended to push the limits to identify when and why individuals retain default values. The hypothesis was that when given a "necessary" recommendation, persons would rely more on the default. These instructions identify that when choosing other than the pre-selected option "your satisfaction is not guaranteed." It is not likely a company will suggest severe consequences. However, some websites inform customers that they cannot return customizable products (i.e., www.timbuk2.com). This is interesting to note since the control condition is similar to current instructions available to consumers in electronic commerce websites.

If people are not retaining default values, what are they doing? It is possible individuals use their own mental defaults or internal representations of preferences instead of external defaults. It is equally possible they are seeking variety (McAlister & Pessemier, 1982; Kahn, 1998) or a desire to be unique (Simonson & Nowlis, 2000). These possible explanations may identify default retention.

This investigation attempts to understand when defaults deviate from consumers' preferences. The multidimensional scaling analysis in Experiment 3 identified disparities between the default configuration and the products participants create. This approach was built on the assumption that individuals' seek an ideal option (Beach, 1998) with a single-peaked preference for that ideal (Coombs, 1964). The ideal product and default configuration can be thought of as separate planes or maps that may or may not overlap. When the default configuration is closer to the ideal, consumers may be more favorable to the default and choose it instead. It would be interesting to understand how close the default configuration must be to the ideal before the consumer chooses the default instead. What strategy would consumers use? Would they use an optimal strategy that selects the ideal product or a satisficing strategy that picks the default (Simon, 1957)? How much distance is needed in the overlapping product space to select the ideal/default? In addition, as the ideal moves closer to the default, do individuals re-interpret the defaults? Furthermore, if there is a disparity between the default configuration and the ideal product, do individuals view the default as "manipulation" their choice (Brown & Krishna, 2004)?

Exploring the dynamics of product customization can extend our understanding of default retention. Customizing a product is a complex process of selecting multiple attributes. The dynamic nature of this decision suggests multiple factors can influence a choice. Identifying variables influencing default retention is important. The logistic regression in Experiment 3 identified a model accounting for 76% of the cases, however it has a low variance accounted for (Nagelkerke R2 = 0.06). In logistic regression, when variables in the overall model are significant but with a small variance, other explanatory variables in addition to product type may be helpful to predict default retention, see O'Connell (2006) for a similar example. Exploring variety seeking behaviors or desires to be unique may help explain default retention.

The result in this investigation may be a by-product of a complex decision involving products with six attributes containing between four to six attribute levels. A limitation of this investigation is the frequency of default retention where defaults were retained in 23% to 25% of the time. When defaults are seldom retained, identifying factors influencing default retention can be problematic.

This current investigation revealed that presenting neutral default values results in a high purchase intent (M=75.13 out of 100) with low difficulty (M=15.84 out of 100). This is especially important since individuals prefer to customize products with defaults than without (Crow, 2005a). In addition, defaults are prevalent. Whether in an online environment creating an ideal product or an off-line retail setting, consumers generally begin with a starting point. The starting point may be an electronic default such as presented here or it may be a suggestion by a salesperson.

In summary, individuals do not an automatically retain default values. Instead, they retain their own mental defaults. Results suggest that an individual's involvement in discovering preferences and actively creating a product weakens the influence of default values. In addition to these important findings, the methodological approach of using Interactive Choice makes exploration of this type of complex decision making feasible. This investigation broadens our understanding of the influence of default values, while further understanding of the role of product customization on consumer choice.

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CHAPTER 3 - PREPARATION OF THE DECISION MAKER – A PROBLEM SOLVING APPROACH

Laura heard that she could her own design a pair of jeans. Entering the MeJeans website (www.mejeans.com) with some hesitation, she reads the “how it works” section. She is reassured especially knowing that the customs jeans will fit any body type. The guarantee makes her feel more comfortable and she proceeds to create her jeans. She chooses the style, fabric, and waistband. While the choices are numerous, some are easy and others are not. She must select the number of belt loops. Not knowing what she wants, she counts the belt loops on the pair she is wearing. She does not have much interest in the type of accent stitching and yarn color, and so chooses with some uncertainty. The material finish called “rub” is more challenging. Despite having pictures and a description, she is not sure what to choose and selects the first option. After carefully taking her body measurements as illustrated with a video, she completes the order.

Laura is an actual case of an individual making an unstructured decision. By definition, unstructured decisions are ones that an individual has not previously encountered and there is no predetermined set of responses (Mintzberg, Raisinghani & Theoret, 1976; Fischhoff, Slovic, & Lichtenstein, 1980). Laura knew she would be getting a pair of jeans. However, creating a pair of jeans is something that she has never done. In this novel situation, can she create her ideal pair of jeans? As a young adult, jeans are considered a clothing “staple” and she has been wearing jeans from an early age. Previous research suggests experience with a product should make a difference (Alba & Hutchinson, 1987; Coupey, Irwin & Payne, 1998). Yet, there were aspects of the decision process she has not encountered or does not know how to answer. Prior to this experience, she had never considered the yarn stitching, the number of belt loops, or material finish. She did not have predetermined preferences. While the information the company provides reassures Laura, did it hinder or help achieve her ideal pair of jeans?

Unstructured decision making can be challenging especially when an individual does not have predetermined or clear set of preferences. In addition, a decision maker may be uncertain how different aspects of the decision relate to his or her goal (Svenson, 1999). Individuals may engage in problem solving activities to develop preferences. Problem solving helps individuals find, evaluate, and implement ideas. The goal of this project is to explore problem solving approaches to get individuals to think clearly about their preferences.

Many problem solving techniques exist. Some sources identify as many as 101 to 172 techniques (VanGrundy, 1988; Smith, 1998). For an exploratory study, it would be impossible to test every technique. Instead, the research here arbitrarily focuses on three main categories. The techniques are to have the decision maker focus on (a) his or her goals, (b) the object (i.e., the product), or (c) using the object. It is anticipated that when presenting problem solving instructions to an individual in an unstructured decision task, the outcome would be more favorable than without the instructions. The following is a subset of supporting research on applied problem solving techniques.

Goals Problem Solving Technique

The first technique is for the decision maker to focus on his or her goals. Keeney's Value-Focused Thinking (1992) suggests individuals view an ideal outcome and the steps necessary to achieve that outcome. Procedurally, an individual starts by thinking of a wish list. The wish list then guides the development of objectives. These objectives listed in a hierarchical order identify all important and consequential aspects of the decision. The fundamental objectives are overarching goals that aid the decision maker.

In an application of the goals problem solving techniques, elementary school students were asked to think about their educational goals by using a Self-Determined Learning Model (Palmer & Wehmeyer, 2003). This model advocates assessing the current or actual situation and compare it to a goal state. The three step process involves 1) focusing on the problem at hand, 2) establishing a course of action to accomplish the goal, and 3) reflecting on the progress in achieving the goal. In an empirical test, elementary school student scores as measured with a goal attainment scale improved on academic and behavioral outcomes (Palmer & Wehmeyer, 2003). The approaches of Self-Determined Learning Model and Value-Focused Thinking focuses the individual on what he or she wants to achieve and uses these goals to guide behavior.

