MIS Quarterly

RESEARCH NOTE

USING AN ATTRIBUTE-BASED DECISION SUPPORT SYSTEM FOR USER-CUSTOMIZED PRODUCTS ONLINE: AN EXPERIMENTAL INVESTIGATION[1]

By: **Arnold Kamis**
Department of Information Systems and Operations Management
Sawyer School of Management
Suffolk University
8 Ashburton Place
Boston, MA 02108
U.S.A.
akamis@suffolk.edu

Marios Koufaris
Department of Statistics and Computer Information Systems
Baruch College
City University of New York
55 Lexington Avenue, Box B11-220
New York, NY 10010
U.S.A.
Marios_Koufaris@baruch.cuny.edu

Tziporah Stern
Department of Statistics and Computer Information Systems
Baruch College
City University of New York
55 Lexington Avenue, Box B11-220
New York, NY 10010
U.S.A.
Tziporah_Stern@baruch.cuny.edu

[1]Elena Karahanna was the accepting senior editor for this paper. Mike Morris was the associate editor. Ron Thompson served as a reviewer. Two additional reviewers chose to remain anonymous.

Abstract

In the decision support systems literature, most studies have concentrated on the direct effects of DSS use and design on decision outcomes and user performance in the workplace. Fewer DSS studies have integrated decision process variables, such as user beliefs and attitudes, in their models. In this paper, we examine the mediating role of decision process variables in the use of an online customer DSS. We do so through an experimental study of an alternative-based and an attribute-based DSS for product customization by online customers. Using cognitive fit and flow theories, we develop a theoretical model with four mediating decision process variables (perceived usefulness, perceived ease of use, perceived enjoyment, and perceived control) and two of their antecedents: interface design (attribute-based versus alternative-based) and task complexity (choice set size). Our results show that the impact of DSS interface design on behavioral intentions is fully mediated by perceived usefulness and perceived enjoyment, although not by perceived control. Specifically, we verify that users of an attribute-based DSS express higher perceived usefulness and perceived enjoyment than users of an alternative-based one. In addition, we find that task complexity has an interesting relationship with usefulness and enjoyment, both of which follow an inverted U-shaped curve as choice set size increases. Finally, we find that for users of the alternative-based DSS, perceived ease of use and perceived control decrease as task complexity increases. However, the attribute-based DSS alleviates that decline for both variables. Among other contributions, our results indicate the importance of including decision process variables when studying DSS as well as the complex effect of task complexity on those variables. Our

study also provides some important guidelines for online companies that provide customer DSS on their websites, especially the danger of providing too many product choice options that can overwhelm customers and harm their shopping experience.

Keywords: Decision support systems, attribute-based decision support systems, decision process, choice set size, task complexity, perceived control, perceived ease of use, perceived usefulness, perceived enjoyment, customization

Introduction

Online decision support systems that allow customers to configure products and services can significantly affect customer decision making and behavior (Bharati and Chaudhury 2004; Häubl and Trifts 2000). However, most studies of DSS have focused on their use in the workplace and not in online shopping. Also, traditional DSS research has focused mostly on the direct effects of DSS design and use on decision outcomes and user performance (Bharati and Chaudhury 2004; Garrity et al. 2005; Todd and Benbasat 1991, 1992). Fewer DSS studies have integrated decision process variables, such as user beliefs and attitudes (Kamis and Stohr 2006; Lilien et al. 2004; Poston and Speier 2005; Todd and Benbasat 1999), even though they are often included in studies of user behavior, especially in online commerce (Gefen et al. 2003; Koufaris 2002; Koufaris and Hampton-Sosa 2004; Pavlou and Gefen 2004; Van der Heijden 2003, 2004).

The omission of decision process variables in DSS research may be the result of the often-used organizational context for such studies, where process variables such as attitudes may appear less important in the face of mandatory DSS use by employees. Also, if the work-related task has an objective, optimal solution, the focus of attention is on attaining this optimal objective decision outcome and, thus, process variables are of less relevance. However, DSS are used increasingly outside the workplace, such as in online shopping where they are becoming an integral part of the purchase process, and for tasks without optimal solutions, such as preferential choice tasks. As such, understanding the decision process and especially the DSS users' perceptions and beliefs and their impact on attitudes, intentions, and behavior becomes critical and important to the success of online commerce.

In this paper, we examine how four decision process variables mediate the effect of an attribute-based DSS on intentions to purchase from a website and how the attribute-based DSS moderates the effect of task complexity on such relationships. More specifically, we present a study that compares an online ***attribute-based decision support system*** (ABDSS) for product customization with an alternative-based system. We develop a theoretical model that augments the traditional DSS research model by including four mediating decision process variables: perceived usefulness, perceived ease of use, perceived enjoyment, and perceived control. Such subjective measures of the user experience with online information systems have been used in multiple IS studies that have stressed the importance of both cognitive and affective perceptions, especially in the context of online shopping (Gefen et al. 2003; Koufaris 2002; Koufaris and Hampton-Sosa 2004; Pavlou 2003; Pavlou and Gefen 2004; Van der Heijden 2003, 2004). Our four process variables include both cognitive (perceived usefulness and perceived ease of use) and affective (perceived enjoyment and perceived control) measures of the user experience with a customer DSS.

Though many different aspects of DSS for online shopping exist, we focus on use of DSS for product customization, which is an aspect of interface design. Specifically, we compare an alternative-based DSS interface with an attribute-based one. Non-directive attribute-based decision support systems are commonly offered by online companies for multi-alternative, multi-attribute preferential choice tasks (Lilien et al. 2004; Todd and Benbasat 1999). One such task is user customization of products, which are manufactured in mass customization facilities (Davis 1987; Ives 2003; Pine 1993). Users are presented with all of the available choices of attributes and values per attribute and allowed to custom-design the product. For example, users are presented with the color choices of each customizable part of a shoe at NikeID.com. Users then make their choices for each attribute and are presented with an image of their customized product. They can experiment as much as they want until they feel that they have created a satisfactory customized product.

Further, since user DSS strategies, behavior, task performance, and decision outcomes change as task complexity increases (Häubl and Trifts 2000; Jarvenpaa 1989; Speier and Morris 2003; Vessey 1991), we examine the effect of task complexity on decision process variables. Task complexity has been studied extensively in decision-making research, where it has been operationalized as the number of alternatives and attributes (Olshavsky 1979; Payne 1976; Payne et al. 1988). When making a choice, cognitive capabilities are used to retain each potential option and the individual's preferences. Therefore, when there are a large number of alternatives and/or attributes, the decision task is more complex than one with fewer alternatives and/or attributes. Hence, the number of alternatives and attributes directly affect the complexity of the choice making task (Swait and Adamowicz 2001) and, thus, in this study we use choice set size (i.e., the number of product versions available) as a proxy for task complexity.

In the next section we introduce the research model, present the study's variables, and develop our hypotheses. We follow that with the description of the research design and measurement instrument, data analysis, a discussion of our results, and our study's contributions and limitations.

Research Model and Hypotheses

The theoretical model for the study is presented in Figure 1. The model suggests that the effect of attribute-based DSS use (as opposed to alternative-based DSS) on decision outcomes (intention to purchase and intention to return) is fully mediated by the decision process variables of perceived usefulness, perceived ease of use, perceived enjoyment, and perceived control. Further, use of an ABDSS moderates the effect of task complexity (choice set size) on several decision process variables. Finally, nonlinear effects (inverted U-shaped curves) are hypothesized for the relationship between task complexity and perceived usefulness and perceived enjoyment. We develop the rationale for these relationships below.

The theoretical basis for our examination of the difference between an alternative-based and an attribute-based customer DSS comes from cognitive fit (CF) theory (Vessey 1991). CF theory was first proposed in order to explain how matching problem representations (such as tables, graphs, and matrices) to different tasks can improve problem solving. Human information processing theory suggests that due to the limits of human information processing, reducing complexity enhances problem solving (Newell and Simon 1972). Vessey (1991) proposed that technology could be used to reduce complexity when there was a good fit of the task with the information or problem representation. The result is more efficiency and effectiveness, manifested as increased accuracy and speed in problem solving. CF theory has been applied and validated in a variety of contexts, such as online shopping behavior (Hong et al. 2004) and software comprehension and modification (Shaft and Vessey 2006).

The concept of cognitive fit has been used to explain user behavior and predict the speed and accuracy of decision-making and problem solving. For example, when the information format matches the task, users are able to search the information space more efficiently and have better information recall (Hong et al. 2005; Huang et al. 2006), thus lowering the cognitive costs and increasing the benefits of the interface (Jarvenpaa 1989). However, the relationship between cognitive fit and user beliefs and attitudes has not yet been examined. Given that the context of interest is online shopping and given that the outcome of interest is intentions to purchase and intentions to return to the site, this becomes an important set of relationships in the nomological network. According to the theory of planned behavior, the effect of technology on behavior is mediated by user beliefs and attitudes toward the behavior (Ajzen 1991). Therefore, to understand how the cognitive fit between the manner in which ABDSS represents information and the consumer task of product customization affects purchasing behavior, we must first understand how it directly affects user beliefs and attitudes.

The decision-making task for product customization in online shopping is a preferential choice task (Zigurs and Buckland 1998) of selecting or creating a customized product. The subjects create a product that satisfies their needs or desires by processing multiple types of information and there is no objective, optimal solution. Multiple alternative solutions exist and subjects may compare and evaluate multiple alternatives before settling on a single one. Given the information-processing complexity of our task and based on CF theory, we expect that a technology that reduces that information complexity will be preferred by our subjects. We test two types of DSS for product customization. The first is an alternative-based DSS, which simply displays all of the possible product alternatives to the users who can then pick out the product alternatives they prefer. Users do not actively customize the product themselves. The second type is an attribute-based DSS (ABDSS), which presents users with all of the product attributes that can be customized along with all of the possible values for each attribute. Users then customize their product by selecting a value for each customizable attribute while the ABDSS continuously presents them with an image of their customized product.

