



3-2007


Research Note—User Design of Customized Products

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Recommended Citation

Randall, T., Terwiesch, C., & Ulrich, K. (2007). Research Note—User Design of Customized Products. *Marketing Science*, 26 (2), 268-280. <http://dx.doi.org/10.1287/mksc.1050.0116>

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Research Note—User Design of Customized Products

Abstract

User design offers tantalizing potential benefits to manufacturers and consumers, including a closer match of products to user preferences, which should result in a higher willingness to pay for goods and services. There are two fundamental approaches that can be taken to user design: *parameter-based* systems and *needs-based* systems. With parameter-based systems, users directly specify the values of design parameters of the product. With needs-based systems, users specify the relative importance of their needs, and an optimization algorithm recommends the combination of design parameters that is likely to maximize user utility. Through an experiment in the domain of consumer laptop computers, we show that for parameter-based systems, outcomes, including measures for comfort and fit, increase with the expertise of the user. We also show that for novices, the needs-based interface results in better outcomes than the parameter-based interface.

Keywords

user design, product design, product development, user needs, customer needs, design decisions, customization

Disciplines

Business Administration, Management, and Operations | Marketing | Organization Development | Other Business | Technology and Innovation

USER DESIGN OF CUSTOMIZED PRODUCTS

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Version of July 2003

Abstract

User design offers tantalizing potential benefits to manufacturers and consumers, including a closer match of products to user preferences, which should result a higher willingness to pay for goods and services. However, the user design experience can suffer from a mismatch between user preferences and the resulting product, arising from overwhelming confusion for novice users and daunting design complexity. There are two fundamental approaches that can be taken to user design: *parameter-based* systems and *needs-based* systems. With parameter-based systems, users directly specify the values of design parameters of the product. With needs-based systems, users specify the relative importance of their needs, and an optimization algorithm recommends the combination of design parameters that is likely to maximize user utility. Through an experiment in the domain of consumer laptop computers, we find considerable support for the hypotheses that (1) outcomes for parameter-based systems degrade with the inexpertise of the user, (2) novice users achieve better fit using a needs-based approach, (3) novice users are more comfortable using a needs-based system than a parameter-based system, and (4) users perceive needs-based systems as potentially biased in their recommendations. In practice, the strengths of the two approaches can be combined through the use of hybrid systems, in which users select one of the two alternative systems to perform their user design, or a single system that allows manipulation of both the design parameters and the user needs.

Key words: user design, customization, mass customization, product variety

Acknowledgments

We acknowledge the substantial contributions of Rachel Nation, Gabe Silvasi, Johnny Lee, Martha Eining, Chetan Salian, Noah Springer, Ryan Sundquist, and Mattias Kellmer. We would also like to thank Dell Computer.

1. Introduction

Product customization uses a flexible production system to deliver a product to order that matches the needs of an individual customer or user. *User design* is a particular form of product customization that allows the *user* to specify the properties of that product. Consider three examples. At Cmax.com, athletes can design a running shoe to their specifications, selecting almost every element of the shoe from the material of the sole to the color of the shoelace. General Mills experimented with an on-line service with which consumers could design a customized breakfast cereal. Consumers can design a customized computer from Dell using the company's website. User design has emerged as a mechanism to build brand loyalty, to fit products to the heterogeneous needs of a market, and to differentiate the offerings of a manufacturer (Dahan and Hauser 2002). User design offers the possibility of exploiting the capabilities of the internet to deliver a highly differentiated product instead of intensifying price competition (Lynch and Ariely 2000).

To illustrate the advantages and potential limitations of user design, consider the personal computer industry and the competition between Hewlett-Packard /Compaq (HP) and Dell. When HP introduces new laptop computers targeted for a specific market segment, e.g. college students, it relies on market research to elicit the user needs of that segment. For example, HP might use conjoint analysis to estimate to what extent consumers in a segment are willing to pay for extra features such as a larger disk drive or a faster video processor. Thus, HP aggregates individual consumers into market segments and then uses its product development expertise to translate the user needs for this market segment into product designs.

Dell, in contrast, engages in user design, allowing consumers to set many of the design parameters by themselves. For example, consumers can select which hard drive or video processor they want. Consumers submit these design choices via Dell's web site and Dell then builds and ships the computer. This approach allows Dell to serve a heterogeneous market, without having to take risks in finished goods inventory, and to deliver to consumers exactly the computers they specify.

While this user design approach has the advantage of locating the design decisions with the agent in the value chain that has the most information about the user's utility function (the actual

user), it also leaves the user with the potentially daunting task of finding a design that maximizes this utility function. This is most difficult if the user has little or no background in the underlying technical domain. For example, the consumer may know more about his or her preferences for PC gaming performance than could be statistically inferred by means of broad-based market research. In fact, a particular consumer might actually require a specific level of gaming performance, e.g. 50 frames-per-second refresh rate on *Motocross Madness*. But is the consumer really well equipped to evaluate and optimize potentially interacting design decisions concerning the microprocessor, video processor, and display resolution to achieve this goal?

Hence, we observe a dilemma inherent in the traditional approach to user design and, more broadly, to product customization. The user has the most information concerning his or her utility function, but typically only has a partial understanding of the technical domain underlying the design problem. In contrast, the manufacturer typically understands the technical domain well, but has only partial information about the user's preferences.

In this article, we present and evaluate a novel approach to user design, in which the user expresses needs directly and leaves to the manufacturer the translation of needs into parameter choices. We refer to this approach as the *needs-based* approach. The needs-based approach provides an alternative to the traditional user design approach, in which the user directly manipulates design parameters. We refer to this approach as the *parameter-based* approach.

The parameter-based approach is the standard method of customization in the laptop computer industry as of 2003. Of the top eight laptop computer brands, seven employ parameter-based systems (Compaq, Hewlett-Packard, Gateway, IBM, Apple, Toshiba, and Fujitsu), often with some supplemental text-based information to explain the role of a design parameter. One brand (Sony), offers a "notebook recommender" in addition to a parameter-based customization system. This recommendation system is essentially similar to a needs-based system.

Our research compares the parameter-based approach and the needs-based approach in the context of the consumer laptop business. In collaboration with Dell, we developed two user interfaces. The first one largely resembles Dell's current user design approach (parameter-based) while the second one provides an alternative, needs-based approach.

The objective of this article is to demonstrate the strengths and limitations of alternative approaches and to outline several opportunities for the improvement of user-design interfaces. Using Dell's laptop product line, we conducted an experiment in which subjects designed a laptop computer via the internet. The subjects were randomly assigned to one of the two user interfaces and were surveyed about their satisfaction with the laptop that they chose as well as the process of designing it. After they completed their design, we then exposed the subjects to a "showroom" that included a close approximation to the laptop that they had chosen, an array of alternative laptop configurations, along with educational material about the underlying technical domain of laptop computer design. We then gave the subjects an opportunity to modify the design they had made on the internet and measured the extent to which they chose to modify their initial selection. We use this extent of change as one of the measures of performance of the user design systems.