Product Problem Solving Technique

The approach for the second technique is to have a decision maker think about the object or product. This technique is a compilation of multiple techniques. The object-focused technique includes a suggestion to decompose the problem into parameters (Allen, 1962), drop all constraints and envisioning a perfect solution (Keller & Ho, 1988), and visualize in detail to implement the idea (de Bono, 1992). Instructions to participants will consist of a combination of these strategies.

de Bono has written extensively on problem solving approaches. One approach is the Six Hats technique where an individual "puts on" a metaphorical hat. Each hat connotes a type of thinking style (de Bono, 1999). For example, an individual may put on a "yellow hat" to take a logical position to identify why a product might work for a particular solution. At another time, he or she may put on a "blue hat" to examine the overall process to create a product. de Bono identifies that the hat approach provides an opportunity to switch thinking allowing individuals time and opportunity to decide (de Bono, 1995).

Uses Problem Solving Technique

Finally, the third technique is a variation of Guilford's (1967) "alternative use test" that looks at multiple uses of the object. Guilford focused on the psychometric aspects of problem solving (Guilford, 1950). His emphasis was on divergent and convergent production in problem solving tasks. In a similar approach, Finke (1995) describes "convergent insight" that converges on a unifying pattern or "divergent insight" that diverges from a particular form. The divergent insight technique identifies what kinds of uses may be found for a particular item (Sternberg, 1999). This technique is used to explore how individuals develop new products. This technique explores the divergent production or insightful approach to problem solving.

For this examination, the uses problem solving technique will have individuals focus on how they would use the product. For example, would you use a pair of athletic shoes for working out or for causal dress? In a pre-test, we found individuals had many different uses for different products. Since we want to compare problem solving instructions across different product types, the instructions were not product specific.

Testing Problem Solving Approaches

Interactive Choice – Testing Environment

Unstructured decision making is a dynamic process. As such, the deliberate processes of thinking, considering, and selecting an item can influence the selection of another item. Investigations of an individual's dynamic decision making process have been difficult. However, technology and specifically the Internet allow researchers to investigate this unexplored area of human behavior. These tools make it possible to ask questions researchers could not previously address (Crow, Shanteau & Casey, 2003). Technology allows individuals the ability to do things not previously thought possible. Thus, the Internet provides an ideal tool to explore unstructured decision making.

Interactive Choice is a web-based program developed for this project to test unstructured decisions. Participants access the program remotely presumably in a setting replicating a "natural" decision environment. At the same time, *Interactive Choice* maintains experimental control over the investigation such that procedures and methodologies enable quality data. For instance, the data is checked for multiple participant submissions (Birnbaum, 2000, 2001; Reips & Bosnjak, 2001).

A criticism of online studies concerns the reliability of the results. This is especially problematic for studies that are available to anyone with access to the Internet. Some investigators choose to reduce bias by using online panels. A problem is that the study may over or under represent certain groups (i.e., gender, age, income, etc.).

Unlike other online survey or experimental websites, the methodological protocol of *Interactive Choice* dictates knowing participants identity and examining questions relevant to the subject pool and application. Unique to *Interactive Choice*, participants are presented with multiple stimuli in random order minimizing order effects. *Interactive Choice* disables the web browser's back button so participants cannot compare previous answers. Multiple measures are gathered including behavioral actions and response ratings. Different rating methods include use of radio buttons, open-ended responses, and slider bars to reduce response errors or biases. *Interactive Choice* has gone through extensive testing to create a lab-like environment in a natural setting.

Product Customization – Testing Application

Just as technology and the Internet benefits researchers, it is also benefits consumers. Individuals have greater access to more products in a more convenient method. As well, the dynamic nature and the interactive of the Internet means that an individual does not need to rely on just one variation of the same product. Individuals can create their own unique options or products.

Customization is an unstructured decision making task. When an individual goes to a website that offers product customization, he or she must generally make multiple selections. These selections may be ones an individual perhaps has never previously considered. In the earlier example, Laura who wore jeans most of her life, had never considered her preference for many of the features (i.e., yarn stitching, fabric finishes, etc.). In addition, selection of one option or attribute influences the selection of another. As an individual customizes a product, the exact specifications of the product are not set in advance. The individual may know that he or she is getting a pair of jeans but may not know what it will look like on her or how to select the options.

Customization is different from personalization. Many times these terms are used interchangeably. However, from an individual's perspective they are distinctly different. In personalization, a company offers a "specialized" product with the anticipation that the consumer will view it as an item unique to him or her. For example, an individual buys a book at Amazon.com. When he or she returns, the website recommends books similar to the previous purchase. In this case, the *firm controls* the outcome. On the other hand, when a consumer customizes an item, he or she *controls* the outcome (Newell, 2003). The consumer picks and choose the desire outcome. Customization is a growing area. It is estimated that 5% of companies currently offer some form of customization with approximately 20% to soon offer customization (Solomon, 2003).

Testing Hypotheses

Testing problem solving instructions for unstructured decision making is possible by using *Interactive Choice*, an interactive web-based program created for this investigation. The aim of the investigation is to identify whether problem solving instructions will assist a decision maker. As well, specifying what problem solving technique (goal, product, or uses) can aid the decision process. The investigation uses three measures to assess the effect of problem solving instructions on decision making. Two of the measures are ratings of the product (i.e., likelihood to purchase) and process (i.e., difficulty to customize). The third is a behavioral measure used to create products. These are discussed in the following section.