We propose that the ABDSS reduces complexity more than the alternative-based DSS and is the preferred interface for the multi-attribute, multi-alternative preferential choice task of product customization. One reason is that with the ABDSS, users can immediately see the product's attributes (e.g., color) and their values (e.g., green) and they can construct their most preferred choice. In contrast, alternative-based DSS users must infer both what the customizable attributes are, as well as the different values for each attribute, by scanning all of the different product versions and deconstructing them. This process is called ***intuitive regression*** (Meyer 1987) and is more cumbersome and inefficient than using an ABDSS.

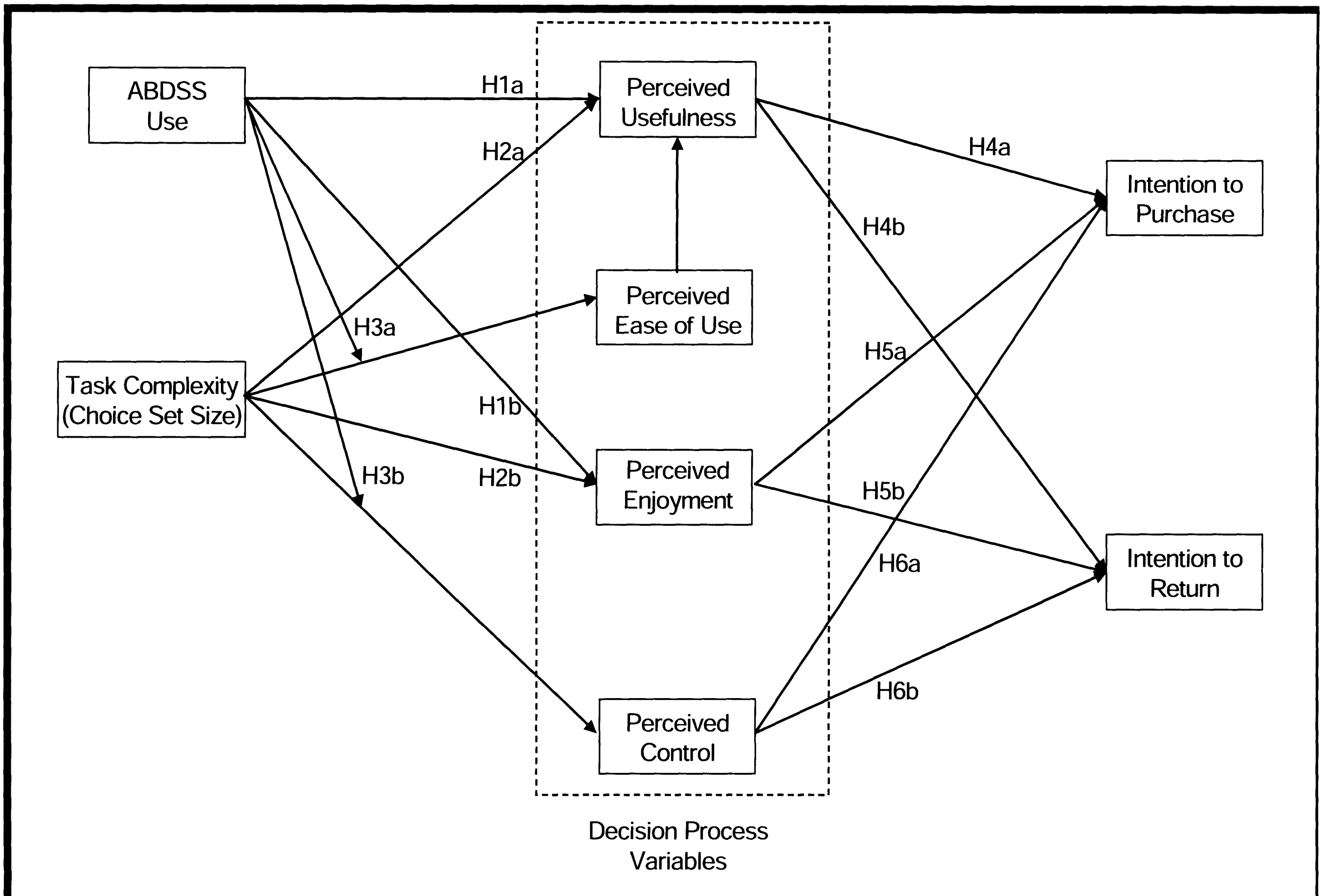

Figure 1. Research Model

A second reason why an ABDSS reduces complexity is that it can provide more accurate representations of the choice set size. For example, a product with 3 customizable attributes that have 5 values each can have 5^3 or 125 different product versions. Users of the alternative-based DSS would face 125 different alternatives and would perceive the task complexity as much higher than someone using an ABDSS that presents only 15 different choices (3 attributes × 5 values each). An ABDSS allows the user to perceive the actual variety of the product, thereby reducing the perceived complexity of the task (Huffman and Kahn 1998; Kahn 1998).

These assertions are supported by empirical studies that have compared ABDSS with alternative-based DSS for similar types of choice tasks. For example, Huffman and Kahn (1998) found that subjects using an ABDSS remembered more choices for each attribute, perceived the choice set as less complex, and made decisions more efficiently than those using a simple list of alternatives. In addition, the subjects were more satisfied with their decisions and the information gathering process.

We believe that one impact of the reduction in information complexity through the use of an ABDSS will be the increase of perceived usefulness of the system. Perceived usefulness is defined as the degree to which users perceive a particular system as enhancing their performance (Davis 1989). In general, DSS use can increase perceived usefulness directly or through perceived ease of use (Todd and Benbasat 1999). However, these effects depend on the fit between the task and the DSS. In general, a good fit between the task and the system used has been shown to have a direct and positive effect on perceived usefulness, including in the context of online shopping (Klopping and McKinney 2004). As argued earlier, an ABDSS is more appropriate for our task because it reduces the complexity of the information needed for the choice task. As information processing complexity is reduced, the effectiveness and efficiency with which users can customize products to their needs increases. Therefore, an ABDSS should increase perceived usefulness more than an alternative-based one. Thus,

H1a: *ABDSS use is positively related to perceived usefulness.*

We believe that good fit can also positively impact affective perceptions. One such perception is perceived enjoyment, which comes from the flow literature and has been used as an affective measure of the individual experience, including in web environments (Csikszentmihalyi 1975, 1977; Hampton-Sosa and Koufaris 2005; Koufaris 2002; Novak et al. 2000). It is defined as the intrinsic enjoyment of the interaction with the website and has been shown to be an important factor in technology acceptance, particularly in business-to-consumer e-commerce. In a state of flow, the user loses self-consciousness, because he or she is immersed in the task. An attribute-based DSS that gives continuous interactive feedback (a pre-condition for flow) through a visual representation of attributes can keep the user's attention focused on the task and can facilitate greater information processing, both of which have been shown to increase intrinsic motivation and enjoyment (Tung et al. 2006).

Flow theory has also proposed that a good fit between skills and challenges of an activity can increase flow, partially measured with enjoyment (Csikszentmihalyi 1975, 1977; Csikszentmihalyi and Csikszentmihalyi 1988). In online consumer behavior, various researchers have extended this idea by examining the fit between the task (online browsing and shopping), which determines the challenges for users, and the technology (websites and their various functions), which can constrain or enable their information processing skills. Their results indicate that a good fit between the technology interface's information representation and the task can increase enjoyment by the user (Koufaris 2002; Koufaris et al. 2001-2002; Novak et al. 2000; Wind and Rangaswamy 2001). Thus,

H1b: *ABDSS use is positively related to perceived enjoyment.*

We also hypothesize that perceived usefulness will follow an inverted U-shaped curve as task complexity (choice set size) increases. According to TAM2, output quality moderates the effect of job relevance on perceived usefulness (Venkatesh and Davis 2000). Both output quality and job relevance are important in the context of our study, where customers use an online DSS in a preferential choice task. In fact, we believe that they can inform the relationship between task complexity, operationalized as choice set size, and perceived usefulness.

First, in the context of a customer DSS, job relevance is task relevance (i.e., the user's perception of the applicability or appropriateness of the DSS for the preferential choice task). Task relevance is positively related to perceived usefulness but the two variables are conceptually distinct (Bhattacherjee and Sanford 2006; Venkatesh and Davis 2000). Perceiving a DSS as applicable or appropriate for a certain choice task means that the user identifies the system as one designed to support the choice task to be made, without specifying how well the system can do that. It is possible, for example, that when using the system, the decision maker may find that even though the functionality of the DSS is intended to support the choice task, it does not actually accomplish that goal very well. In that case, the decision maker will perceive the system as relevant to the task but not very useful.

Second, unlike work-related tasks with optimal solutions, in which users can form objective evaluations of output quality, users in a preferential choice task can only evaluate output quality subjectively. In such a task, satisfaction with the final choice serves as a subjective measure of the output quality of the system (Lilien et al. 2004).

Our basic argument is that when the choice set is small, users will not see the relevance of using the DSS to perform the task (they can customize the product equally well without the DSS) and as such they will perceive the system as less useful. As choice set size increases, use of the DSS becomes task-relevant (i.e., there is a good fit between the task and the system; Goodhue and Thompson 1995) and perceptions of usefulness increase. After a certain choice set size, the users are overwhelmed, even with the use of the DSS. Even though the DSS is still perceived as task relevant, user satisfaction with the decision (output quality) is reduced and so are perceptions of usefulness, resulting in an inverted U-shaped relationship between choice set size and perceived usefulness. We elaborate upon these arguments below.