This research makes three basic contributions:

1. **We find that in the laptop computer domain our sample subjects were generally poorly equipped with the expertise necessary for user design using a parameter-based system.** Based on a nine-question instrument designed to evaluate a subject's ability to link design parameters to user needs, we find that subjects answer less than one third of the questions correctly (mean = 2.64, median=3). The relative lack of expertise raises concerns as to whether consumers have the expertise to design a computer effectively using a parameter-based interface.
2. **We illustrate the needs-based approach to user design in the form of a novel needs-based user interface.** This approach has the advantage of placing the consumer in control of the design process, yet does not require the technical domain expertise of the parameter-based approach.
3. **We test several hypotheses related to the effectiveness of the two user design approaches and the role of user expertise. We find that novice subjects using a needs-based system experience better outcomes than novice subjects using a parameter-based system.** For example, we find that novice subjects achieve better fit, are more comfortable, and make fewer post-selection changes using the need-based approach than with the parameter-based approach.

Our findings have several important implications for how user design can be employed, both in the context of Dell and in more general settings. Despite Dell's success in the overall computer market, the company does not lead the consumer segment, especially among first-time computer buyers. Our results point to challenges in addressing novice consumers with user-design systems, and we generate some insights, which may be helpful in addressing these challenges. The

insights from this research are likely to be relevant in a range of other technology-based industries in which novice consumers are an important market segment.

The remainder of this article is organized as follows. In Section 2, we develop theory and hypotheses. In Section 3, we describe the design of the two user interfaces we test. In Section 4, we describe the experimental design. In Section 5 we present the results. Section 6 contains discussion and concluding remarks.

2. Theory and Hypotheses

For customized products, a design problem can be thought of as a search for a set of values for the product design parameters that maximizes user utility. This problem can be represented by the causal network in Figure 1, in which the design parameters on the left drive product performance specifications, which in turn relate to user needs, which underlie user utility. This is the basic theoretical framework for product design taught in schools of engineering and management (Ulrich and Eppinger 2004).

For customized products, the product concept and product architecture are almost always established in advance and customization occurs within a basic product template. This is in contrast to an open-ended design problem, for which the product concept and product architecture are typically not specified in advance, and so even the definition of design parameters may not be known in advance. In such cases, the causal network would not be static, but would depend on the concept and product architecture (Ulrich 1995).

Typically, a professional product designer is in charge of understanding this causal network and linking design parameters to user needs. Furthermore, the professional designer will elicit the relative importance of needs from the potential user of a product. Based on this information, the product designer, who is typically equipped with professional training and substantial experience, then searches for values of the design parameters that are likely to maximize user utility. Finding the best (utility maximizing) design solution constitutes a challenging information processing task. In some cases, the designer may be supported by analytical tools or simulation tools, which allow product performance specifications to be predicted and their effect on user utility estimated before the user receives the new product.

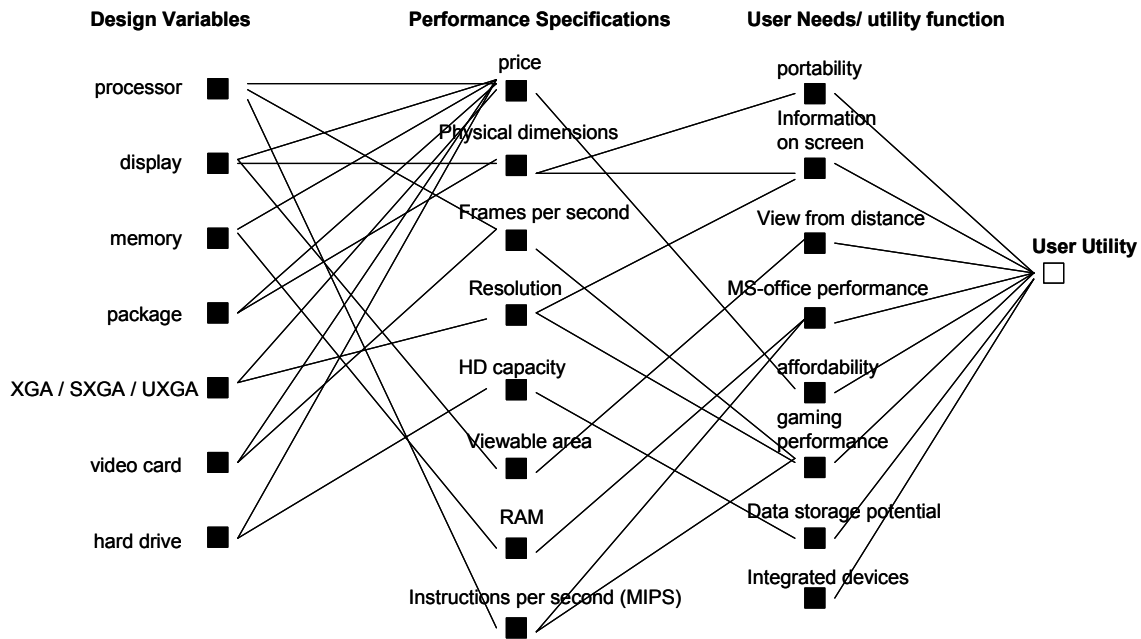


Figure 1: Causal structure relating design parameters to user utility for laptop computers.

Design Defects using Parameter-Based User Design Systems

With user-design systems, the professional designer is replaced by the user. However, under the parameter-based approach to user design, the same information processing challenges persist. That is, the user must understand the causal network relating design parameters to user needs and must understand his or her own needs. Given that the user in a consumer setting typically does not have substantial technical domain knowledge or access to analytical tools, the parameter-based approach inherently bears the risk of what we call a *design defect* – a choice of design parameters that does not maximize user utility. Such a design defect reflects a misfit between the product designed and the utility maximizing product that might have been designed, despite the fact that the user is in control of all the design decisions.

Design defects can arise for several reasons. First, utility may depend on subjective user needs, whose potential satisfaction is hard to communicate to the consumer, especially if the user design is executed over the internet (Lal and Sarvary 1999; Srinivasan, Lovejoy and Beach 1997; Dahan and Srinivasan 2000). In the case of laptop computers, such subjective specifications include the portability of the laptop or the ergonomics of the keyboard. For example, a user who

chooses a laptop with a weight of 8 lbs. and thickness of 1.7 inches, might later be surprised by how heavy the product feels when carrying it around in a backpack. Interpreting product performance specifications in terms of the user experience depends on an accurate understanding of the mapping between these specifications and the user needs, which may require subtle expertise that does not reside with the typical user. Such defects can arise even with respect to objective and tangible performance specifications. Consider the simple case of a performance specification that is driven by exactly one design parameter. For example, the information storage potential of a laptop is solely driven by the capacity of the disk drive. In this case the user can easily understand qualitatively how the design parameter influences the utility function (more capacity is always better). However, in order to correctly trade off performance with price (since more capacity is also more expensive), the user has to understand the exact shape of this utility function. This would require the user to (a) anticipate future usage patterns of the laptop (e.g., how many MP3 files will be stored) and (b) to correctly translate this usage pattern into a required value for a product performance specification (e.g., how many megabytes of storage are needed to store one MP3 file). While the user may be best equipped to anticipate future usage, he or she may lack the specific technical expertise to apply that knowledge to the design problem.

Design defects can also result from holistic user needs, the case in which several design parameters interact in determining a product performance specification, thus creating a complex mapping from design parameters to user needs (Ulrich and Ellison 1999). For example, the ability of a laptop to deliver good video gaming performance is driven by an interaction between the central processor and the video processor. These interactions can create mathematical complexity from the combinatorics of the design space and/or the possible non-monotonicity of utility with respect to design parameters. Previous studies have shown that even for simple online tasks, many consumers perceive the disutility related to “clicking” and exploring as too high and are willing to settle with a sub-optimal solution (Hann and Terwiesch 2003). Experts develop heuristics or specific problem solving procedures for navigating complex design spaces, but novices are likely to stumble when faced with many choices and a complex relationship between these choices and desired outcomes.