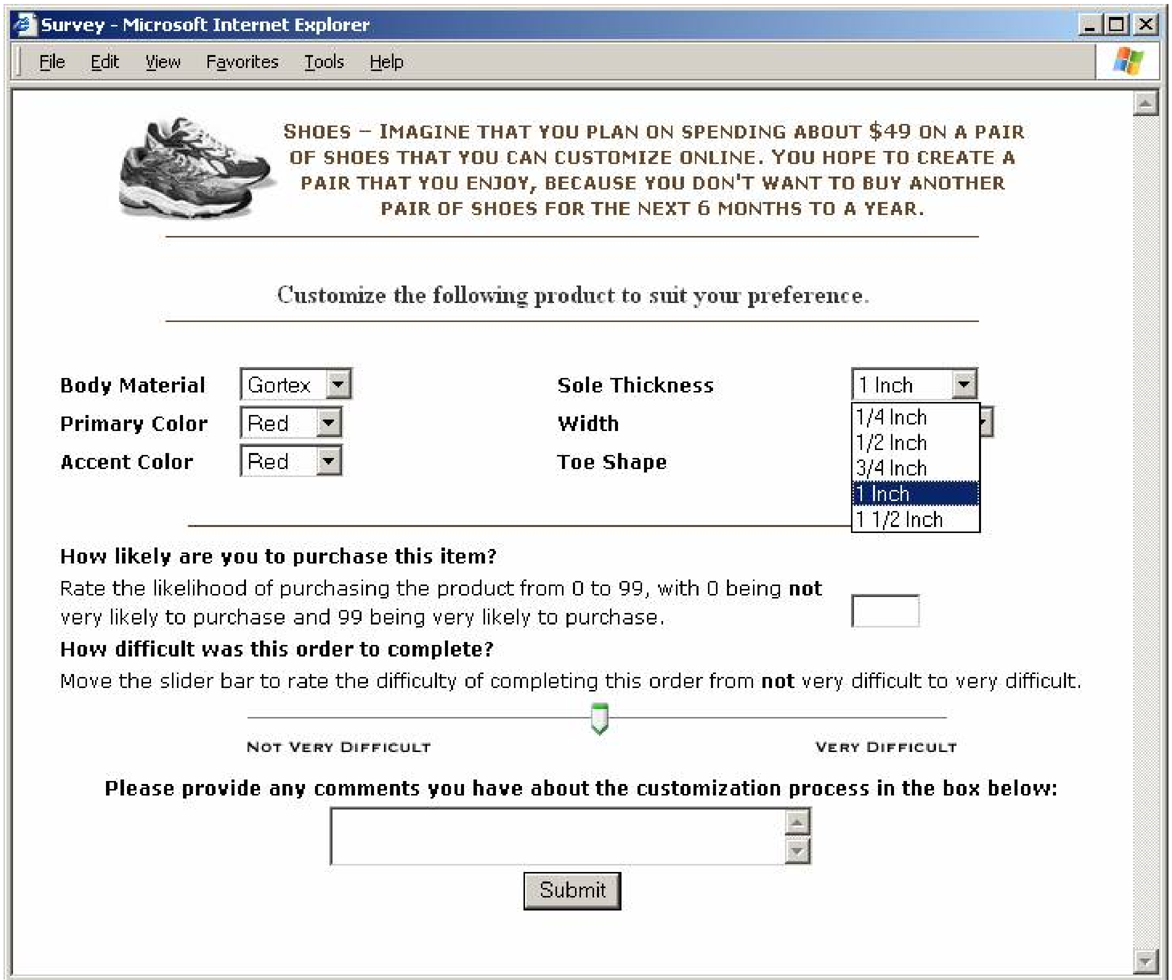
It is anticipated that individuals will be more favorable to the product and process of creating it when given problem solving instructions. There are no specific predictions for what technique is more helpful to the decision maker. In addition, it is anticipated that the presentation of attribute information will influence decision making. Previous investigations found that individuals prefer having a start or default value when customizing a product (Crow, 2005a). This investigation explores whether providing a default interferes or assists in the decision making process. There is an expectation that when providing default values individuals will rate the product and process more favorably.

Methods

A 4 (instructions) x 2 (default format) x 3 (products) mixed repeated measures design was used. The instructions and default format were between subjects factor and products was a within subjects factor. Participants were randomly placed into one of three problem solving instructions conditions or a control condition. The problem solving instruction focused the participants on their goals, the product, or uses of the product. The text was written for an individual with the reading level of a sixth grade education and was pre-tested to assure comprehension.

Participants were presented attributes with defaults or without defaults. Figure 3.1 illustrates a pair of shoes with defaults provided. The drop-down box for sole thickness lists the attribute levels a participant can select. The 1 inch sole thickness located to the right of the page was the default. Participants choose the default or another attribute from the list. The defaults were pre-tested to be neutral in preference desirability i.e., not the least or most favored attribute. For participants receiving the non-default option, the drop-down box was blank and participants were encouraged to select the attribute of their choice. All other information was identical to the default pages (i.e., attributes, product description, etc.).

Figure 3.1 Stimulus page for shoes with defaults provided



The products participants customized are commonly used by the subject pool of young adults. Participants created cellular phones, pizzas, and shoes. Special attention was paid to elements of the decision known to influence consumer decision making (i.e., brand names and pricing). Research identifies that consumers use brand names as a cue when evaluating product attributes (Maheswaran, Mackie, & Chaiken, 1994). Therefore, instructions explained that the products were brand named products, but the names were withheld for proprietary reasons.

In addition to brand names, product prices can influence consumer investigations. Studies demonstrate consumers use price as an indicator of quality (Monroe, 1976). Omitting pricing information, however could lead participants to wrong assumptions. Thus, a price was shown for the products as displayed in the upper portion of Figure 3.1 describing the product. The price of the product was based on the typical cost from retail, mail order, and online catalogs ($200 cell phone, $49 shoes, $12 pizza). In previous examinations exploring the effects of default values, the price used for cell phones was $250. Prior to this investigation, prices of cell phones dropped and the new price was reflected in this examination.

The attributes participants customize are price-neutral. That is, it does not cost more to select one attribute level over another. For example, when selecting the color of a pair of shoes at Nike's website, there is no additional charge to choose a blue over a red accent color. Many websites offer such price neutral attributes. Other investigations have explored price specific attribute choice (Park, Jun & McInnis, 2000; Liechty, Ramaswamy, & Cohen, 2001). Little exploration has been conducted with price-neutral attributes.

The products vary in the amount of customization currently available. A pizza when ordered is commonly a customizable product. Shoes typically are purchased "as-is". However, some websites offer customizable shoes (www.nikeid.com, www.adidas.com). Presently, cell phones are currently not customizable. Cell phone services may be customized, but the phone itself is not.

Measures

Three dependent variables measured the effects of problem solving instructions on unstructured decision making. Two of the dependent variables were participants' ratings of the product and the process. These are commonly used variables in consumer studies to identify purchase behavior (Huber, Wittink, Fiedler, & Miller, 1993) and effort in processing consumer information (Johnson & Payne, 1985). However, most studies use one or the other of these measures and only a few use them in combination. To assess purchase behavior, product ratings measure participant's likelihood to purchase the product he or she customized. Using a 100 point scale, participants placed a number from 0 to 99 in the box identified in Figure 3.1 located in the middle-right of the figure. In assessing effort, participants rated the process by identifying the difficulty to customize. Participants moved a pointer on a slider bar to the desired location. The scale endpoints were labeled with the terms "not very difficult" and "very difficult" as is shown at the bottom of Figure 3.1. Each increment of the slider bar registers a point on a scale from 0 to 99. Thus, the range of the scales was identical but participants used different tasks to avoid response halo effects.

A third variable was the behavioral response of selection/de-selection of default values. When a participant customizes a product, he or she can select the default or another attribute in the list. The investigation explores this behavioral response. In addition, individual difference variables of gender, age, and product experience were collected. These variables were analyzed separately.

Procedure

Participants were upper level students from a University general education course with diverse educational backgrounds. In exchange for participation, students received course credit. Students in the course were emailed a link to the *Interactive Choice* website. In the email, participants were told their participation would help determine the effectiveness of online ordering systems for personalized products. They also were informed of the products they would be designing. The methodological approach of soliciting volunteers via an email that links participants to the *Interactive Choice* website assumes participants complete the experiment in familiar surroundings on their own time. Thus, it was likely to replicate the environment of an actual consumer decision.