When the choice set size is small, users are able to view and compare all choice options easily. When they make their final choice, they are confident that they have considered all of the possible options and they are satisfied that they have selected the best choice available to them (Huffman and Kahn 1998). However, they also know that doing so was possible without the DSS. In other words, the perceived task relevance of the DSS is low, leading to low perceptions of usefulness of the system.

As the choice set size increases, however, users start to be constrained by their cognitive limitations because of bounded rationality (Simon 1972, 1982). Since people are boundedly rational, they tend to satisfice rather than optimize when making decisions. Without the help of information technology, users may resort to heuristics and other simplification strategies, even ones which they themselves view as suboptimal (March and Simon 1958; Speier and Morris 2003). Research has shown that users readily adopt information technologies to reduce their cognitive workload and improve their decision-making efficiency, which results in higher levels of decision satisfaction (Speier and Morris 2003; Todd and Benbasat 1991, 1992). In the context of a preferential choice task, using a DSS can help users make their choices more efficiently and therefore maintain their satisfaction with the final choice, despite the increase in choice set size. As users rely increasingly on the DSS to make their choice, the perceived task relevance of the system improves, leading to an increase in its perceived usefulness. However, this effect does not scale linearly.

As the choice set size increases beyond a certain point, the customer DSS reaches its limits in improving the user's efficiency. As a result, the user satisfices and leaves behind an increasingly large number of unexamined choice options. Such an increase in choice set size has been found empirically to have detrimental effects on decision makers, including choice deferral (Tversky and Shafir 1992) and decreased satisfaction (Huffman and Kahn 1998). One reason is that rather than simply ignoring the additional choice options, the user doubts that he or she has examined the search space exhaustively, leading to feelings of remorse and dissatisfaction (Desmeules 2002). Thereafter, consistent with TAM2, the users' measure of output quality, their decision satisfaction, begins to decline and the relationship between task relevance of the DSS and perceived usefulness begins to decline as well.

In summary, we hypothesize that as choice set size initially increases, perceived usefulness will also improve because of the increase in perceived task relevance for the DSS while maintaining choice satisfaction. However, as the choice set size increases beyond a certain point, perceived usefulness stops increasing and starts to decrease—following an inverted U-shaped curve—due to the decrease of the user's choice satisfaction.

H2a: ***Perceived usefulness for all users will follow an inverted U-shaped curve as the choice set size increases.***

We believe that a continuous increase in task complexity will have a similar effect on perceived enjoyment. Flow theory suggests that a user is likely to experience enjoyment when the challenges of a task are matched with the ability to perform it.[2] In the context of a preferential choice task, when the challenges are too low due to a very small choice set size, the chance of error is too low and the user's skills are unnecessary. The emotional result is boredom. If the challenges are too high, due to a very large choice set size, the chance of making an error is too high. The emotional result is anxiety, specifically the fear of making an inadequate choice. At either extreme, the user perceives less enjoyment. With a good match, the chance of making an objective error is small (but nonzero) and the user perceives enjoyment (Johnson and Wiles 2003).

Similarly, Desmeules (2002) proposed an inverted U-shaped relationship between product variety and enjoyment of decision-making to theorize about consumer happiness. She argued that the plateau and subsequent decline in the shopping experience are due to "stress, frustration, disengagement from the process, or anticipated/experienced regret caused by heightened expectations and/or an inability to conduct all the evaluations and calculations necessary to arrive at a choice" (p. 9). The decline of the experience when task complexity increases is the result of customers setting higher goals for themselves as the number of choices increases. They assume that with more choice options they should be able to make a better choice (Wind and Rangaswamy 2001). In other words, users perceive a decline in their experience because of heightened expectations and heightened anxiety about making an adequate choice. Thus, we have a hedonic analogue to H2a:

H2b: ***Perceived enjoyment for all users will follow an inverted U-shaped curve as the choice set size increases.***

Perceived ease of use comes from the technology acceptance model (TAM) (Davis 1989; see also Agarwal and Karahanna 2000; Hu et al. 1999; Venkatesh et al. 2003). It has been shown to be a significant predictor of online consumer behavior mostly through its effect on perceived usefulness (Gefen et al. 2003; Koufaris 2002; Moon and Kim 2001). Studies have shown that increasing task complexity can lower perceptions of ease of use, usability, and effectiveness of the technology (Ziefle 2002). However, using technology that provides an appropriate fit of task with information representation can increase user perceptions of ease of use (Dishaw

[2]We are only focusing on the enjoyment dimension of flow in our argument. We are not suggesting that using the ABDSS will induce a state of flow, as flow consists of five other dimensions besides enjoyment (Csikszentmihalyi 1975).

and Strong 1999; Klopping and McKinney 2004). We believe that the same opposing effects will hold in the context of our study.

As the choice set increases, it becomes harder for alternative-based DSS users to view and evaluate all of the product versions available. In order to compare two or more product versions, they must first view them separately, sometimes having to scroll up and down the web page to do so. They must also deconstruct more product versions to infer the attributes and their values. Therefore, we expect that perceived ease of use of the interface will decrease as the choice set size increases. We do not believe that perceived ease of use follows an inverted U-shaped curve, because an increase in choice set size should not make the interface seem any easier to use, even if it temporarily increases enjoyment and usefulness due to the greater variety of choices.

For ABDSS users, however, we believe that the negative effects of increasing the choice set size on perceived ease of use will be alleviated by the interface. Since the ABDSS allows the users to process the additional information easily, the decline in perceived ease of use observed for alternative-based DSS users will not occur. Of course, a very large increase in the choice set size is likely to eventually cause a decrease in perceived ease of use in both interfaces. However, in our study we test reasonable choice set sizes that allow the users to make a decision while considering all of the possible alternatives within a few minutes. Thus,

H3a: ***ABDSS use positively moderates the negative relationship between choice set size and perceived ease of use.***

Perceived control comes from flow theory and is an affective perception by individuals of their level of control over the environment and their actions.[3] It is similar to the emotional response of dominance in environmental psychology where it is defined as feeling "unrestricted or free to act in a variety of ways" (Mehrabian and Russell 1974, p. 19). Perceived control has also been used previously in research looking at the interaction between users and web-based environments. It measures the level of control, frustration, and confusion that the user experiences as a result of interacting with the system. Prior studies have generally found that it has a positive effect on both online user perceptions and behavior (Ghani et al. 1991; Koufaris 2002; Novak et al. 2000).

We posit that task complexity will influence perceived control but that, just as for perceived ease of use, this relationship will be moderated by ABDSS use. Although no research exists on how task complexity or cognitive fit affect perceived control, prior research has examined the impact of these two variables on confusion and frustration, which are affective measures directly related to (and part of) perceived control. In terms of the effect of task complexity on perceived control, studies in decision-making have consistently shown that an increase in task complexity can increase mental workload demands beyond the limits of the decision maker's capabilities. As a result, the inability to process and compare all available information can increase the feelings of confusion and frustration by the decision maker (Johnson and Payne 1985; Kahn 1998; Speier and Morris 2003). Furthermore, the necessary use of heuristics and simplifying strategies in such situations can also lead to the experience of loss of control (Desmules 2002). In terms of the effect of cognitive fit on perceived control, research has shown that the use of an appropriate technology, such as a DSS, or problem representation, such as a visual interface versus a text-based one, can complement the decision makers' information processing capabilities, reduce their need for the use of heuristics, and decrease their confusion and frustration (Huffman and Kahn 1998; Speier and Morris 2003), suggesting that cognitive fit moderates the effect of task complexity on perceived control. Thus,

H3b: ***ABDSS use positively moderates the negative relationship between choice set size and perceived control.***

While much DSS research has concentrated on the direct effects of DSS use on decision outcomes (Häubl and Trifts 2000; Jarvenpaa 1989; Speier and Morris 2003; Todd and Benbasat 1991, 1992), recent studies have introduced the mediating effects of the decision process between DSS use and decision outcomes (Kamis and Stohr 2006; Poston and Speier 2005). This is consistent with the theory of planned behavior and the technology acceptance model, which state that the effect of technology on behavioral intention is mediated by behavioral beliefs and attitudes toward the behavior (Ajzen 1991; Davis 1989). We expect the same to be true for the effect of ABDSS.

Our study deviates from most traditional DSS research that has focused on objective measures of decision outcomes when individuals or employees use organizational systems as part of their work (Lilien et al. 2004; Todd and Benbasat 1991). Researchers have often studied decision quality, operationalized as "the deviation of a particular solution from the solution that would be provided by a normative strategy, such

---

[3]Perceived control from flow is different from the variable of perceived behavioral control (one's perceptions of one's ability to perform a given behavior) as described in the theory of planned behavior (Ajzen 1991).

as expected value maximization or utility maximization" (Todd and Benbasat 1991, p. 89). Since our study uses a preferential choice task, we cannot employ such a measure for the impact of ABDSS on the quality of individual decision outcomes. Instead, we use intention to purchase and intention to return to the website as the subjective measures of the impact of ABDSS use on the decision outcomes. Both have been used extensively in business-to-consumer e-commerce research (Gefen et al. 2003; Hampton-Sosa and Koufaris 2005; Koufaris 2002; Pavlou 2003; Van der Heijden and Verhagen 2004).