These potential defects in parameter-based user design systems threaten the ability of user design to live up to its promise of delivering a product uniquely suited to a user’s needs. This threat is

especially severe if consumers do not have detailed knowledge about the underlying technical domain.

Comparative Advantages of Parameter-Based and Needs-Based Systems

An alternative approach to the design problem for customized products is to specify the relative importance of the user needs for a particular individual, and then allow an automated system, with an embedded model of the causal network, to find a feasible set of design parameters to maximize the user's utility given the relative importance of the needs. We call this the "needs-based" approach. The needs-based approach has been explored in theory (Ramaswamy and Ulrich 1993), yet it has seen limited use in industrial practice. Because with this approach, a user would need not understand the causal structure of the design problem, technically difficult domains may be tractable by novice user designers.

Essentially, the difference between the parameter-based approach and the need-based approach is the "knobs" that are made available to the designer, whether the designer happens to be a user designer or a professional designer. While in the parameter-based approach the knobs are design parameters (left side of Figure 1), the knobs in the need-based approach are actual user needs (right side of Figure 1), which are closer to the user's utility function and thereby typically require less knowledge about the underlying design space. An example of a need-based system for laptop computers is presented in the next section.

Each approach offers some potential advantages and disadvantages.

- The parameter-based approach allows direct and predictable navigation of the design space. This approach also allows fine tuning of a design with small perturbations of design parameters. Whereas, the needs-based approach allows fine perturbation of the relative importance of a need, but such a perturbation in the "needs space" may require large and discontinuous changes to several design parameters by the embedded optimization system. For users who understand deeply both the mapping of design parameters to product performance specifications, and how those specifications relate to their own utility, a parameter-based system allows precise control of the design of the product and therefore a precise and direct tool to achieve the desired outcome.

- The parameter-based approach requires that the designer know the technical language of the domain. Whereas, the needs-based approach requires only that the designer be able to express the relative importance of user needs, a task that can be completed by almost any potential user. Thus, novice users are likely to be more comfortable operating the controls of a needs-based system than a parameter-based system.
- The parameter-based approach is transparent to the user. Whereas, the needs-based approach requires an automated optimization procedure, which is typically a “black box” to the user. Because of this lack of transparency, needs-based systems could be designed to profit opportunistically from the user’s ignorance and may therefore be perceived as more biased than parameter-based systems.

Expertise in consumer decision making in general has been established as an important element of transaction success (Sujan 1985, Bettman and Sujan 1987, Wood and Lynch 2002). Therefore, it is not surprising that expertise plays a critical role in user design systems. These potential strengths and weaknesses of the two approaches lead us to hypothesize that neither approach will dominate for all users, and that domain expertise will play a critical role in determining satisfaction and the quality of actual outcomes.

Specifically, we pose four hypotheses. There are at least three dimensions of outcome performance for user-design systems: the optimality or *fit* of the resulting product with respect to the user’s utility function, the *comfort* of the user with the design process, and the *speed* with which a user can design a product. For simplicity in articulating our hypotheses, we refer to all of these as *outcomes*, although in our discussion of the experiment we will more precisely test these dimensions separately. For convenience in exposition, we coin a term *inexpertise*, which we define as the opposite of expertise.

Hypothesis 1: The quality of outcomes for the parameter-based interface increases in the expertise of the user. (The quality of outcomes for the parameter-based interface decreases in the inexpertise of the user.)

This is the baseline hypothesis for our research: users risk design defects with parameter-based systems, and these risks increase with the inexpertise of the user.

Hypothesis 2: The advantage of the needs-based interface relative to the parameter-based interface decreases in the user's expertise. (The advantage of the needs-based interface relative to the parameter-based interface increases in the user's inexpertise.)

Hypothesis 2 focuses on the relationship between expertise and the magnitude of relative advantage of the needs-based system. We hypothesize that the relative advantage of needs-based systems decreases as the user's expertise increases. Note that technically we do not imply with Hypothesis 2 that the needs-based system always delivers better outcomes, only that as user expertise increases, the relative advantage of the needs-based system declines. In the event that the needs-based system delivers worse outcomes than the parameter-based systems, Hypothesis 2 implies that this disadvantage is diminished with the inexpertise of the user.

Hypothesis 3: For novices, the needs-based interface results in better outcomes than the parameter-based interface.

In contrast to Hypothesis 2, Hypothesis 3 does explicitly hypothesize that for novices, the needs-based interface produces better outcomes than the parameter-based interface. We do not formally pose a hypothesis about the outcomes for experts, as theory does not necessarily predict that they would do worse with a needs-based system than with a parameter-based system, only that novices face difficulties with parameter-based interfaces. We will, however, address the question of absolute quality of outcomes for experts when we discuss our results.

Hypothesis 4: Perceived bias is greater for the needs-based interface than for the parameter-based interface.

There is documented theoretical and empirical evidence linking trust and transaction success (Morgan and Hunt 1994, Torkzadeh and Dhillon 2002, Bhattacharjee 2002, Doney and Cannon 1997). Given that transparency of information is potentially lower for the needs-based approach, we would expect that users would perceive the needs-based approach as more biased in favor of the manufacturer than the parameter-based approach. We hypothesize that this is the case regardless of the expertise of the user.

3. Parameter-Based and Needs-Based Systems for Laptop Computers

A parameter-based system forms the baseline against which we test the needs-based system. The current web-based user interface for Dell Computer's consumer laptop business is essentially a

parameter-based system. The system requires the user to specify the values of design parameters such as the microprocessor type, microprocessor speed, memory size, hard drive size, and video processor type. The system then computes the price, and with some effort on the part of the user will also provide information on size and weight.

For experimental purposes, we designed a parameter-based system (Figure 2) that differs in two ways from the Dell commercial site. First, we stripped away much of the extraneous information associated with promotions, discounts, and links to pages with related product and services. Second, in addition to price, we compute for each product the values of several performance specifications: size, weight, storage capacity of the hard drive, as well as benchmarks for gaming and image editing performance.

In addition to the main screen, the system includes a “shopping list”-- a separate web page with a table to which the user can add product configurations for comparison. When the user finds a desirable configuration, it can be added to the shopping list and can then be “purchased.”

We encoded essentially Dell’s entire consumer laptop computer product line with this system, so that a user could in theory design any consumer laptop product offered by Dell.

We also designed and built a needs-based system for the Dell consumer laptop product line. The main screen of this interface is shown in Figure 3. Using the need-based system, the user first positions slider bars to indicate the relative importance of nine user needs. These needs are:

1. My computer is light enough that I can easily carry it in my bag.
2. My computer screen can display a lot of information at once.
3. My computer screen is physically large enough that I can read it from a decent distance.
4. My computer can store most of my music and photo collection.
5. My computer can quickly edit digital images.
6. My computer is superior for video games with three-dimensional animation.
7. The CD/DVD drive is integrated in the computer (vs. externally connected by a cable).
8. My computer has more capability than I need now, just in case I need it in the future.
9. My computer costs less than average.