Once at the website, a participant received an instruction page describing the study's purpose and the task. Participants were asked to confirm they read the informed consent before proceeding to the experiment. At this point, a participant was randomly assigned to one of four instructions conditions, either one of the three problem solving conditions or a control condition. The instructions were presented on the product page. Then the participant was presented with one of three product pages as shown in Figure 3.1. Participants received a different random order of product pages. The participant customized each of the three products.

Participants designed each product by selecting its features. For example, to customize a shoe as illustrated in Figure 3.1, an individual would choose the material, color, accent color, sole thickness, width, and toe shape. Next, the participant rated the likelihood of purchasing the product they customized and indicate the difficulty of completing the order by using the pointer on the slider bar. Next, participants had the option of providing comments. This process was repeated for the remaining two products.

After completing the first set of products, participants received another set of the same products in a different random order. They customized the products in the same manner by selecting attributes. On the last page, participants completed demographic information including age, gender, previous online shopping experience, and product experience. In addition, participants answered two questions indicating the helpfulness of the instructions by using a slider bar; one question assessed whether the instructions helped them think about customizing the product; the another question asked if the instructions interfered with their thinking. Finally, participants were thanked, debriefed, and given contact information if questions should arise.

Results

Three hundred ninety participants completed the experiment. There were 185 females, 200 males and 5 unknown. The median age was 21. For each participant, 107 data points were collected including participants behavior and responses to stimuli. To ensure data quality, the data was checked for qualified participants against the participant list. In addition, the data was examined for multiple participant submissions by reviewing the log data from the website's server (Reips, 2001).

The following describes the analysis for all products combined. The analysis was conducted in phases using univariate and multivariate analysis of variance. For the ratings of the product and process, the multivariate analyses did not reveal anything additional. Thus, the following presents the univariate ANOVA analyses for the likelihood to purchase and difficulty to customize. Additional multivariate analyses explain the behavioral response (default retention) on problem solving instructions. For proprietary reasons, the problem solving conditions are labeled as conditions 1 through 3.

Likelihood to Purchase

When participants were presented with defaults and rated the likelihood to purchase significant differences appear between instruction conditions, $F\ (3, 1226) = 5.93$, power = 0.96. Table 3.1 lists the descriptive statistics including 95% confidence intervals. A Dunnett post hoc test compares the control to the experimental problem solving conditions (Keppel, 1991). Dunnett's post hoc reveals significant differences between the control ($\underline{M} = 71.78$) and #1 problem solving condition ($\underline{M} = 78.81$), $F\ (1, 562) = 15.92$, power = 0.98. Table 3.1 identifies the number of participants per condition, means, and confidence intervals for the likelihood to purchase. Figure 3.2 shows the plots for the instruction conditions. In the upper left plot in Figure 3.2 displays the likelihood to purchase when defaults are presented.

When no defaults were present, significant differences appear between conditions for the likelihood to purchase, F (3, 1106) = 2.85, power = 0.68. Dunnett's post hoc tests reveals significant differences between the control (M = 69.83) and the #1 problem solving condition (M = 75.29), F (1, 550) = 7.51, power = 0.78. In the upper right plot in Figure 3.2 displays the likelihood to purchase when defaults are presented.

No significant interactions were identified for the type of product and instructions for the likelihood to purchase, F (14, 2316) = 1.41. As well as, no significant interactions were identified for the type of product and the default/non-default formats for the likelihood to purchase, F (2, 2334) = 1.91.

Table 3.1 Number of participants per condition, means, and confidence intervals for the likelihood to purchase and difficulty to customize

		Likelihood to Purchase			Difficulty to Customize		
			95% Confidence Interval			95% Confidence Interval	
Condition	N	Mean			Mean		
control/default	51	71.78	69.20	74.35	15.50	13.45	17.55
#1/default	43	78.81*	76.58	81.04	20.81*	18.29	23.33
#2/default	57	75.20	72.62	77.78	20.46*	18.23	22.69
#3/default	54	71.71	68.87	74.56	17.65	15.48	19.83
control/non-default	52	69.83	67.13	72.53	16.44	14.21	18.66
#1/non-default	40	75.29*	72.52	78.07	24.61*	21.85	27.36
#2/non-default	39	69.70	66.38	73.03	21.75*	19.03	24.47
#3/non-default	54	71.81	69.03	74.59	17.79	15.59	20.00