Our discussion for hypotheses H1 through H3 already explains why we expect ABDSS use to have a direct effect on the decision-making process. Many studies in technology acceptance have shown that the set of variables that represent the decision-making process in this study has a direct effect on behavioral intentions (for perceived usefulness, see Agarwal and Karahanna 2000; Davis 1989; Koufaris 2002; Van der Heijden 2004; for perceived enjoyment, see Koufaris 2002; Moon and Kim 2001; Van der Heijden 2003, 2004; for perceived control, see Koufaris et al. 2001-2002). Further, the theory of planned behavior suggests that behavioral beliefs such as the decision process variables mediate the effect of external variables on intentions. As such, we expect that the impact of ABDSS use on behavioral intentions will be mediated by this set of beliefs. Thus, we posit

H4a: *The effect of ABDSS use on intention to purchase is fully mediated by the users' perceived usefulness.*

H4b: *The effect of ABDSS use on intention to return is fully mediated by the users' perceived usefulness.*

H5a: *The effect of ABDSS use on intention to purchase is fully mediated by the users' perceived enjoyment.*

H5b: *The effect of ABDSS use on intention to return is fully mediated by the users' perceived enjoyment.*

H6a: *The effect of ABDSS use on intention to purchase is fully mediated by the users' perceived control.*

H6b: *The effect of ABDSS use on intention to return is fully mediated by the users' perceived control.*

We do not hypothesize for any effect of perceived ease of use, because prior TAM research has consistently shown that, for users with experience with the technology, perceived ease of use affects behavioral intentions indirectly through perceived usefulness (Davis 1989; Davis et al. 1992). Thus, the theoretical model includes this relationship.

Methodology

Study Design

We employed a 2 × 2 × 3 factorial design.[4] There were two versions of the website (ABDSS, alternative-based DSS) that were used for two products (watch, backpack) using three choice set sizes (8, 54, and 150 product versions available). A total of 329 subjects were recruited via e-mail from a national panel of U.S.-based online users maintained by Zoomerang, an online survey company. The sample was representative of the total U.S. population of online users. We chose backpacks and watches as our products for several reasons: (1) both products appeal equally to both genders, (2) we found existing websites with user-customizable options for both products, enabling us to adapt them for our experiment, (3) both products have similar prices, and (4) both products are nonessential but can be high-involvement goods. For each product we developed our own websites using images from Factory121.com, a customized watch retailer, and NikeId.com, Nike's online mass customization website. We decided to build our own websites instead of using the existing ones, in order to remove brand identification from the websites and the products, and to control the number of product choices and the interface in order to make them identical for both products.

For both the ABDSS and alternative-based sites, we created three versions of the website, each having a different choice set size (8, 54, and 150). In order to determine the maximum number of product versions for each condition, we consulted prior research on choice variety in decision making. Studies varied widely in the range of available alternatives. For example, Huffman and Kahn (1998) used sofas and hotels, with 18 and 19 attributes each, with each attribute having four different levels. In testing an attribute-based interface, they allowed subjects to see all attributes and all of their levels. An alternative-based interface that showed all possible alternatives would need to cover 418 or 419 alternatives, which would not be feasible. Instead, the authors showed the subjects in the alternative condition only four alternative products, where each product alternative had one level of each of the 18 or 19 attributes. On the other hand, Iyengar and Lepper (2000) ran experiments on the effect of increasing variety using different kinds of jams, essay topics, and chocolates. In their study, the numbers ranged from 6 to 24 types of jams, 6 to 30 different essay topics, and 6 to 30 dif-

[4]We used two different products for greater generalizability of the results. The product condition in the factorial design was not part of our research model but was included in our data analysis to ensure that the results were the same for both products used.

Figure 2. The Alternative-Based (non-ABDSS) Website for Backpacks with 54 Product Versions Available

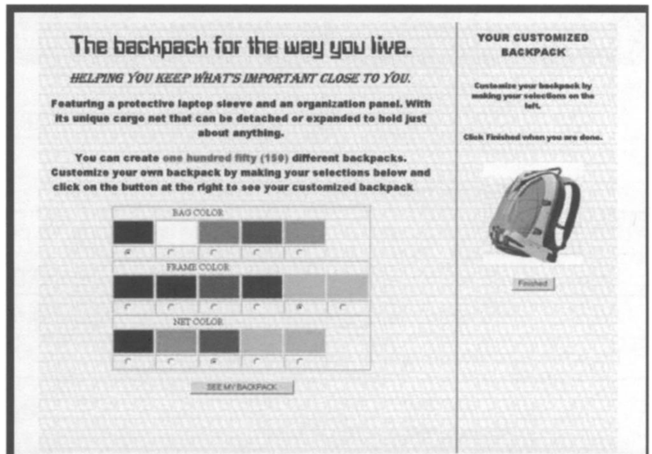

Figure 3. The ABDSS Website for Backpacks with 150 Product Versions Available

ferent types of chocolates. The numbers we used in our study (8, 54, 150) were the result of careful pretesting in a pilot session. One of the problems was that the number of alternatives grows very quickly with each value added to an attribute. Therefore, 3 attributes with 4 values each result in 64 alternatives but adding a value to only one of those attributes raises the number to 80, and one more value to a second attribute raises the number to 100.

In the alternative-based DSS version for both products, all possible product versions were displayed on one web page. Subjects scrolled down to view all of the products and clicked on the product they desired. Then, they were directed to another page that displayed the product they chose and they were given the opportunity to go back and choose a different product if they were unhappy with their choice. In the ABDSS version, all of the customizable attributes of the product were displayed on the left side of the web page. The subjects chose values for each attribute and then clicked a button to display the customized product on the right side of the same page. The subjects could repeat this process as many times as desired. Samples of the two versions of the website for backpacks can be seen in Figures 2 and 3.

Adaptation-level theory states that individuals judge any stimulus based on their past experiences (Helson 1964). Therefore, before asking them to customize a watch and a backpack, we first required all subjects to customize a different product (gift packaging for a candle), using both site versions with a choice set size of 54. In that way, all subjects started with the same baseline experience both in terms of DSS use as well as choice set size (Todd and Benbasat 1991). Once they finished the baseline task, they were randomly assigned to one of the 12 conditions. In order to provide an incentive for the subjects to customize the products and to increase task involvement, they were told that they would be entered into a drawing where they could win the watch or the backpack they customized. After they finished customizing their product, they were asked to fill out an online survey regarding their experience with that specific website.

Instrument

For our survey instrument, we adapted established scales for perceived enjoyment, perceived control, perceived usefulness, perceived ease of use, intention to purchase, and intention to return from prior literature (Koufaris 2002; Venkatesh and Davis 1996). All of the items of the survey can be seen in Table 1.

Data Analysis

Sample and Tests of Assumptions

The sample used for this study consists of 329 subjects. The demographics of our sample can be seen in Table 2 and they indicate that our sample is representative of the entire online customer population in the U.S. (Intermarket Group 2002). Our subjects are primarily between the ages of 26 and 55,

Table 1. Survey Instrument and Descriptive Statistics

	Construct Scale item wording	Scale Reliability and Descriptives Standardized factor loadings
	Perceived Usefulness:	**Cronbach's α = 0.953, Mean = 4.32, St. Dev. = 1.61**
USE1	Using this web site can improve my shopping performance	0.932
USE2	Using this web site can increase my shopping productivity	0.923
USE3	Using this web site can increase my shopping effectiveness	0.929
USE4	I find using this web site useful	0.859
	Perceived Ease of Use:	**Cronbach's α = 0.843, Mean = 5.85, St. Dev. = 1.34**
EOU1	Learning to use this web site would be easy for me	0.637
EOU2	My interaction with this web site is clear and understandable	0.624
EOU3	It would be easy for me to become skillful at using this web site	0.771
EOU4	I find this web site easy to use	0.876
	Perceived Control:	**Cronbach's α = 0.822, Mean = 5.72, St. Dev. = 1.34**
	While using the web site…	
CON1	...I felt confused *(reversed)*	0.632
CON2	...I felt in control	0.922
CON3	...I felt frustrated *(reversed)*	0.614
	Shopping Enjoyment:	**Cronbach's α = 0.947, Mean = 4.92, St. Dev. = 1.51**
	While using the web site…	
ENJ1	...I found my visit interesting	0.937
ENJ2	...I found my visit enjoyable	0.933
ENJ3	...I found my visit fun	0.918
	Intention to Purchase:	**Mean = 4.62, St. Dev. = 1.73**
PRCH	If you actually had the money, how likely is it that you would buy the product from *this* web site?	N/A
	Intention to Return:	**Mean = 4.56, St. Dev. = 1.72**
RTRN	If you needed to purchase a similar product in the future, how likely is it that you would return to this web site?	N/A

Table 2. Subject Demographics

Variable	Frequency (%)	Variable	Frequency (%)
Age		**Household Income**	
Under 25	25 (7.6%)	Under $10,000	14 (4.3%)
26–35	86 (26.1%)	$10,000–$19,999	14 (4.3%)
36–45	90 (27.4%)	$20,000–$29,999	23 (7%)
46–55	80 (24.3%)	$30,000–$39,999	29 (8.8%)
Over 55	48 (14.6%)	$40,000–$49,999	37 (11.2%)
Gender		$50,000–$74,999	76 (23.1%)
Male	128 (38.9%)	$75,000–$99,999	38 (11.6%)
Female	201 (61.1%)	Over $100,000	55 (16.7%)
Education		Rather not say	46 (13.1%)
Grammar/Elementary School	5 (1.5%)		
High School or Equivalent	49 (14.8%)		
Vocational/Technical School (2 year)	24 (7.3%)		
Some College or University	99 (30.1%)		
Bachelor's Degree (4 year)	92 (28%)		
Master's Degree	46 (14%)		
Professional Degree (MD, JD, etc.)	9 (2.7%)		
Doctoral Degree	3 (0.9%)		
Other	1 (0.3%)		
Rather not say	1 (0.3%)		

61 percent are female, 76 percent have at least some college education, and 64 percent have a household income of over $50,000 per year.