Once the values are set for the relative importance of the needs, the user clicks “recommend computer” and the system displays a laptop computer with its associated product performance

specifications, including price. This approach resembles Sony's "notebook recommender". Exactly the same product performance specifications are displayed for a computer in both the parameter-based and need-based systems.

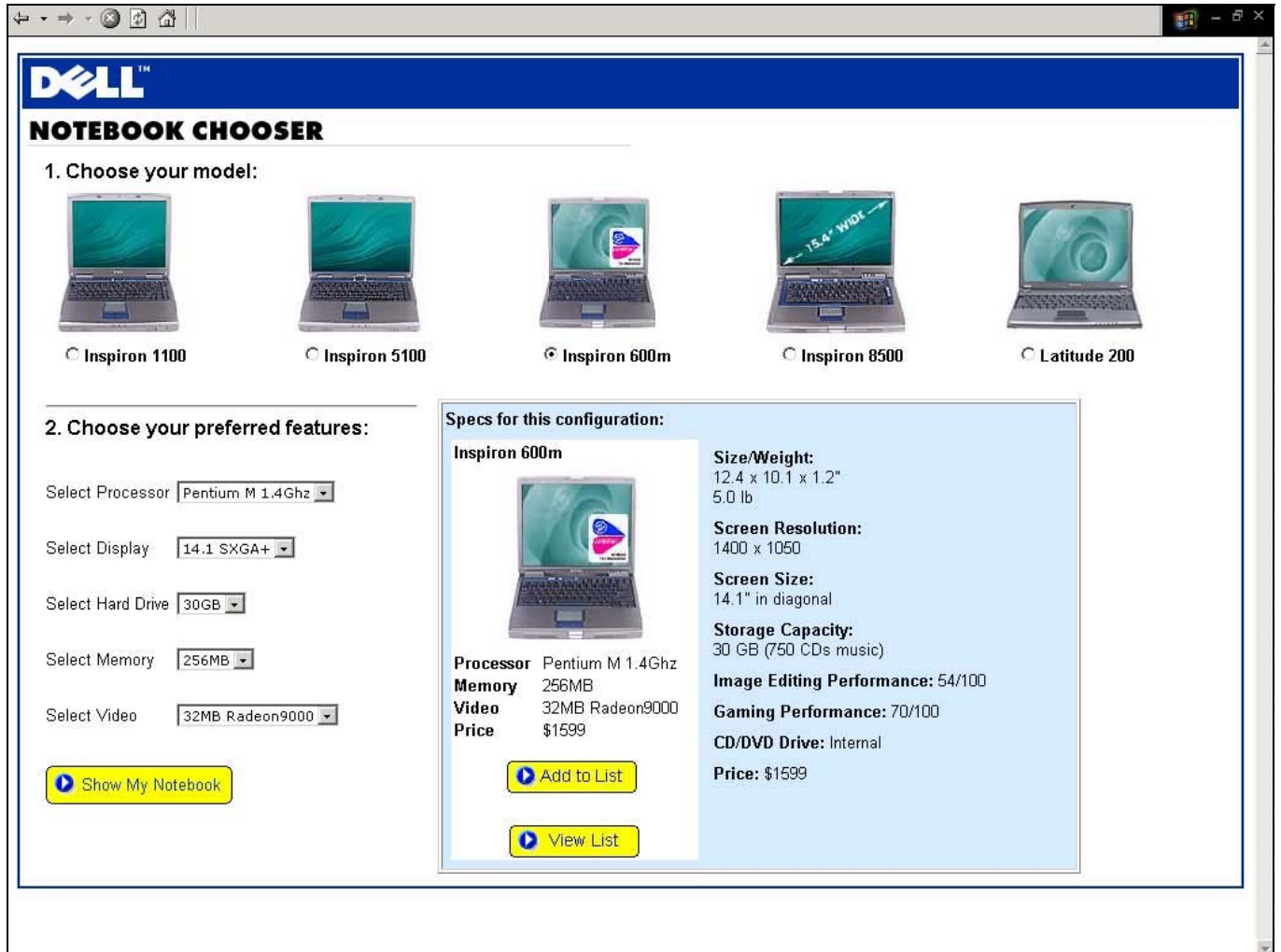


Figure 2: The main screen for the experimental parameter-based interface.

To recommend a configuration, the needs-based system computes performance specifications for each configuration in the design space, and then estimates the utility of each of these configurations using a linear multi-attribute utility model, with the values of the slider bars (0-99) as the weights in the utility function. The needs-based system as designed employs *self-explicated* consumer weights. There is an active debate in the marketing community as to whether self-explicated weights are as reliable as other methods for estimating preference (e.g., conjoint analysis). See work by Leigh, McKay and Summers (1984), Huber (1993), Srinivasan

and Park (1997), and Pullman (1999) for research on the relative merits of different approaches. In our case, speed and ease of use were of paramount concern, and in such situations the self-explicated approach offers substantial benefits.