* Dunnett’s post hoc identifies significant difference over control, $p < 0.05$

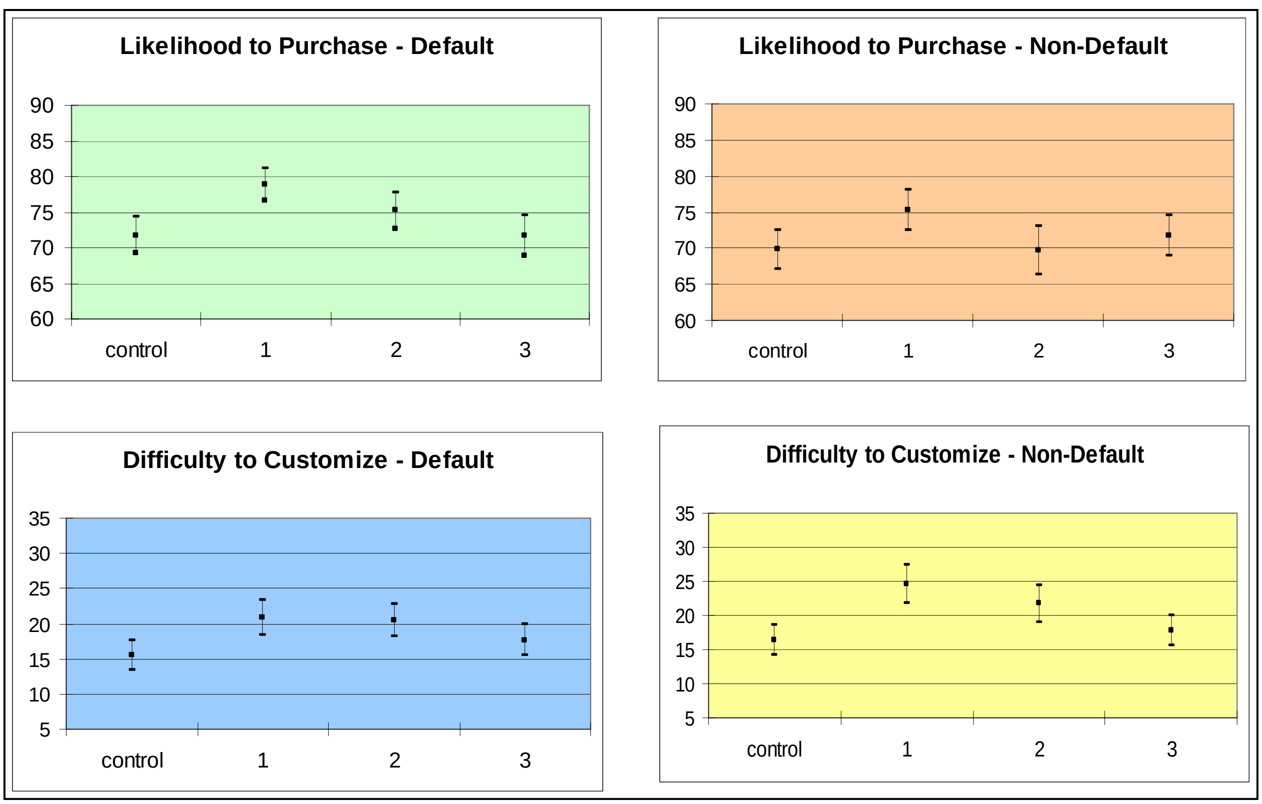
Difficulty to Customize

When exploring difficulty to customize, differences appear between instruction conditions when presenting defaults, F (3, 1226) = 4.78, power = 0.90. Dunnett's post hoc reveals significant differences between the control (M = 15.50) and (a) #1 (M = 20.81) problem solving condition, F (1, 562) = 10.56, power = 0.90 and (b) #2 (M = 20.46) problem solving condition F (1, 562) = 10.23, power = 0.89. Table 3.1 lists the descriptive statistics. In the lower left plot in Figure 3.2 displays the difficulty to customize when defaults are presented.

When presented without defaults, significant differences appear between conditions for the difficulty to customize, F (3, 1106) = 8.81, power = 1.00. Dunnett's post hoc test reveals significant differences between the control (M = 16.44) and (a) the #1 (M = 24.61) problem solving condition F (1, 550) = 21.06, power = 1.00, and (b) #2 (M = 21.75) problem solving condition F (1, 550) = 9.00, power = 0.85. In the lower right plot in Figure 3.2 displays the difficulty to customize when defaults are presented.

No significant interactions were identified for product type and instructions for the difficulty to customize, F (14, 2316) = 0.91. In addition, no significant interactions were identified for product type and the default/non-default formats for the difficulty to customize, F (2, 2334) = 0.78.

Figure 3.2 Instruction conditions plots with means and 95% confidence intervals for the likelihood to purchase and difficulty to customize by default and non-default format



Default Retention

The analysis of the behavioral response shows whether participants retains the pre-defined default values or select another attribute. In addition, the examination explores whether covariates explain default retention. This analysis was conducted on conditions where default values were provided. Thus, four out of the eight instruction conditions were explored.

Selecting or deselecting a default value is a discrete choice. Other variables such as the likelihood to purchase, difficulty to customize, participant's age, and product experience are continuous variables; gender is a discrete categorical variable. For this type of experimental design, logistic regression can predict a discrete outcome from variables that are a mixture of continuous and dichotomous variables (Tabachnick & Fidell, 2000). More importantly, logistic regression models the odds of an event outcome (retention of default values) while estimating the effects of covariates on those odds (O'Connell, 2006).

A forward logistic regression was conducted to determine which variables (problem solving instructions, likelihood to purchase, difficulty to customize, age, gender, and purchase experience) were predictors of retaining defaults. Mahalanobis' distance identified seven multivariate outliers that were removed from further analysis.

The logistic regression results indicate the overall model with four predictors (likelihood to purchase, difficulty to customize, age, and gender) was statistically reliable in distinguishing default retention (-2Log Likelihood = 8056.84, χ^2 (3, N = 7128) = 93.16, $p < 0.0001$). The model correctly classified 74.1% of the cases. However, while these results were significant, the variance accounted for was low, Nagelkerke $R^2 = 0.02$.

Regression coefficients, Wald statistics, and odds ratios for each of the three predictors are presented in Table 3.2. The Wald statistic indicates that gender, product, and difficulty to customize were predictors for default retention. Odds ratios greater than one indicate an increase in the probability of an outcome (Tabachnick & Fidell, 2000). Thus, gender (odds ratio = 1.36) and product (odds ratio = 1.24) were predictors of retaining defaults.

Table 3.2 Results of logistic regression analysis on default retention

Predictor Variable	*B*	Wald Test	Odds Ratio	95% Confidence Interval Odds Ratio *Lower*	*Upper*
Gender	0.31	33.47*	1.36	1.23	1.51
Product	0.21	40.73*	1.24	1.16	1.32
Difficulty to customize	0.01	16.56*	1.01	1.00	1.01
Constant	-2.06	326.92*			

*$p \leq 0.00$

Since the product type and gender were indicators of default retention, further analyses of individual products using logistic regression was conducted. For simplicity, results identify that gender was a predictor for each product type. The odds ratio for gender of cell phones = 1.42; pizza = 1.35; shoes = 1.36. In summary, these results suggest that over one third of the time, gender predicts the retention of default values regardless of product type. Notably, males retain proportionally more defaults than females (cell phone, male 24.2% v females 19.9%; pizza, male 27.6% v females 22.5%; shoes, male 33.6% v females 27.4%).

Examining Problem Solving Instructions

An important question in this analysis was the effect of the specific problem solving instructions on the dependent variables. As shown in Table 3.2, the #1 problem solving instructions were consistently better (higher likelihood to purchase and lower difficulty to customize) for default and non-default format. Thus, analysis of problem solving instructions was conducted with participants in the #1 condition for all products combined. In addition, because participants were more "favorable" toward default values, only the default/#1 problem solving conditions were explored.

An approach to understand the relationship of problem solving instructions with multiple measures is cluster analysis. Cluster analysis is an exploratory technique that groups variables by identifying distances. Distances reveal similarities and dissimilarities of variables (Norusis, 2006). A common approach especially in consumer research is to cluster participants into groups (Punj & Stewart, 1983). However, cluster analysis can explore relationships between variables

(Cramer, 2004). Hierarchical clustering analysis identifies similarities and dissimilarities of variables and with variables measured using different scales (Norusis, 2006). This type of clustering analysis divides stimuli into subsets by describing each subset as “a meaningful feature of the stimuli” (Davidson, 1983, p. 208) or more specifically the problem solving instructions. In this examination, cluster analysis was used as an exploratory approach, similar to other multivariate techniques that combine dependent variables and covariates (i.e., logistic regression). The purpose of the analysis is not to prove differences between treatment effects (i.e., problem solving instructions) but rather the relationship of the variables within a problem solving technique.