In order to confirm the random assignment of subjects to the different experimental conditions, we performed a multivariate analysis of variance (MANOVA). There were no significant differences in gender ($F = 0.357$, $p = 0.971$), age ($F = 1.157$, $p = 0.316$), education ($F = 1.349$, $p = 0.197$), or household income ($F = 1.024$, $p = 0.425$) among the 12 experimental conditions. Also, since there were more women than men in our sample, we used analysis of variance (ANOVA) to test whether there were any significant differences in our dependent variables between genders. None of the dependent variables showed any significant differences.

In order to test the validity of our constructs, we performed confirmatory factor analysis (CFA) using structural equation modeling with AMOS 4.0. The CFA model's fit statistics ($\chi^2 = 170.24$, df = 67, $p < 0.001$; $\chi^2/df = 2.54$; GFI = 0.934; AGFI = 0.897; NFI = 0.960, CFI = 0.975; RMSEA = 0.069) showed that the model had good fit. The significant χ^2 value can be disregarded due to its sensitivity to the sample size and large number of items (Hair et al. 1998). All of the items loaded significantly on their assigned latent constructs. Although some indicators had loadings slightly below the recommended value of 0.70, we retained them in order to maintain continuity with prior research using the same scales. Therefore, our scales show good convergent validity. The Cronbach's alpha values for all constructs are above the recommended 0.7 value, indicating good reliability (Nunnally 1967). The factor loadings, Cronbach's alpha values, and descriptive statistics of all constructs can be seen in Table 1.

Discriminant validity was tested using the guidelines by Segars (1997) and followed by Pavlou and Gefen (2004) and Gefen et al. (2003). We compared the χ^2 value of the full measurement model with four latent constructs with a series of models with three latent constructs where every possible pair of two constructs was combined. If the difference in the χ^2 value between the two models was significant, it was an indication of discriminant validity between the constrained constructs. All χ^2 value differences were at least 24.32, which is the threshold in order to be significant at the $p < 0.001$ level. Therefore, our constructs also show good discriminant validity.

Since all of our items were measured with the same method, we tested for common method variance using Harman's one factor test (Podsakoff and Organ 1986). Using a principal components analysis for all of the variables measured in the study, we found multiple factors with eigenvalues greater than one and no single factor explained the majority of variance. Therefore, common method bias was not significant.

Results

In order to test the model, we conducted partial least squares (PLS) analysis using PLS-Graph version 3.0 with the bootstrapping resampling procedure (Chin 2000). We tested the moderating effect of ABDSS use by creating an interaction term between ABDSS use and choice set size and testing its relationship with perceived ease of use and perceived control. Testing the hypothesis on the nonlinear, inverted U-shaped relationships between choice set size and perceived usefulness and perceived enjoyment was more challenging. Since PLS-Graph assumes linear relationships between all the variables in the PLS model, we needed to model the two nonlinear relationships using statistical contrasts. Given that choice set size has only three distinct values (8, 54, 150), we created two dummy variables (D1 and D2) for it as follows:

Choice set size = 8; D1 = 0; D2 = 0
Choice set size = 54; D1 = 1; D2 = 0
Choice set size = 150; D1 = 1; D2 = 1

We then tested the coefficients for the relationships of D1 and D2 with perceived usefulness and perceived enjoyment. A significant positive coefficient for D1 would indicate that perceived usefulness and perceived enjoyment increase when choice set size increases from 8 to 54 and a significant negative coefficient for D2 would indicate that the two variables decrease when choice set size increases from 54 to 150.

The results of the PLS analysis of our model can be seen in Figure 4. First, the coefficient between ABDSS use and perceived usefulness is positive and significant ($\beta = 0.148$, $p < 0.01$), as is the coefficient between ABDSS use and perceived enjoyment ($\beta = 0.299$, $p < 0.001$), indicating support for H1a and H1b. The coefficients between the dummy variables D1 and D2 with perceived usefulness and perceived enjoyment are as predicted. D1's coefficients are positive and significant ($\beta = 0.092$, $p < 0.05$ for perceived usefulness and $\beta = 0.144$, $p < 0.05$ for perceived enjoyment) and D2's coefficients are negative and significant ($\beta = -0.129$, $p < 0.05$ for perceived usefulness and $\beta = -0.215$, $p < 0.001$ for perceived enjoyment). This supports H2a and H2b on the inverted U-shaped relationships with choice set size. To verify those results, we graphed the estimated means for perceived usefulness and perceived enjoyment for each of the three choice set sizes. The results, seen in Figures 5 and 6, show that both variables at first increase but then decrease as choice set size increases.

To test the hypotheses on the moderating effects of ABDSS use, we first look at the coefficients between choice set size and perceived ease of use and perceived control. Both coefficients are negative and significant ($\beta = -0.423$, $p < 0.05$ and $\beta = -0.506$, $p < 0.01$), verifying that the relationship between choice set size and the two process variables is negative. However, the coefficients between the interaction term (ABDSS use × choice set size) and the two process variables are both positive and significant ($\beta = 0.459$, $p < 0.05$ and $\beta = 0.541$, $p < 0.05$). This indicates that ABDSS use positively moderates (attenuates) the negative relationships between choice set size with perceived ease of use and perceived control. Therefore, H3a and H3b are supported. Once more, in order to visually verify the results, we graphed the estimated means for the two process variables. As seen in Figures 7 and 8, when an ABDSS is used, the negative impact of increasing choice set size on both perceived ease of use and perceived control is alleviated.

Finally, we tested the mediating role of the process variables between ABDSS use and the two behavioral intention variables. The nonsignificant coefficients of the direct relationships of ABDSS use with purchase intention and intention to return indicate that the effects of ABDSS use on the behavioral intention variables are in fact indirect. This is supported for two of the three hypothesized mediators: perceived usefulness and perceived enjoyment. The effect of ABDSS use on both of those variables is positive and significant ($\beta = 0.148$, $p < 0.01$ for perceived usefulness and $\beta = 0.299$, $p < 0.001$ for perceived enjoyment). Also positive and significant are the direct effects of perceived usefulness and perceived enjoyment on both behavioral intention variables. For perceived usefulness, $\beta = 0.399$, $p < 0.001$ and $\beta = 0.492$, $p < 0.001$ for intention to purchase and intention to return respectively. For perceived enjoyment, $\beta = 0.247$, $p < 0.01$ and $\beta = 0.217$, $p < 0.01$ for intention to purchase and intention to return respectively. For perceived control, however, the coefficients both for its relationship with ABDSS use and its relationships with intention to purchase and intention to return are all nonsignificant. Therefore, H4a, H4b, H5a, and H5b are supported, while H6a and H6b are not.