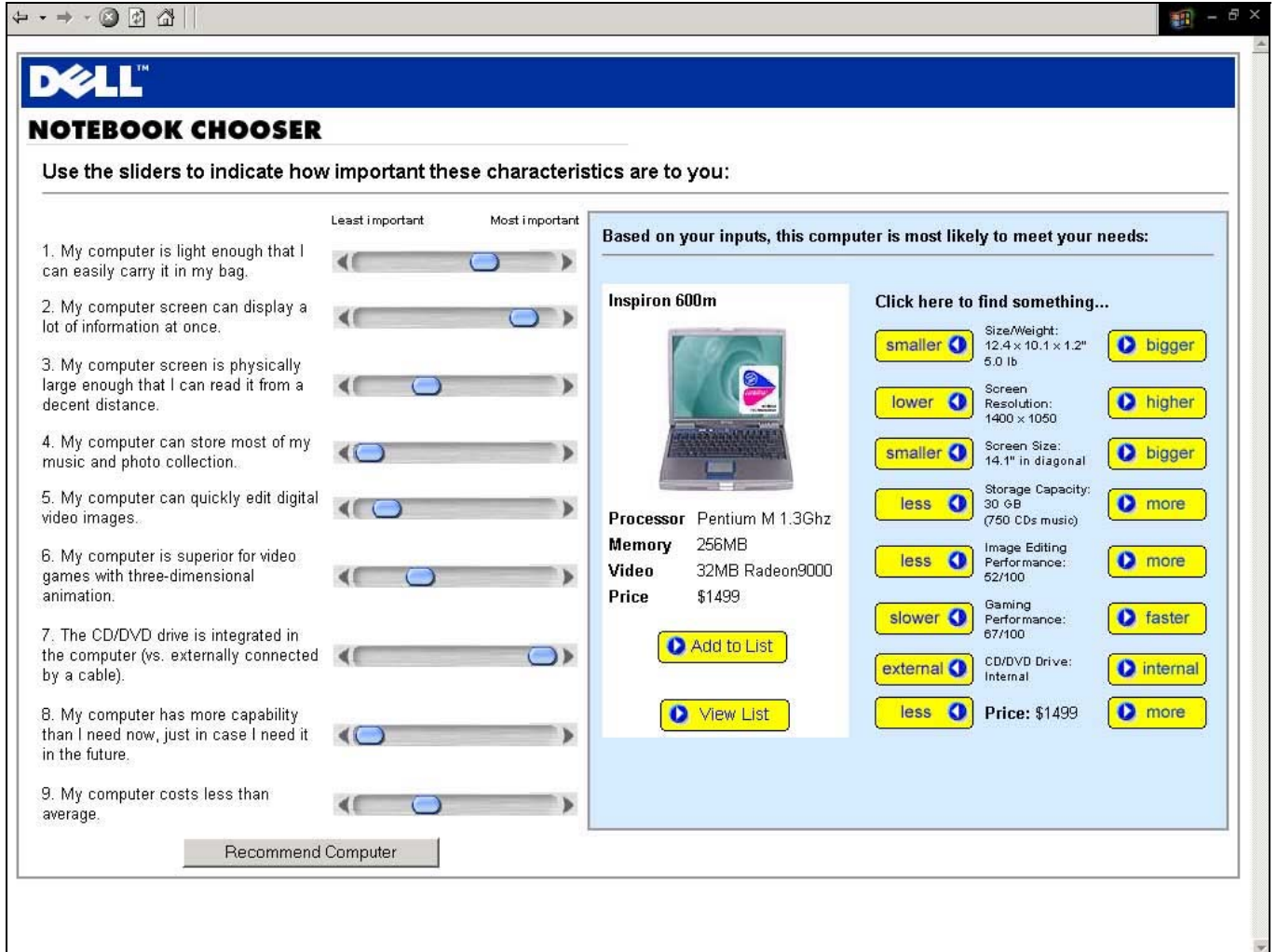


Figure 3: The main screen for the experimental needs-based interface.

To navigate the design space, the user can either reset the slider bars and click for another recommendation, or can incrementally improve or diminish the performance of the current recommendation with respect to one of the product performance specifications. For example, if the recommended configuration is too expensive, the user can simply click on “less” (price) to see one that is less expensive. This feature is implemented by finding the configuration with the next highest utility that also is an incremental improvement in the desired direction with respect

to the user's input. The mechanics of implementing this kind of directed search are described in by Ramaswamy and Ulrich (1997).

The incremental navigation of the “needs space” proved to be an important feature of our implementation of the needs-based approach, as it has several advantages. First, it mimics the interaction a consumer (especially a novice) would engage in when purchasing a laptop with the help of a sales person in a retail store. As design is inherently an iterative process, it is unlikely that the first recommendation from the sales person would provide the consumer with the right computer. Directing the subsequent iterations in the need-based world (“show me a computer which has better image editing performance”) as opposed to in the parameter-based world (“show me a computer with 256 MB more memory”) is intuitive and matches the language of the novice. Directed iterations will lead to significantly faster resolution of uncertainty (Terwiesch and Loch 2003). Second, iterating in this fashion allows the consumer to find out the extra price associated with higher performance. Given that the system restricts incremental recommendations to those computers with high scores on the utility function, it is possible to explore the marginal impact of one need (e.g., portability), holding everything else nearly constant. Third, complex design spaces exhibit local optima, leading to an overall rugged solution landscape. In such an environment, using design parameters as the knobs is likely to lead to local optimization in one area of the solution space. In contrast, our implementation of the needs-based approach allows for jumps from one local optimum to another, if so desired by the user. For example, the user might have configured an Inspiron 5100 that is satisfying in most respects. Yet, this computer weighs almost 7 pounds and the only way to find a lighter computer using the parameter-based system would be to choose a different model (e.g., the Inspiron 600m) and start the customization procedure from scratch. In contrast, in our implementation of the need-based approach, the user only needs one click to request a lighter system, keeping all other user needs at their previous level of importance.

4. Experimental Design

Our experiment can be broken up into four parts: an initial survey, the actual web-based purchase experience, a second survey, and a simulated showroom. Figure 4 summarizes this set-up, which is now explained in greater detail.

In the initial survey, we gather data about the demographics of the subjects and their prior experience purchasing computers. At this stage, we also measure the computer expertise of the subjects. We do this via an instrument that measures computer literacy based on a set of nine multiple-choice questions, to which the subject has to select an answer from several possible solutions or can select “I don’t know.” This instrument is provided in Appendix I.

In the second part of the experiment, we randomly assigned subjects to either the parameter-based system or the needs-based system. Subjects were asked to use the assigned interface and design a laptop computer to meet their own preferences. There was no constraint on how much time subjects could spend on this task.

The web server that we used to host the user interface collected data about clicks, session durations, and the final configuration the consumer selected. When the subject pressed the “buy” button, the selected configuration was printed and the subject was then asked to fill out a second survey.

The second survey collected information about the users’ satisfaction, both with respect to their experience using the interface as well as their satisfaction with the configurations they selected. We also asked questions about the subjects’ intent to purchase the exact configuration selected as well as to what extent the subjects felt that they could trust the recommendations provided by the interface.

Following the second survey, the subjects were directed to a simulated showroom, where they were told that they would be provided with additional information and given an opportunity to revise any of the choices they had made with the web-based system. In order to ensure a consistent treatment, this briefing and all other instructions to the subjects were based on a script. The role of the showroom was to measure how well the laptop configurations selected by the subjects actually fit their needs. One way to measure fit would be to provide the subject with this exact configuration and then let the subject use the laptop for an extended period of time (e.g., one year). While this approach has the advantage that it allows the subject to experience the laptop in a personal use environment, it does not expose the subject to any alternative (and potentially better) configurations. Obviously, this approach is also difficult to implement from a

logistical standpoint, reflecting both budget constraints (paying for the computer) and time constraints (waiting for one year) of our research study.

To overcome these two problems, we introduce two simplifications. First, rather than providing the subjects with the exact configuration that they had chosen, we provided them with a set of 10 laptops. The 10 laptops were chosen so that they would cover all physical dimensions of Dell-laptops, all screen sizes, all video cards, and span the range of microprocessor and memory choices. In this respect, the showroom product assortment resembles a classical fractional factorial design. While this approach does not provide the subject with the exact post-purchase experience they would get if they actually purchased a computer, it has the advantage that it demonstrates to the subject the alternative choices for each design parameter. Second, we did not have the opportunity to provide a laptop to the subjects for an extended period of time (e.g. several days). However, we installed some common applications so that the subjects could see their configurations in a setting resembling normal usage.

In addition to the 10 laptops we obtained from Dell, we provided the subjects with information about laptops, both verbally and graphically (supported by posters). This information covered the following aspects: (a) disk drive characteristics and how they relate to storage requirements (b) processor information (c) memory information. This purely factual information was created in collaboration with Dell. Performance information was displayed for the applications that would be most likely familiar to consumers (e.g., storing music, editing digital photos).

During their time in the showroom, subjects were shown laptops with the design parameters that were the same as the ones the subjects had customized using the web-interface. Subjects were also shown alternative configurations (e.g., cheaper/lower-performing configurations, more-expensive/higher-performance configurations, lighter/heavier configurations). Subjects were given the opportunity to modify any of their previous decisions. The extent to which they engaged in change at this step was used as a measure of fit between the initial customized design and the subjects' actual needs.