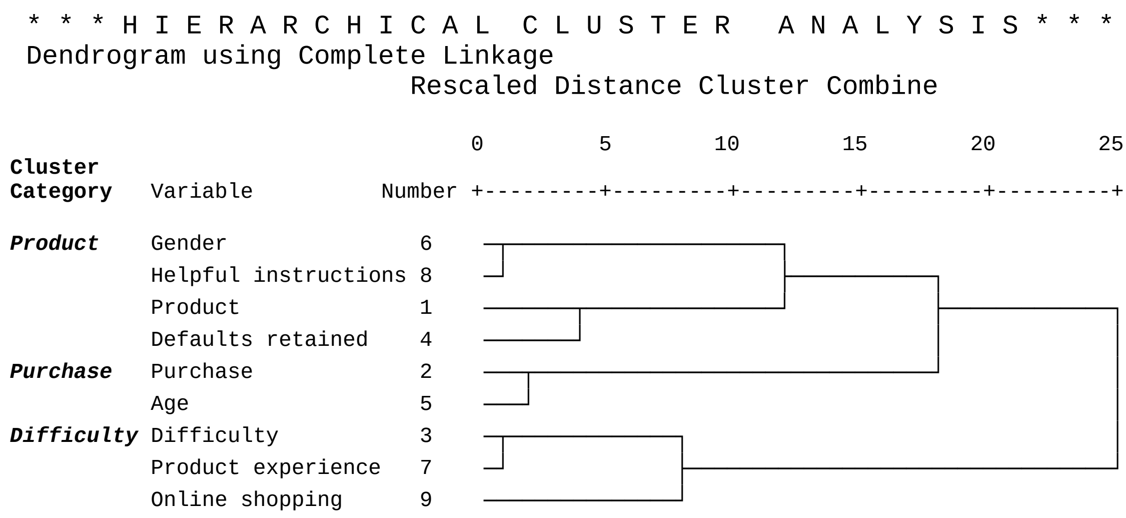
A hierarchical clustering analysis was conducted using complete linkage (furthest neighbor) method with the squared Euclidian distance (Norusis, 2006). The raw scores were standardized using a z-score to accommodate discrete and continuous variables measured on different scales (Norusis, 2006). Table 3.3 lists the proximities of the variables. For example, the first column identifies the distance between the product type and the likelihood to purchase (594.08) and the difficulty to customize (527.06). The variables with the greatest distance were the likelihood to purchase and difficulty to customize (688.55) displayed in column two. In the sixth column, gender and helpfulness of instructions have the shortest distance (410.79) of the variables.

Table 3.3 Cluster analysis proximity matrix for the #1 problem solving/default condition, all products combined

	Product type	Purchase	Difficulty	Defaults retained	Age	Gender	Product experience	Helpfulness of instructions	Previous online shopping
	1	2	3	4	5	6	7	8	9
Product type	0.00								
Purchase	94.08	0.00							
Difficulty	27.06	88.25	0.00						
Number of defaults	51.88	99.63	14.33	0.00					
Age	14.00	31.48	29.19	94.77	0.00				
Gender	14.00	75.32	67.04	35.90	65.80	0.00			
Product experience	18.80	21.48	19.23	41.80	72.97	71.68	0.00		
Helpfulness of instructions	14.00	94.70	50.64	37.57	91.76	10.79	46.60	0.00	
Previous online shopping	14.00	67.03	95.76	92.36	12.79	20.44	66.82	33.95	0.00

The proximity matrix can best be explained with a dendrogram that graphically displays the distances and relationships between the variables identified by the proximity matrix (Norusis, 2006). Greater distances shown in Figure 3.3 indicate dissimilarities where as, shorter distances reflect similarities between the variables.

Figure 3.3 Dendrogram hierarchical cluster analysis



The grouping of the clusters was identified by the variables with the greatest distance within a cluster. The three main clusters are labeled as *Product, Purchase,* and *Difficulty* to the left of Figure 3.2. The analysis to the right of the category label identifies the variables in each cluster and the distances as illustrated in the diagram. The *Product* cluster describes similarities with the type of product, gender, number of defaults retained, and helpfulness of the instructions. The second cluster, *Purchase*, in the middle of Figure 3.3 groups the likelihood to purchase with the age of the participant. The third cluster, *Difficulty*, groups previous online purchase experience and product experience with the difficulty to customize. These clustering results suggest that participants view the product, the likelihood to purchase, and difficulty to customize as unique dimensions of the decision.

It is important to note that the clustering of variables was supported by other analyses in this phased investigation. Specifically, logistic regression identifies that gender and the type of product were grouped together when exploring default retention. In addition, other analyses reveal that participants view the likelihood to purchase and the difficulty to customize differently.

Discussion

The investigation reveals problem solving instructions have an effect on unstructured decision making. Differences appear between the control and problem solving instructions for the product and process measured by the likelihood to purchase and the difficulty to customize. The biggest effect, related to the control condition, was for the #1 problem solving condition. For those in the #1 condition when defaults were presented, participants rated the likelihood to purchase higher than without defaults. Differences also appear between the control and the #2 problem solving condition.

Intuitively, one would expect as the likelihood to purchase increases that difficulty would decrease. However, the opposite occurred such that when the likelihood increased difficulty also increased. Incidentally, this relationship was appears in previous examinations (Crow, 2000; Crow, 2005b). The relationship perhaps taps into different dimensions of unstructured decision making. Possibly, individuals who create their own products may view that working harder means they are more pleased with the outcome. Support for this proposition comes by exploring the relationships between variables using cluster analysis. This analysis reveals greater distances between the likelihood to purchase and the difficulty to customize. Thus, suggesting consumers view these dimensions differently.

Default values have an influence when presented with problem solving instructions. Previous explorations show individuals were more favorable when presenting default values (Crow, 2000). The present examination reveals higher ratings of the likelihood to purchase and difficulty to customize in the default than the non-default condition. Thus, providing a starting point with a pre-set default value requires less effort to make a decision (Johnson, Bellman & Lohse, 2002). An implication of these results is that vendors should provide neutral default values.

Certain predictors emerge when presenting default values with problem solving instructions. Specifically, gender and product type were likely to predict default retention. Males retained proportionally more defaults than females. Even though the overall proportion retained was small (24%-34%), remember that the default values were neutral. These results may suggest one of two things. The defaults may have a greater influence on males or males took a less effortful strategy to create a product.

In logistic regression to explain the odds of an outcome such as default retention, the Chi-square statistic tests the likelihood of the overall model and the Wald statistic tests the significance of individual predictors (Tabachnick & Fidell, 2000). In this analysis while the individual predictors and the overall model is significant, the small R^2 indicates other explanatory variables in addition to product type and gender may be helpful to predict default retention, see O'Connell (2006) for a similar study and explanation.

Ultimately, this body of research attempts to identify variables than can assist an individual with an unstructured decision. These variables can be used to design a decision aid. Detailed analysis of the problem solving instructions reveals relationship of variables that are a precursor to defining a decision tool. Of special interest was presence of default values. When presenting defaults, it is important to consider the type of product and the gender of the consumer. Because likelihood to purchase and difficulty to customize were different aspects of unstructured decision making, there must be a balance between these elements. A vendor does not want to increase the difficulty at the expense of purchase intent. This investigation suggests that in order to minimize difficulty, it was necessary to know an individuals' product and online shopping experience. Age of the decision maker was also a consideration. Therefore, an effective decision aid must be tailored for individual products and adaptable to individual consumer characteristics.