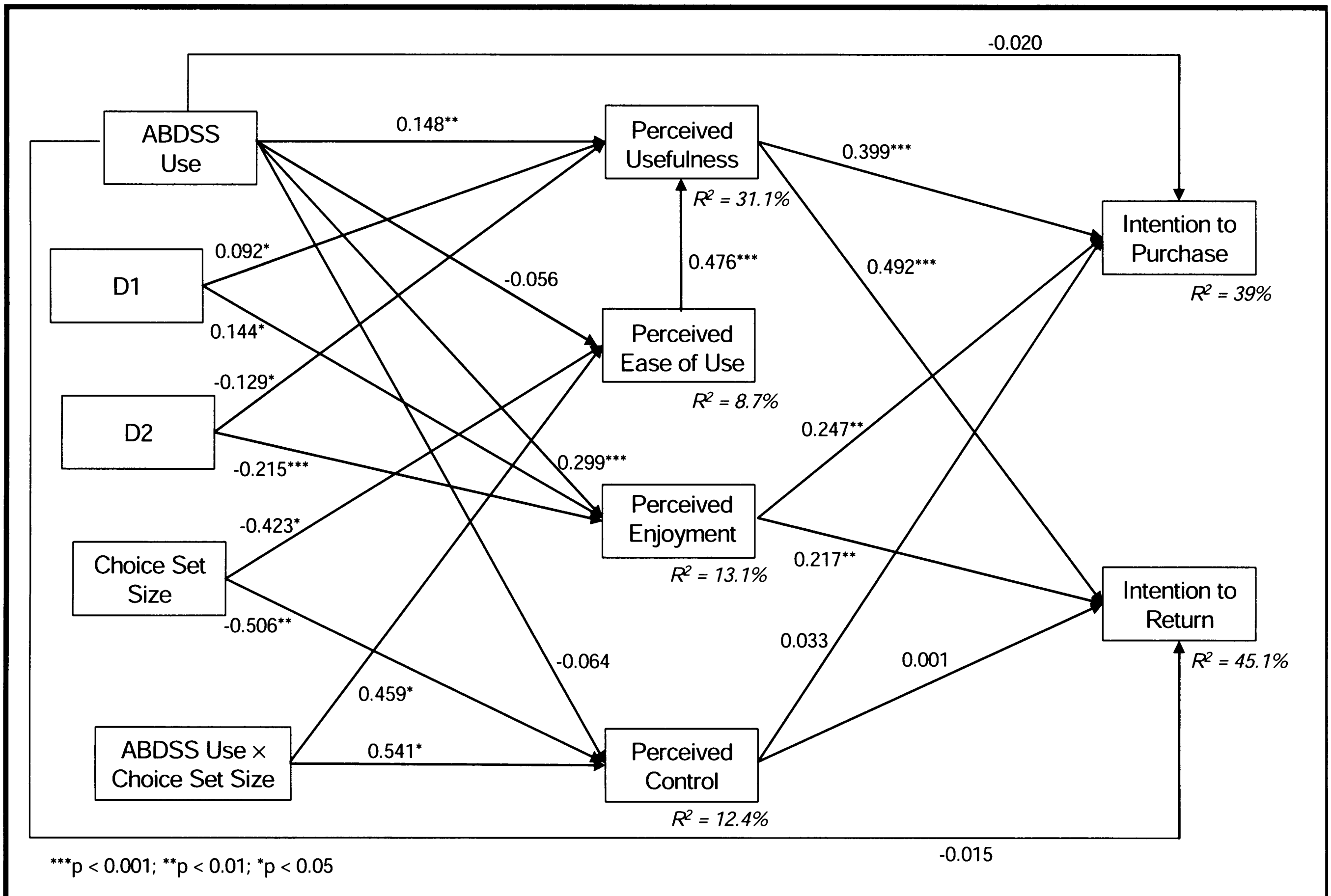

Figure 4. Results of PLS Analysis

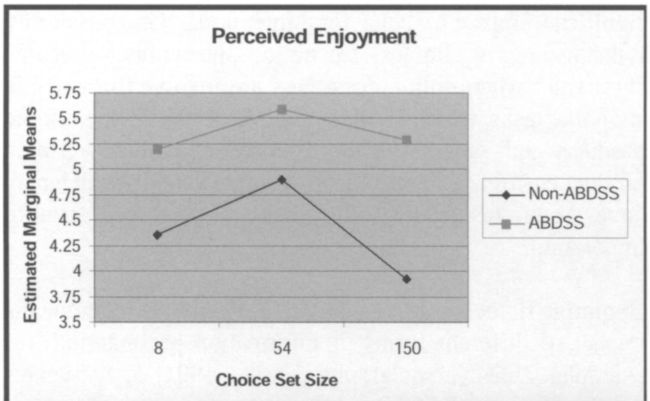

Figure 5. Estimated Means of Perceived Employment for Both Products

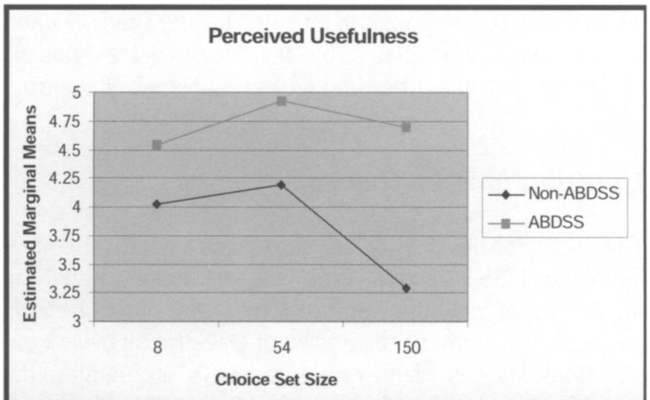

Figure 6. Estimated Means of Perceived Usefulness for Both Products

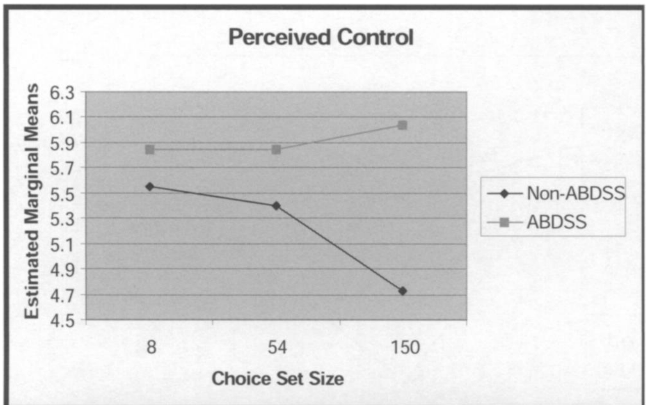

Figure 7. Estimated Means of Perceived Control for Both Products

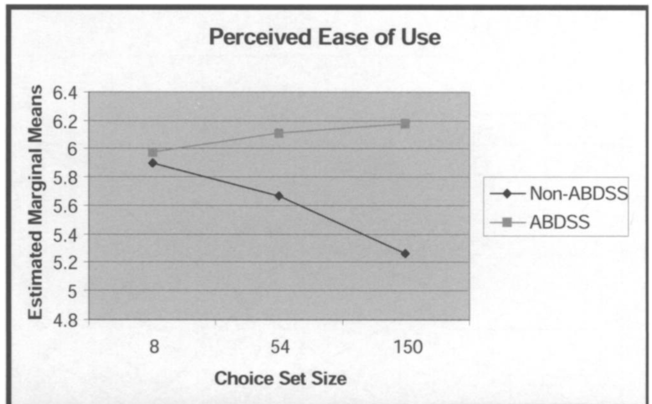

Figure 8. Estimated Means of Perceived Ease of Use for Both Products

Discussion

Our study examined the mediating role of decision process variables when online users employ a DSS to customize products. We found that users of an attribute-based DSS (ABDSS) experienced higher perceived usefulness and perceived enjoyment than alternative-based DSS users. We also found that for all users, perceived enjoyment and perceived usefulness follow an inverted U-shaped curve as the choice set size increases. In addition, we found that using an ABDSS alleviates the decrease in perceived control and perceived ease of use observed in non-ABDSS users as the choice set size increases but that perceived control does not influence intentions to purchase or intentions to return. Finally, we found that the effects of ABDSS use on the decision outcome variables of intention to return and intention to purchase are mediated by the user's perceptions of usefulness and enjoyment, though not by perceived control.

Contributions to Theory

The results of our study make important theoretical contributions to DSS research. First, we have demonstrated the importance of including subjective measures of the decision process when studying the impact of DSS use on behavioral intentions, such as whether to reuse a DSS or commit to the decision. Consistent with the theory of planned behavior, we tested a mediated model and found that in the context of our study, ABDSS use does not directly influence behavioral intentions but is instead mediated by perceived usefulness and perceived enjoyment. However, we did not find a similar mediation effect for perceived control. Our results complement recent DSS research that has used more complex research models to better understand how and why DSS use impacts decision making (Bharati and Chaudhury 2004; Chenoweth et al. 2004; Garrity et al. 2005; Kamis and Stohr 2006). The inclusion of both cognitive and affective decision process variables is especially important in a context such as ours (online shopping) where there is a large affective aspect. Unlike organizational DSS used in work-related tasks, it is important for decision makers (i.e., customers) to enjoy the process and feel comfortable using the customer DSS in a shopping environment.

The nonsignificant results for perceived control are surprising. While we found that ABDSS use and choice set size affect perceived control as expected, perceived control itself had no significant impact on behavioral intentions. One possibility is that feelings of calmness, frustration, and confusion become significant when online customers are involved in real-life shopping tasks, which involve multiple decisions on multiple products and vendors. Our experiment involved a single product customization task from a single vendor, which may have been insufficient for making perceived control important.

Cognitive fit theory has been used in research to examine the impact of different forms of information presentation, for example, tables versus graphs (Vessey 1991) or list versus matrix (Hong et al. 2005), on decision-making performance, for example, comprehension (Khatri et al. 2006; Shaft and Vessey 2006), product recall and search efficiency (Hong et al. 2005), and solution time and error rate (Crossland et al. 2000). Our study highlights the importance of including, where appropriate, decision process variables as mediators in this type of research. More specifically, we show that perceived usefulness and perceived enjoyment can fully mediate the impact of cognitive fit on the user's behavioral intentions. This may be important, for instance, when use of DSS is not mandated but users engage in its use of their own accord.

Another important contribution of our study is in examining two key antecedents of decision process variables: interface design and task complexity. Most TAM research has focused on the impact of perceived usefulness and perceived ease of use on user behavior. While those impacts have proven to be very robust across multiple studies, less attention has been focused on the antecedents of both perceived usefulness and perceived ease of use (Benbasat and Barki 2006). Also, much research has shown that affective measures, such as perceived enjoyment and perceived control, are important antecedents of user behavior but there has been less attention focused on the system design characteristics that can affect them.

For perceived ease of use, a cognitive variable, and perceived control, an affective variable, we found that an ABDSS interface alleviates the negative effects of increased task complexity. That indicates that when it comes to perceptions of usability of the system, both cognitive (ease of use) and affective (control), ABDSS use can be effective in alleviating the additional complexity of an increasing choice set size. Although we did not hypothesize for it, we tested whether the same was the case for perceptions regarding the expected benefits of using the system, either cognitive (usefulness) or affective (enjoyment). We did not find a similar attenuation effect of ABDSS use (see Figures 5 and 6 for a graphical representation of those results). These results pose some interesting questions about the ability of ABDSS users to identify the potential benefits of its use when the choice set is large (i.e., when the task complexity is high). We understand that our results are specific to the context of users of a customer DSS for product customization and we welcome new research that examines this phenomenon in other contexts.

Regarding perceived usefulness and perceived enjoyment, our results provide some unique insights. First, our study shows that an attribute-based DSS can increase both perceived usefulness, partly through perceived ease of use, and perceived enjoyment, both of which can increase a user's behavioral intentions. Second, we have shown that the impact of choice set size on perceptions of usefulness and enjoyment is nonlinear. As we predicted, both perceptual variables followed an inverted U-shaped path as the choice set size increased. Showing such nonlinear effects on both variables is a significant contribution to our theoretical as well as practical understanding of how user perceptions change while interacting with a DSS. For perceived enjoyment, our results show a nonlinear relationship between task complexity and affective perceptions regarding the ***task***. The inverted U-shaped relationship between choice set size and perceived enjoyment is an indication that increasing the number of options in a preferential choice task does not guarantee an increase in enjoyment of the process. In fact, too many choices can feel overwhelming and with increased effort by the decision makers, perceived enjoyment can decrease. The similar result for perceived usefulness indicates that the complexity of the task can also have a nonlinear relationship with cognitive perceptions regarding the ***system***. As the number of possible choices increases, users may start recognizing the system's limitations in increasing their efficiency and perceived usefulness can begin to decrease. As research on the antecedents of system user perceptions and beliefs grows, we hope that our results will highlight the need for researchers to consider more than simple linear effects.