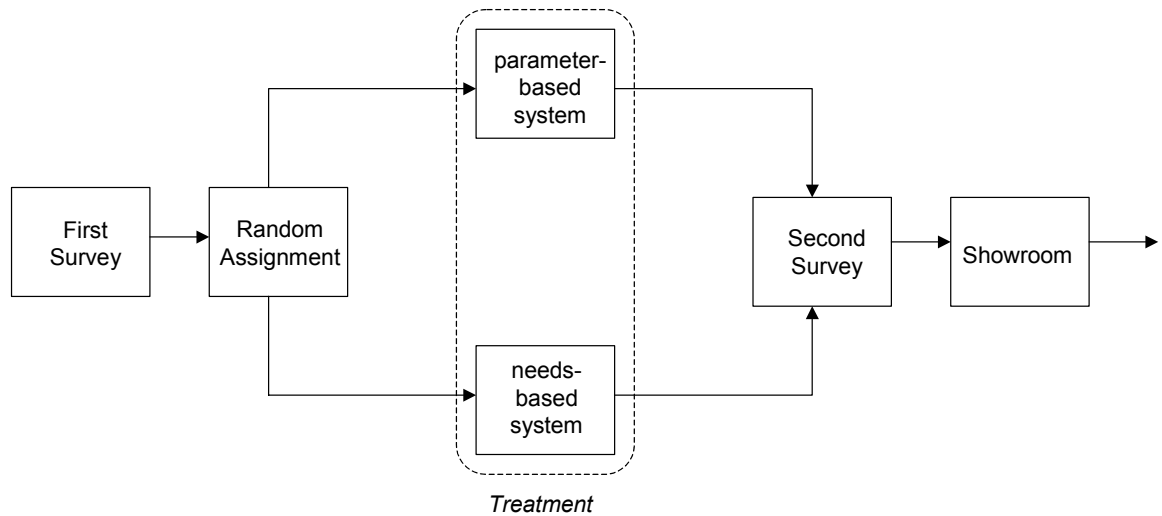


Figure 4: Process flow diagram for experiment.

Subjects

Subjects for the experiment were recruited from the students and staff at the University of Utah. While our sample is predominantly college students, we purposely recruited from evening students and staff to obtain a wider range of demographic characteristics. The characteristics of the sample are provided in Table 1 – Panel A. Female subjects make up 36.7 percent of the sample. The median age of the sample is 24 with median income of approximately \$25,000. Married subjects represent 46.6 percent of the sample and 16.4 percent have children. 18.9 percent of the sample had previously purchased a computer using the internet.

The experiment took about 1 hour in total and subjects were given \$10 for their time.

The entire experiment, ranging from initial survey to the showroom was pre-tested in several independent iterations and then the final version of the experimented was piloted with a group of 10 subjects.

Measures

In the following paragraphs we describe the dependent and independent variables used in the experiment. Throughout the discussion, we refer to descriptive statistics of each variable found in Table 1 – Panel B.

Outcome Variables

Perceived Fit: Perceived fit captures the extent to which subjects believed they chose a product that would suit their uses and needs. Perceived fit is an aggregate construct based on the average response to three statements. Following the selection of a computer, subjects were asked to indicate on a 1-to-9 scale the extent to which they agreed with the following statements. 1) From the computers available on the system, I believe I found the one that would be best for me. 2) If I were to buy a Dell computer in the near future, I would purchase essentially the one I selected. 3) I'm satisfied that the computer I selected would meet my needs. Question 3 and the 9-point scale were adapted from Haubl and Trifts (2000). The Cronbach alpha score for the combined measure is 0.83, which exceeds acceptable limits on construct validity (Nunnally and Bertstein 1994). We report a relatively high degree of perceived fit by subjects (mean = 7.23, median=7.33).

Perceived Comfort: Perceived comfort captures the extent to which subjects felt comfortable during the process of selecting a computer. Perceived comfort is an aggregate construct based on the average response of a subject to five statements. Following the selection of a computer, subjects were asked to indicate on a 1-to-9 scale the extent to which they agreed with the following statements. 1) I felt it was easy to explore the alternatives that were available to me. 2) I felt that I was able to easily find a computer that would meet my needs. 3) I wish an independent person could have helped me select the right computer (reverse coded). 4) I felt confused during the selection process (reverse coded). 5) I felt comfortable with the process of selecting a computer. The Cronbach alpha score for the construct is 0.72, which exceeds conventional limits for construct validity. We report an average perceived comfort level of 6.44 (median=6.6).

Table 1: Descriptive Statistics.

Panel A: Subject Descriptive Statistics

Total Subjects	164
Subjects spending less than 90 seconds on the computer	11
Total Subjects for Analysis with Computer Data	153
Subjects not responding to Fit, Comfort and Bias Questions	3
Total Subjects for Analysis with Fit, Comfort and Bias Questions	150
Percent Female	36.7%
Median Age	24
Median Household Income	\$25,000
Percent Married	46.4%
Percent with children	16.4%
Median # of times purchased a laptop	1
Median # of times purchased a desktop	0
Percent that previously purchased computers via the internet	18.9%

Panel B: Study Variable Descriptive Statistics

			Percentiles		
	mean	std dev.	10th	50th	90th
<i>Dependent Variables</i>					
Perceived Fit	7.23	1.27	5.67	7.33	8.67
Perceived Comfort	6.44	1.39	4.5	6.6	8.2
Absolute Value of Price Change	233.23	264.65	0	170	575
Time Spent	306.85	151.93	153	272	481
Number of Changes ^a	1.40	1.20	0	1	3
Perceived Bias	4.38	2.25	1	5	7
<i>Independent Variables</i>					
Expertise	2.64	1.90	0	3	6

^aDue to exclusion of observations with model changes, statistics for number of changes are for subsample of 122 subjects.

Absolute Value of Price Change: This variable is measured as the absolute value of the price changes a subject made while in the showroom. For example, a change from an Inspiron 600M to a Latitude 200x increases the base price of the computer by \$250. Decreasing the hard drive by 60 gigabytes to 30 gigabytes would decrease the price by \$199. The net effect of this change is \$51. The absolute value of the price change in this case is \$51. On average, the absolute value of the price change was \$233 (median=\$170).

Number of Changes: The number of changes is measured as the raw quantity of changes a subject made to their chosen computer configuration when in the showroom. A value of zero implies the best fit. In our analysis of number of changes, we exclude the 28 subjects that make a model change. This adjustment is necessary because a model change almost always requires a change to many other attributes of the computer. For example, a subject that changes from the Latitude X200 to the Inspiron 8500 is forced to change screen size, screen resolution, processor, and video processor because the same values of these parameters are not available on the Inspiron 8500. We reduce this confounding effect by examining changes only for subjects that do not change models. On average, subjects who did not change models made 1.40 changes (median = 1).

Time Spent: Time Spent is the time a subject spends selecting a computer configuration from the web site. The time begins when the subject enters the password to begin the design process and ends when the subject purchases a computer configuration. To guard against individuals that did not put significant effort into the experiment, we exclude subjects that spend less than 90 seconds on the web site. This cutoff eliminates 5 percent of the subjects. On average subjects spent 306 seconds on the site (median = 272 seconds).

Perceived Bias: Perceived Bias captures the extent to which a subject believes the web interface results in a purchase that biased towards the manufacturer. Perceived bias is a single-item construct measured on a 1-to-9 scale based on the extent to which a subject agrees with the following statement: I am concerned that the system was biased towards recommending a computer that would be most profitable for Dell. The average bias score was 4.38 (median=5).

Independent Variables

Treatment: Subjects were randomly assigned to the parameter-based system or the needs-based system. In the analysis that follows, the assigned system is coded as an indicator variable with Treatment=1 for the needs-based system and Treatment=0 for the parameter-based system. Examination of both treatment groups indicated no statistically significant differences between groups in terms of expertise, age, gender, income and education.