The results of this investigation could be applied in different decision environments. An individual may or may not use technology to make a decision. In a non-technological environment, an expert may aid the decision maker by providing guidance for disposing of nuclear waste, for example (Brown, 2005). In retail brick and mortar stores such as Creative Leather, a salesperson is available to answer questions or guide the decision maker in creating a custom sofa. The present investigation suggests when helping a customer, problem solving instructions can aid a decision maker. As well, providing a starting point makes the process less difficult.

In environments where it is possible to use technology, these results are vital. For example, the rise of self-service technologies allows employees to enroll themselves in insurance plans, students to apply for and enroll in college online, and consumers to checkout their own groceries. Can an electronic decision aid enhance human interaction? From these findings, it appears perhaps possible. As self-service technologies replaces humans these questions become imperative. One such self-service technology is product customization. Product customization is not something for the future. It is here now (Solomon, 2003). As such, it is crucial to understand and develop technology that can help and not hinder the decision making process.

Problem solving approaches in general requires that an individual find, evaluate, and implement of an idea. This examination explores only the latter two stages (evaluation and implementation). Although the investigation replicates an immediate decision task, it does not explore the first stage of problem solving. To understand unstructured decision making processes, it is necessary to explore individuals seeking an ideal option without defined attributes. For example, having an individual address what he or she would like for ideal pair of shoes. In this case, features like arch supports or fabric colors are not offered as a starting point. A challenging but interesting question is to understand the cognitive processes when an individual is free to design a product.

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CHAPTER 4 - COGNITIVE EXPLANATIONS OF UNSTRUCTURED DECISION MAKING

"There is a fine line
Between recklessness and courage
It's about time
You understood which road to take
It's a fine line
And your decision makes a difference
Get it wrong you'll be making a big mistake

There is a long way
Between chaos and creation
If you don't say
Which one of these you're going to choose
It's a long way
And if every contradiction seems the same
It's a game that you're bound to lose

Whatever's more important to you
You've gotta choose what you want to do
Whatever's more important to be
Well that's the view that you got to see"

Fine Line
Paul McCartney

The song *Fine Line* captures the essence of unstructured decision making. Former Beatle Paul McCartney (2005) writes it is "*time to understand which road to take"* that "*your decision makes a difference. Getting it wrong could be a big mistake."* The song suggests to know *"what you want to do"* you should "*choose…what is important"* to you.

Knowing and choosing what is important may be a challenge (Svenson, 1990, Fischhoff, 1996; Beach & Mitchell, 1998) especially for decisions not previously encountered (Mintzberg, Raisinghani & Theoret, 1976). Decisions that are familiar and directly experienced are less difficult (Fischhoff, Slovic, & Lichtenstein, 1980). When an alternative is lacking and individuals must identify "*what's important*" to them, "*there is a fine line…between chaos and creation."*

Cognitive Processes

Interactive Choice makes exploring unstructured decision making possible with a web-based simulation of product creation. The phased examination finds individuals rarely retain pre-selected defaults and problem solving instruction influences decision making. These results can help explain the cognitive processes involved as well outline a new theoretical approach to unstructured decision making.

To explain the cognitive processes involved, it is necessary to discuss them in a context. Unstructured decision making is a complex, dynamic process of creating an alternative. Processes are different for creating an alternative than selecting from existing alternatives (Maier, 1960; Svenson, 1990). Little known is about creating alternatives while more research examines selecting from existing alternatives.

Cognitive processes in unstructured decision making are *active* processes. The dynamic nature of evaluating and implementing an idea suggest that individuals cannot solely react to given alternatives. As a result, individuals maintain a personal investment in their selection of attributes. The domain of unstructured decision making means that individuals are more involved and have more control of the outcome. Whereas, when selecting from an existing set of alternatives, the decision maker has less control and is more likely to be prone to context influences that include default values. In addition, focusing individuals with problem solving instructions can lead them perhaps to understand their preferences better.

A Theory for Unstructured Decision Making

The investigation builds on the assumption that individuals seek an ideal option (Beach, 1998) with a single-peaked preference for that ideal (Coombs, 1964). This dissertation finds that the presentation of information and the preparation by the decision maker influences unstructured decisions. Extending beyond on these results, this dissertation proposes a theory for unstructured decision making.

The essence of a proposed theory is that decision makers identify their values to arrive at a decision. Values define an ideal point. Values can be thought of as preferences. While much work has been done on preference formation, models do not address when preferences change (Slovic, 1995). This is especially important in dynamic decision environments.

When exploring preferences between alternatives, one contention is that individuals hold preferences for basic attribute combinations and during the decision process construct preferences for other attributes (Bettman, Luce, & Payne, 1998). Alternatively, individuals construct consistent decision strategies but because of different contexts, preferences change (Amir & Levav, 2005).

The assertion of this dissertation is that in dynamic environments individuals use both approaches. That is, individuals must <u>construct decision strategies as well as preferences</u> while creating an alternative. It is assumed a decision maker has some decision making strategies developed and some preferences developed however, there are aspects of the decision unknown.

To get to an ideal point, a decision maker must develop a strategy to achieve the desired outcome. Through an active process of acquiring and evaluating information, an individual forms a strategy and updates their values. Thus, the catalyst for making a decision is an updating mechanism that solidifies decision makers' values.

The theory recognizes this updating process builds from the decision maker's base knowledge and experience. In a Bayesian updating decision making approach (i.e., Edwards, 1954), using an iterative process an individual gains more information that he or she considers and evaluates. The information is used to from a strategy of how to choose while forming preferences. As the individual gains more information, values congeal. As some point, the clarity of the individuals' values crystallize to where the decision maker "discovers" his or her values and thus, able to make a decision.

Choice Builder **– A Decision Aid**

While the emphasis of this investigation is to understand the cognitive processes of unstructured decision making, an outcome is a decision aid called *Choice Builder*. Overall, a decision aid's objective is not to prescribe a particular choice but to improve the process from which a decision may emerge (Brown, 2005).

In 1772, Benjamin Franklin wrote to Joseph Priestley describing how to make a decision. He explained that individuals should evaluate the pros and cons of the decision until the best option becomes apparent (Bigelow, 1877). In addition to Franklin, others have followed his footsteps to define decision aids, most notable Ward Edwards' multiattribute utility assessment (Edwards, 1977). In this vein of improving decision processes, *Choice Builder* is an electronic decision aid that helps an individual through an unstructured decision process. The ultimate goal of the tool is for decision makers to think clearly through the decision so they may reach their ideal outcome.