Implications for Practice

Our results regarding the impact of choice set size on user perceptions also have practical implications for online companies. The empirical verification of the inverted U-shaped curve for perceived enjoyment and perceived usefulness with the increase of the choice set size highlights the danger of overwhelming customers with too many choices. Companies that sell products on the web may be tempted to dramatically increase the variety of their offerings, since they do not need additional shelf space or retail stores to display the products. While the optimum level of variety depends on many factors, too much variety may prove too confusing and frustrating for some customers. They may find themselves making a hasty and regrettable decision or find themselves unable to make any purchase decision at all. Our results show that this happens even when there is an ABDSS available for customers.

We are not suggesting that companies should limit the number of products they offer. After all, profitable companies like Amazon and e-Bay offer an enormous variety of products. What our results do show, and what both Amazon and e-Bay illustrate, is that online companies need to provide appropriate tools for users to deal with the increase in product choices. Amazon, for example, has a powerful internal search engine, a sophisticated recommender system, and a vocal customer community that provides its own advice and suggestions to other customers.

For companies that have mass customization capabilities and want to introduce user-customization of products on their websites, our results clearly show that an ABDSS can be effective, especially as the number of attributes and their values increase. As the number of possible customized versions of the product increases, users require a tool that helps them recognize the product attributes and their corresponding values, allowing them to interactively experiment with customizing the final product. Companies such as Dell and Nike have been successfully offering such an interface.

Finally, our results indicate that providing an appropriate ABDSS on a website can allow customers to enjoy their shopping experience more and perceive the system as improving their decision making and shopping efficiency. Consequently, customers might make more purchases and return to an online company for future purchases.

Limitations and Future Research

One limitation of our study is the fact that we only used two products: watches and backpacks. This may limit our results to those products and their categories. Future research should test other products including those with attributes that cannot be easily communicated over the web. Examples of such products are fragrances and food that rely heavily on the use of smell, taste, and touch. Although technology that transmits such sensory information over digital networks is possible, it is still under development and not widely available. Research on alternative ways to allow users to customize such products and what is the best interface to enable that could provide interesting insights.

Another limitation of our study is the limited number of choice set sizes: 8, 54, and 150 alternatives. It is possible that the user experience varies with different choice set sizes. Ideally, one would conduct an experiment by changing a single attribute by one value at a time, thus trying all possible choice set sizes. That would allow the creation of an actual curve between choice set size and the two process variables. Such an experiment, however, would require a very large number of subjects. Future research could take a more detailed approach and examine the impact of a gradual increase in the attributes and/or their values on the user experience.

While our sample consisted of real web users representative of the general web user population, it also limited our control over the experimental procedure. Each subject was invited to participate via e-mail and did so privately. Therefore, it is possible that the participation of some subjects was not entirely according to the experimental design. We had a few ways of controlling for who actually participated or for possible distractions that may have interrupted the flow of the experiment. Subjects were required to provide a unique ID number that was given to them with the e-mail invitation in order to prevent multiple entries by the same subject. We were also able to monitor the time stamps of each step of the study for each subject and eliminated subjects who participated in the experiment over multiple time periods.

Our results may be specific to the context of product customization by online users. Our findings may only apply to non-organizational settings or preferential-choice tasks. However, attribute-based DSS use is not limited to online retail companies and their customers. Such systems may be used for work-related tasks with objective, optimal solutions. In such systems, the affective perceptions of users may be less significant. We encourage additional research that examines the impact of using a customer ABDSS in other settings and on different task types and complexities.

Finally, based on TAM2 we posited that underlying mechanisms for the inverted U-shaped relationship between task complexity and perceived usefulness were perceptions of task relevance and output quality (customer satisfaction with their decision). Although this theoretical rationale has face validity, our study did not include measures of task relevance or output quality. As such, the inverted U-shaped relationship and its underlying mechanisms warrant further investigation and are fruitful directions for future research.

Acknowledgments

This project was funded by a Eugene M. Lang Research Fellowship award at Baruch College, City University of New York. The authors would also like to thank Matthew Johnson for his valuable statistical advice, as well as the senior editor, associate editor, and anonymous reviewers for their constructive and helpful comments and suggestions.

References

Agarwal, R., and Karahanna, E. 2000. "Time Flies When You're Having Fun: Cognitive Absorption and Beliefs About Information Technology Usage," *MIS Quarterly* (24:4), pp. 665-694.

Ajzen, I. 1991. "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes* (50:2), pp. 179-211.

Benbasat, I., and Barki, H. 2006. "Quo Vadis TAM," unpublished working paper, Sauder School of Business, University of British Columbia, Vancouver, Canada, November.

Bharati, P., and Chaudhury, A. 2004. "An Empirical Investigation of Decision-Making Satisfaction in Web-Based Decision Support Systems," *Decision Support Systems* (37:2), pp. 187-197.

Bhattacherjee, A., and Sanford, C. 2006. "Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model," *MIS Quarterly* (30:4), pp. 805-825.

Chenoweth, T., Dowling, K. L., and Louis, R. D. S. 2004. "Convincing DSS Users That Complex Models Are Worth the Effort," *Decision Support Systems* (37:1), pp. 71-82.

Chin, W. W. 2000. "Frequently Asked Questions: Partial Least Squares & PLS-Graph," available online at http://disc-nt.cba.uh.edu/chin/plsfaq/plsfaq.htm; accessed on March, 2006.

Crossland, M. D., Herschel, R. T., Perkins, W. C., and Scudder, J. N. 2000. "The Impact of Task and Cognitive Style on Decision-making Effectiveness Using a Geographic Information System," *Journal of End User Computing,* (12:1), pp. 14-24.

Csikszentmihalyi, M. 1975. "Play and Intrinsic Rewards," *Humanistic Psychology* (15), pp. 41-63.

Csikszentmihalyi, M. 1977. *Beyond Boredom and Anxiety*, San Francisco: Jossey-Bass.

Csikszentmihalyi, M., and Csikszentmihalyi, I. S. 1988. *Optimal Experience: Psychological Studies of Flow in Consciousness*, Cambridge, England: Cambridge University Press.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), pp. 319-340.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. 1992. "Extrinsic and Intrinsic Motivation to Use Computers in the Workplace," *Journal of Applied Social Psychology* (22:14), pp. 1111-1132.

Davis, S. M. 1987. *Future Perfect*, Reading, MA: Addison-Wesley.

Desmeules, R. 2002. "The Impact of Variety on Consumer Happiness: Marketing and the Tyranny of Freedom," *Academy of Marketing Science Review* (12), pp. 1-18.

Dishaw, M. T., and Strong, D. M. 1999. "Extending the Technology Acceptance Model with Task-Technology Fit Constructs," *Information & Management* (36:1), pp. 9-21.

Garrity, E. J., Glassberg, B., Kim, Y. J., Sanders, G. L., and Shin, S. K. 2005. "An Experimental Investigation of Web-Based Information Systems Success in the Context of Electronic Commerce," *Decision Support Systems* (39:3), pp. 485-503.

Gefen, D., Karahanna, E., and Straub, D. W. 2003. "Trust and TAM in Online Shopping: An Integrated Model," *MIS Quarterly* (27:1), pp. 51-90.

Ghani, J. A., Supnick, R., and Rooney, P. 1991. "The Experience of Flow in Computer-Mediated and in Face-to-Face Groups," in *Proceedings of the 12th International Conference on Information Systems*, J. I. DeGross, I. Benbasat, G. DeSanctis, C. M. Beath (eds.), New York, pp. 229-237.

Goodhue, D. L., and Thompson, R. L. 1995. "Task-Technology Fit and Individual Performance," *MIS Quarterly* (19:2), pp. 213-236.

Hair, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. 1998. *Multivariate Data Analysis*, Upper Saddle River, NJ: Prentice Hall.

Hampton-Sosa, W., and Koufaris, M. 2005. "The Effect of Website Perceptions on Initial Trust in the Owner Company," *International Journal of Electronic Commerce* (10:1), pp. 55-87.

Häubl, G., and Trifts, V. 2000. "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science* (19:1), pp. 4-21.

Helson, H. 1964. *Adaptation-Level Theory*, New York: Harper & Row.

Hong, W., Thong, J. Y. L., and Tam, K. Y. 2005. "The Effects of Information Format and Shopping Task on Consumers' Online Shopping Behavior: A Cognitive Fit Perspective," *Journal of Management Information Systems* (21:3), pp. 149-184.

Hu, P. J., Chau, P. Y. K., Sheng, O. R. L., and Tam, K. Y. 1999. "Examining the Technology Acceptance Model Using Physical Acceptance of Telemedicine Technology," *Journal of Management Information Systems* (16:2), pp. 91-112.

Huang, Z., Chen, H., Guo, F., Xu, J. J., Wu, S., and Chen, W. H. 2006. "Expertise Visualization: An Implementation and Study Based on Cognitive Fit Theory," *Decision Support Systems* (42:3), pp. 1539-1557.

Huffman, C., and Kahn, B. E. 1998. "Variety for Sale: Mass Customization or Mass Confusion," *Journal of Retailing* (74:4), pp. 491-513.

Intermarket Group. 2002. "Business-to-Consumer E-Commerce Report," The Intermarket Group L.P., San Diego, CA.

Ives, B. 2003. "Custom Made Apparel and Individualized Service at Lands' End," *Communications of the Association for Information Systems* (11), pp. 79-93.

Iyengar, S., and Lepper, M. R. 2000. "When Choice Is Demotivation: Can One Desire Too Much of a Good Thing?," *Journal of Personality and Social Psychology* (79:6), pp. 995-1006.