Expertise: Similar to Sujan (1985) and Bettman and Sujan (1987), we measured a subject's expertise via a nine-question multiple choice instrument that asked subjects specific questions about their knowledge of laptop computers. (See Appendix I for questions.) On average, subjects answered 2.64 questions correctly (median=3).¹

Table 2 presents Pearson correlation coefficients for the dependent and independent variables. While many significant relations exist among the dependent variables, in this discussion we highlight the relations between expertise and the dependent variables. We report a positive significant association between Expertise and Perceived Comfort. We report a negative significant association between Expertise and Absolute Value of Price Change, Expertise and Number of Changes, and Expertise and Time Spent.

Table 2: Pearson correlation coefficients (n=150, n=122 for Number of Changes)

	Perceived Fit	Perceived Comfort	Perceived Bias	Abs. Value of Change in Price	Time Spent	Number of Changes	Expertise
Perceived Fit	1.00						
Perceived Comfort	0.51***	1.00					
Perceived Bias	-0.06	-0.11	1.00				
Abs. Value of Change in Price	-0.10	-0.11	0.07	1.00			
Time Spent	-0.07	-0.16**	0.00	0.14*	1.00		
Number of Changes	0.05	-0.01	-0.03	0.67***	0.22**	1.00	
Expertise	0.01	0.21***	-0.06	-0.19**	-0.17**	-0.18**	1.00

***, **, * indicate values significant at p < .01, .05 and .10 levels respectively.

¹ On each question subjects were allowed to answer "I don't know." We formulated an alternative measure of expertise, based on the number of questions that subjects explicitly admitted they did not know. This alternative measure was highly correlated with our primary measure of expertise ($r=0.76$, $p>.01$). Tests of hypotheses using this measure did not qualitatively differ from results of tests using our primary measure of expertise.

5. Results

We use two different statistical techniques to test our four hypotheses: ordinary least squares regression and ANOVA. To test Hypotheses 1 and 2, we use ordinary least squares to estimate the following model.

$$\text{Outcome} = \alpha + \beta_1 \times \text{Treatment} + \beta_2 \times \text{Expertise} + \beta_3 \times \text{Treatment} \times \text{Expertise} + \varepsilon \quad [1]$$

Where outcome is one of the dependent variables described in the previous section. This formulation provides two equations to interpret results based on the two different treatments. For subjects using the parameter-based interface (Treatment=0) the relevant model is:

$$\text{Outcome} = \alpha + \beta_2 \times \text{Expertise} + \varepsilon \quad [2]$$

For subjects using the needs-based interface (Treatment=1), the relevant model is:

$$\text{Outcome} = (\alpha + \beta_1) + (\beta_2 + \beta_3) \times \text{Expertise} + \varepsilon \quad [3]$$

Under our hypotheses, the above equations can be represented with a graph as shown in Figure 5.

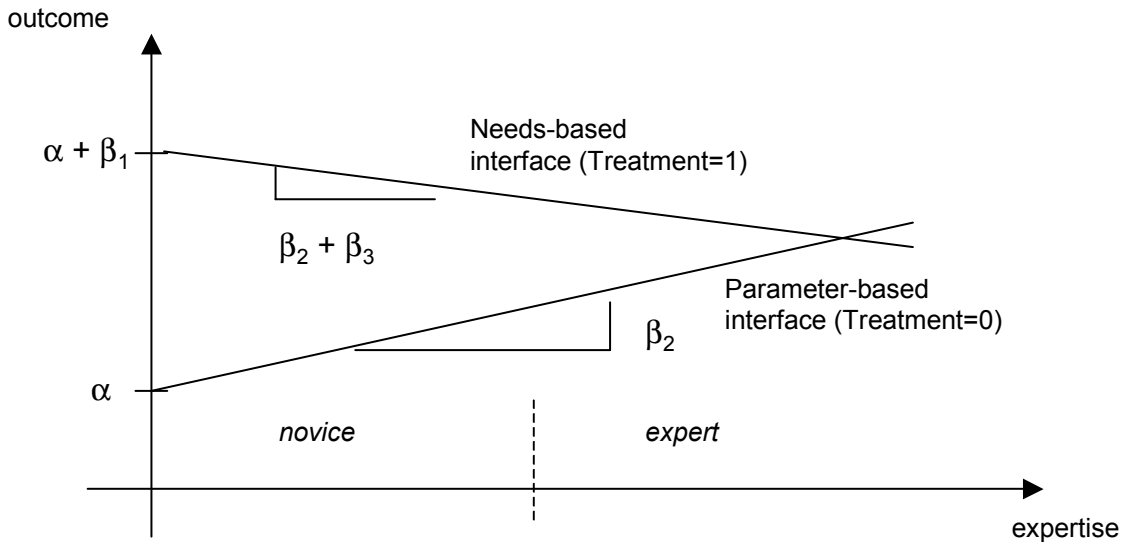


Figure 5: Graphical representation of Equations 2 and 3.

Assuming a more-is-better outcome measure, for Hypothesis 1 to hold, β_2 must be significant and positive. This would indicate that as a subject's expertise increases the quality of outcome using a parameter-based interface increases. For Hypothesis 2 to hold, we expect β_3 to be significant and negative. This would indicate that the relative advantage of the needs-based interface decreases with the user's expertise ($\beta_2 > \beta_2 + \beta_3$). Note that Hypothesis 2 does not strictly posit that the outcome for the needs-based interface decreases with expertise ($\beta_2 + \beta_3 < 0$), although it is shown this way in Figure 5, only that the relative advantage of the needs-based interface decreases with expertise. For a less-is-better outcome, such as Time Spent, Absolute Value of Price Change or Number of Changes, the signs in the preceding argument would be reversed.

Table 3 reports results of the regression analysis. The adjusted r-squared for models ranges from 0.00 for the Perceived Fit measure to 0.05 for the Absolute Value of Price Change. We report statistically significant overall models for Perceived Comfort, Bias, Absolute Value of Price Change, Time Spent, and Number of Changes. To facilitate the discussion of these results, we show plots in Figure 6 of the outcomes as a function of expertise using the coefficient estimates from the regression models.

Consistent with Hypothesis 1— that quality of outcomes for the parameter-based approach increases in expertise— we report positive and significant coefficients for β_2 in models for Perceived Comfort, and a negative and significant coefficient for the Absolute Value of Price Change, Time Spent and for the Number of Changes. We do not report a significant positive coefficient for β_2 in the Perceived Fit model.

Consistent with Hypothesis 2— that the advantage of the needs-based interface relative to the parameter-based interface decreases in the expertise of the user— we report negative and significant coefficients for β_3 in models for Perceived Fit and Perceived Comfort. We report a positive and significant coefficient for β_3 in the model for Absolute Value of Price Change and for Time Spent. We do not find a significant coefficient for β_3 in the model for the Number of Changes.

Table 3: The relation between outcomes, expertise, and design interface (t statistics in brackets).