The relevancy of this investigation and the need for a decision aid becomes apparent when explaining how a consumer selects a product. In addition, compounding this decision process is the changing dynamics around how a consumer makes a decision. First, individuals must choose from a broader selection of products. In a period of 12 years, consumer packaged goods such as toothpaste, shampoo, aspirin, etc., grew six fold from 4,414 to 24,965 items (Federal Reserve Bank of Dallas Annual Report, 1998). With an overabundance of options, research suggests consumers are overwhelmed by too much choice to the point of becoming frustrated (Huffman & Kahn, 1998; Iyengar & Lepper, 2000; Schwartz, 2004). Individuals may engage in self-limiting strategies such as "precision shopping" where shoppers visit fewer stores on a less frequent basis and demand more convenience, service, and functionality (Kerin, Hartley, Berkowitz &, Rudelius, 2006).

Second, customers must carry out additional work to complete a transaction. More and more companies in order to reduce costs require customers to do part of their work. For example, as customers clear tables at fast-food restaurants, businesses reduce or eliminate staff time, thus cutting costs. The importance of a decision aid is necessitated by 1) a larger assortment of products, 2) more companies adding self-service technologies (i.e., ATM's), and 3) technological advances allowing consumers more options to create an ideal outcome. As well, it is necessary to understand the impact of technology on decision making. More importantly, growth in customization is expected to increase (Solomon, 2003).

This investigation identifies a framework for establishing a decision aid for unstructured decision making. With the use of *Interactive Choice* maintaining the control of a lab-like environment in a natural setting and a methodology that matches the decision problem to the application (product customization) for the appropriate subjects (young consumers), the project establishes a foothold in creating a decision aid, *Choice Builder*.

Limitations and Future Directions

Limitations and future directions lie in understanding the effects of default values and problem solving techniques on unstructured decision making. For default values, the investigation left some unanswered questions as to when and why the effects occur. A possible explanation may have to do with the attribute itself. Individuals may hold a default because 1) the attribute serves a purpose, 2) the attribute may be important to the decision maker, and/or 3) the decision maker may prefer a starting value. These assumptions were tested during this investigation and are briefly summarized below.

Attributes Serve a Purpose

An attribute may serve a purpose and as such, the purpose may drive individuals to rely on a default value. The attribute's purpose may influence the application of decision makers' goals. The purpose may be that the attribute serves an aesthetic or a functional use. It could be hypothesized that an aesthetic attribute has a degree of attraction attributed to a sensory experience (e.g., sight, sound, smell, taste, and touch) and functional attributes may be necessary for the product to perform. Recent investigations of visual aesthetics (Bloch, Brunel, & Arnold, 2003) and tactual aesthetics (Peck & Childers, 2003) find individual differences for these sensory experiences. This line of research is not new (Thorndike, 1916); however, investigations of other aesthetic experiences (sound, smell, and taste) for products are lacking (P. H. Bloch, personal communication, January 30, 2004).

It was hypothesized that for aesthetic features individuals are more likely to rely on personal preferences and thus less likely to use a default. Conversely, participants may view functional features as necessary for the product to perform and are likely to rely on the company to provide a suggested (default) value. Thus, it was expected that as product features change from a functional purpose to purely aesthetic one, individuals would move from retaining defaults to not selecting default values.

Interactive Choice was used to test this hypothesis. After customizing the products in the problem solving experiment, 126 participants indicated the aesthetic or functional aspects of each attribute. Participants indicated their responses using the slider bar anchored on one end "aesthetic" and the other "functional." The values classifying attributes were used in analyzing the effect of default retention in the problem solving experiment. When incorporating the attribute purpose into the forward logistic regression model, it was not significant in explaining default retention. These results find aesthetic and functional attributes are not a predictor of default retention. The hypothesis that attributes serve a purpose may still be valid. The purpose they serve however may not be because consumers classify them as "aesthetic" or "functional."

Attribute Importance to the Decision Maker

How important an attribute is to a decision maker may indicate whether he or she will retain a default value. If the attribute is important, assumedly an individual is less likely to be swayed by the presence of the default value. Conversely, if the attribute is not important, the default value may influence the selection of the attribute.

Following the problem solving experiment, 205 participants were asked to indicate using a slider bar the importance of each attribute. Anchored of the slider bar were the terms "important" and "not important." The rating scale ranged from 0 to 99. Incorporating attribute importance ratings into the model using a forward logistic regression identifies that the odds ratio (1.00) for attribute importance was not a sufficient indicator to predict whether an individual would retain a default value.

Preference for Starting Value

In another exploration to explain the presence of default values, participants were asked to indicate whether they preferred to have a starting value. Following the problem solving experiment, 183 participants using a slider bar indicated if a pre-selected option would help choose the item. All attributes were rated using a scale of 0 (not wanting) to 99 (wanting). When incorporating the attribute suggestion ratings into the forward logistic regression model, it was not a significant factor in explaining default retention.

In summary, the hypotheses of attribute purpose, importance, or preference for starting value does not explain why individuals retain default values. Further investigation is necessary to understand the effect of these or other factors influencing default retention.

Limitations of Examining Problem Solving Instructions

Methodological constraints can limit the understanding of problem solving instructions on unstructured decision making. One of the limitations is identifying the "appropriate" problem solving technique especially, with a large number of possible techniques available (VanGrundy, 1988). The investigation had participants focus on their goals, the product, or using the product. Other techniques may or may not be effective for choosing an ideal product. Future investigations should explore this possibility.

Throughout this investigation, a consistent finding when explaining default retention and problem solving techniques is that these effects are dependent on the type of product. An obvious direction is to narrow the problem solving techniques applicable for individual products.

Other Directions

It is worth testing the effects found from this investigation to an off-line environment. Does offering a starting value or having a salesperson help a customer through the creation process transfer in a brick and mortar setting? It is also interesting to understand the effects to other populations. What are the cognitive processes of older or younger individuals in an unstructured decision?

Another obvious area of exploration deals with participants' experience. Product experience was not an indicator for default retention. For consistency, experience was measured across all examinations using self-reports of product frequency. Participants were asked to indicate how frequently they purchased an item (never, weekly, monthly, yearly, or greater than 1 year). This measure of product frequency is a common surrogate for product experience (Alba & Hutchinson, 1987). Decision makers' experience may predict default retention. It could be that the method to assess experience was inadequate. With a five-point scale, it is easy to have responses pool around certain categories especially for certain products (e.g., pizza versus cell phones). Product frequency could be assessed by using a larger scale (i.e., 100 point scale) or perhaps a product specific-scale. In another direction, future examinations could assess participant's knowledge of the product as a substitute for experience. For unstructured decision making, knowledge of a domain may be more important.

Conclusions

This dissertation adds four main contributions to the understanding of unstructured decision making. The first contribution is the development of a tool, *Interactive Choice*, to explore unstructured decisions. Second, this investigation provides an explanation of the cognitive process involved. Third, it establishes the groundwork for a theoretical understanding for these types of decisions. Finally, an outcome of this research is an electronic decision aid, *Choice Builder*, to assist individuals with an unstructured decision.

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