Jarvenpaa, S. L. 1989. "The Effect of Task Demands and Graphical Format on Information Processing Strategies," *Management Science* (35:3), pp. 285-303.

Johnson, D., and Wiles, J. 2003. "Effective Affective User Interface Design in Games," *Ergonomics* (46:13/14), pp. 1332-1345.

Johnson, E. J., and Payne, J. W. 1985. "Effort and Accuracy In Choice," *Management Science* (31:4), pp. 395-414.

Kahn, B. 1998. "Dynamic Relationships with Customers: High-Variety Strategies," *Journal of the Academy of Marketing Science* (26:1), pp. 45-53.

Kamis, A. A., and Stohr, E. A. 2006. "Parametric Search Engines: What Makes Them Effective When Shopping Online for Differentiated Products?," *Information & Management* (43:7), pp. 904-918.

Khatri, V., Vessey, I., Ram, S., and Ramesh, V. 2006. "Cognitive Fit Between Conceptual Schemas and Internal Problem Representations: The Case of Geospatio-Temporal Conceptual Schema Comprehension," *IEEE Transactions on Professional Communication* (49:2), pp. 109-127.

Klopping, I. M., and McKinney, E. 2004. "Extending the Technology Acceptance Model and the Task Technology Fit Model to Consumer E-Commerce," *Information Technology, Learning & Performance Journal* (22:1), pp. 35-48.

Koufaris, M. 2002. "Applying the Technology Acceptance Model and Flow Theory to Online Consumer Behavior," *Information Systems Research* (13:2), pp. 205-223.

Koufaris, M., and Hampton-Sosa, W. 2004. "The Development of Initial Trust in an Online Company by New Customers," *Information & Management* (41:3), pp. 377-397.

Koufaris, M., Kambil, A., and LaBarbera, P. A. 2001-2002. "Consumer Behavior in Web-Based Commerce: An Empirical Study," *International Journal of Electronic Commerce* (6:2), pp. 115-138.

Lilien, G. L., Rangaswamy, A., van Bruggen, G. H., and Starke, K. 2004. "DSS Effectiveness in Marketing Resource Allocation Decisions: Reality Vs. Perception," *Information Systems Research* (15:3), pp. 216-235.

March, J. G., and Simon, H. A. 1958. *Organizations*, New York: John Wiley & Sons, Inc.

Mehrabian, A., and Russell, J. A. 1974. *An Approach to Environmental Psychology*, Cambridge, MA: MIT Press.

Meyer, R. J. 1987. "The Learning of Multiattribute Judgment Policies," *Journal of Consumer Research* (14:2), pp. 155-173.

Moon, J. W., and Kim, Y. G. 2001. "Extending the TAM for a World-Wide-Web Context," *Information and Management* (38:4), pp. 217-230.

Newell, A., and Simon H. A. 1972. *Human Problem Solving*, Englewood Cliffs, NJ: Prentice-Hall.

Novak, T. P., Hoffman, D. L., and Yung, Y.-F. 2000. "Measuring the Customer Experience in Online Environments: A Structural Modeling Approach," *Marketing Science* (19:1), pp. 22-42.

Nunnally, J. C. 1967. *Psychometric Theory*, New York: McGraw-Hill.

Olshavsky, R. W. 1979. "Task Complexity and Contingent Processing in Decision Making: A Replication and Extension," *Organizational Behavior and Human Performance* (24:3), pp. 300-316.

Pavlou, P. A. 2003. "Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model," *International Journal of Electronic Commerce* (7:3), pp. 101-134.

Pavlou, P. A., and Gefen, D. 2004. "Building Effective Online Marketplaces with Institution-Based Trust," *Information Systems Research* (15:1), pp. 37-59.

Payne, J. 1976. "Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis," *Organizational Behavior and Human Performance* (16:2), pp. 366-387.

Payne, J., Bettman, J., and Johnson, E. 1988. "Adaptive Strategy in Decision Making," *Journal of Experimental Psychology: Learning, Memory, and Cognition* (14:3), pp. 534-552.

Pine, J. P. 1993. *Mass Customization*, Boston: Harvard Business School Press.

Podsakoff, P. M., and Organ, D. W. 1986. "Self-Reports in Organizational Research: Problems and Prospects," *Journal of Management*, (12:4), pp.531-44.

Poston, R. S., and Speier, C. 2005. "Effective Use of Knowledge Management Systems: A Process Model of Content Ratings and Credibility Indicators," *MIS Quarterly* (29:2), pp. 221-244.

Segars, A. H. 1997. "Assessing the Unidimensionality of Measurement: A Paradigm and Illustration within the Context of *Information Systems Research*," *Omega* (25:1), pp. 107-121.

Shaft, T. M., and Vessey, I. 2006. "The Role of Cognitive Fit in the Relationship Between Software Comprehension and Modification," *MIS Quarterly*, (30:1), pp. 29-55.

Simon, H. A. 1972. "Theories of Bounded Rationality," in *Decision and Organisation: A Volume in Honor of Jacob Marschak*, C. B. McGuire and R. A. Radner (eds.), Amsterdam: North Holland Publishing Company, pp. 161-176.

Simon, H. A. 1982. *Models of Bounded Rationality*, Boston: MIT Press.

Speier, C., and Morris, M. G. 2003. "The Influence of Query Interface Design on Decision-Making Performance," *MIS Quarterly* (27:3), pp. 397-423.

Swait, J., and Adamowicz, W. 2001. "The Influence of Task Complexity on Consumer Choice: A Latent Class Model of Decision Strategy Switching," *Journal of Consumer Research* (28:1), pp. 135-149.

Todd, P., and Benbasat, I. 1991. "An Experimental Investigation of the Impact of Computer Based Decision Aids on Decision Making Strategies," *Information Systems Research* (2:2), pp. 87-115.

Todd, P., and Benbasat, I. 1992. "The Use of Information in Decision Making: An Experimental Investigation of the Impact of Computer-Based Decision Aids," *MIS Quarterly* (16:3), pp. 373-393.

Todd, P., and Benbasat, I. 1999. "Evaluating the Impact of DSS, Cognitive Effort, and Incentives on Strategy Selection," *Information Systems Research* (10:4), pp. 356-374.

Tversky, A., and Shafir, E. 1992. "Choice under Conflict: The Dynamics of Deferred Decision," *Psychological Science* (3:6), pp. 358-361.

Tung, W., Moore, R., and Engelland B. 2006. "Exploring Attitudes and Purchase Intentions in a Brand-Oriented, Highly Interactive Web Site Setting" *Marketing Management Journal* (16:2), pp. 94-106.

Van der Heijden, H. 2003. "Factors Influencing the Usage of Websites: The Case of a Generic Portal in the Netherlands," *Information & Management* (40:6), pp. 541-549.

Van der Heijden, H. 2004. "User Acceptance of Hedonic Information Systems," *MIS Quarterly* (28:4), pp. 695-704.

Van der Heijden, H., and Verhagen, T. 2004. "Online Store Image: Conceptual Foundations and Empirical Measurement," *Information & Management* (41:5), pp. 609-617.

Venkatesh, V., and Davis, F. D. 1996. "A Model of the Antecedents of Perceived Ease of Use: Development and Test," *Decision Sciences* (27:3), pp. 451-481

Venkatesh, V., and Davis, F. D. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Management Science* (46:2), pp. 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.

Vessey, I. 1991. "Cognitive Fit: A Theory-Based Analysis of the Graphs Versus Tables Literature." *Decision Sciences* (22:2), pp. 219-240.

Wind, J., and Rangaswamy, A. 2001. "Customerization: The Next Revolution in Mass Customization," *Journal of Interactive Marketing* (15:1), pp. 13-32.

Ziefle, M. 2002. "The Influence of User Expertise and Phone Complexity on Performance, Ease of Use, and Learnability of Different Mobile Phones," *Behaviour and Information Technology* (21:5), pp. 303-311.

Zigurs, I., and Buckland, B. K. 1998. "The Theory of Task/ Technology Fit and Group Support Systems Effectiveness," *MIS Quarterly* (22:3), pp. 313-334.

About the Authors

Arnold Kamis is an associate professor in Information Systems and Operations Management at Suffolk University. He received his Ph.D. in Information Systems from the Stern School of Business of New York University and his B.S. in Applied Mathematics (Computer Science) from Carnegie Mellon University. His research interests are in electronic business, decision support technologies, and human–computer interaction. His publications appear in the *International Journal of Electronic Commerce*, *Information & Management*, *The American Statistician*, *Communications of the Association for Computing Machinery*, *Communications of the Association for Information Systems*, and *The DATABASE for Advances in Information Systems*. He serves as a chair for the HICSS Minitrack on Electronic Marketing and is web site editor for the *Journal of Management Information Systems*.

Marios Koufaris is an associate professor in Computer Information Systems at Baruch College, City University of New York. He received his Ph.D. in Information Systems from the Stern School of Business of New York University, his B.Sc. in Decision Sciences from the Wharton School of Business, and his B.A. in Psychology from the College of Arts and Sciences, both at the University of Pennsylvania. His research interests include consumer behavior in web-based commerce and the social impact of IT. His work has been published in *Information Systems Research*, *Journal of Management Information Systems*, *International Journal of Electronic Commerce*, *Information & Management*, *The DATABASE for Advances in Information Systems*, and *Communications of the ACM*.

Tziporah Stern is a doctoral student in Baruch College, City University of New York. She received her B.Sc. in Computer Science from Touro College in New York. Her research interests include information privacy and e-commerce. Her work has been published in the *Encyclopedia of Multimedia Technology and Networking*, and in the proceedings of the Northeast Decision Sciences Institute and the Americas Conference on Information Systems.