<i>Dependent Variable:</i>	Perceived Fit	Perceived Comfort	Abs. Value of Price Change	Time Spent	Number of Changes
Intercept	7.09*** [30.46]	5.59*** [22.36]	372.77*** [7.86]	371.34*** [3.02]	1.97*** [7.97]
Treatment	0.39 [1.07]	1.04*** [2.68]	-158.52** [-2.18]	-72.28** [-1.71]	-0.59* [-1.60]
Expertise	0.08 [1.16]	0.24*** [3.34]	-38.22*** [-2.74]	-23.07*** [-2.86]	-0.18** [-2.33]
Expertise x Treatment	-0.20** [1.78]	-0.25** [-2.05]	31.66* [1.40]	24.71** [1.89]	0.14 [1.21]
F Statistic	1.23	4.78***	3.64**	2.77**	2.29*
Adjusted R-squared	0.00	0.07	0.05	0.03	0.03
N	151	150	153	153	122

***, **, * indicates coefficient significance at the $p < .01$, $.05$, and $.10$ levels respectively (one-tailed test).

We also report a main effect for the needs-based interface in all models except Perceived Fit. That is, β_1 is positive and significant for Perceived Comfort and negative and significant for Absolute Value of Price Change, Time Spent and Number of Changes. This implies that for a subject with no expertise there are significant differences in outcomes when using the needs-based interface. In this case, the outcomes are better when using the needs-based interface.

The plots of the mean outcomes by expertise (Figure 6) graphically illustrate the results for Hypotheses 1 and 2. We see that for Perceived Fit, Perceived Comfort, Absolute Value of Price Change, Time Spent and Number of Changes the relationship between outcome and expertise is consistent with our hypotheses. That is, we observe that outcomes for the parameter-based interface improve with expertise and that compared to the parameter-based interface, the relative advantage of the needs-based interface decreases in the user's expertise (increases in the user's inexpertise). These plots combined with the main effect results in Table 3 provide preliminary support for the notion that novices enjoy better outcomes using the needs-based interface than when using the parameter-based interface (Hypothesis 3). We observe that at the extreme

(expertise =0), the model predicts that the needs-based interface produces better outcomes (higher Perceived Fit, Perceived Comfort, lower Absolute Value of Price Changes, lower Number of Changes) for novices.

We formally test Hypothesis 3 using the ANOVA framework. To facilitate this test, we dichotomize the expertise variable at the median score for expertise. Subjects answering three or fewer questions correctly are categorized as novice.² We then compare outcomes for novice subjects using the parameter-based system and novice subjects using the needs-based system. The results are shown in Table 4-Panel A. Consistent with Hypothesis 3, we report significantly higher levels of Perceived Comfort and lower values for Absolute Value of Price Change and lower Number of Changes for novice users that use the needs-based interface than novice users that use the parameter-based interface. We report no significant difference in the Perceived Fit or Time Spent.

While not part of our formal hypothesis tests, Table 4-Panel B shows results of tests for expert subjects (those answering more than three questions correctly). With the exception of Time Spent, there are no significant differences in outcomes for expert subjects using the needs-based versus parameter-based interface. In the case of Time Spent, expert subjects take more time to make purchases with the needs-based interface.

Our final hypothesis (Hypothesis 4), posits that the perceived bias is greater for the needs-based interface than for the parameter-based interface. This bias should exist regardless of level of expertise. In support of this hypothesis, we report a mean bias score of 4.84 for the needs-based interface and a mean bias score of 3.89 for the parameter-based interface. This difference is significant at the $p < 0.01$ level. A more sophisticated model, using interaction terms for expertise and interface, yielded similar results. Only the main effect of interface was significant.

Table 5 summarizes the results of our hypothesis tests for each of the dependent variables.

² We also use a 3rd quartile cutoff to classify subjects as novice. Any subject answering 4 or fewer questions correctly are classified as novice. Results of these tests are not qualitatively different from those reported in Table 4-Panel A.

Table 4: Differences in outcomes for novice subjects and expert subjects

Panel A: Novice Subjects (N=112)				
	Mean Values		Difference	p-value
	Needs-based Interface	Parameter-based Interface		
Perceived Fit	7.30	7.29	0.01	0.94
Perceived Comfort	6.67	6	0.67	0.01
Absolute Value of Price Change	200	309	-109	0.04
Number of Changes	1.27	1.68	-0.41	0.09
Time Spent	294	336	-42	0.17

Panel B: Expert Subjects (N=39)				
	Mean Values		Difference	p-value
	Needs-based Interface	Parameter-based Interface		
Perceived Fit	6.62	7.33	-0.71	0.16
Perceived Comfort	6.50	6.78	-0.28	0.55
Absolute Value of Price Change	183	184	-1	0.99
Number of Changes	1.06	1.33	-0.27	0.56
Time Spent	336	250	86	0.03

Table 5: Summary of results of hypothesis tests.

	Perceived Fit	Perceived Comfort	Perceived Bias	Time Spent	Absolute Value of Price Change	Number of Changes
H1: Outcome increases in expertise for parameter-based interface		✓	N/A	✓	✓	✓
H2: Relative advantage of needs-based interface decreases in expertise	✓	✓	N/A	✓	✓	✓
H3: Outcomes for novices are better with needs-based interface		✓	N/A		✓	✓
H4: Needs-based interface is perceived as biased relative to parameter-based interface.	N/A	N/A	✓	N/A	N/A	N/A

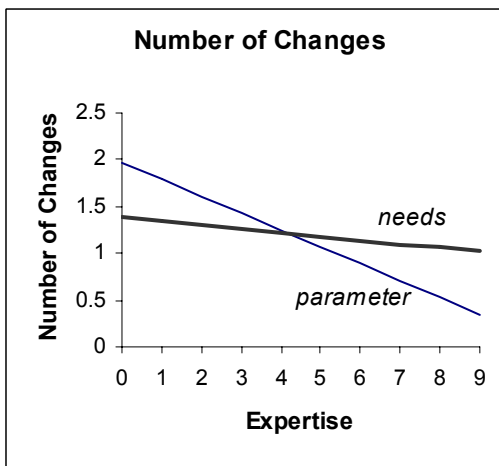
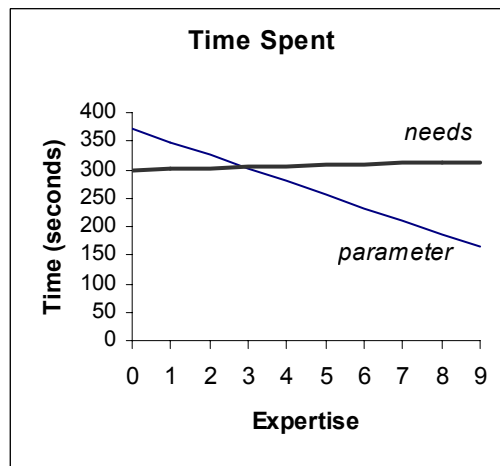
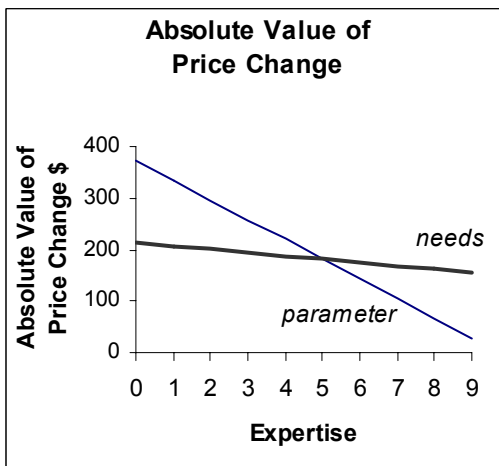
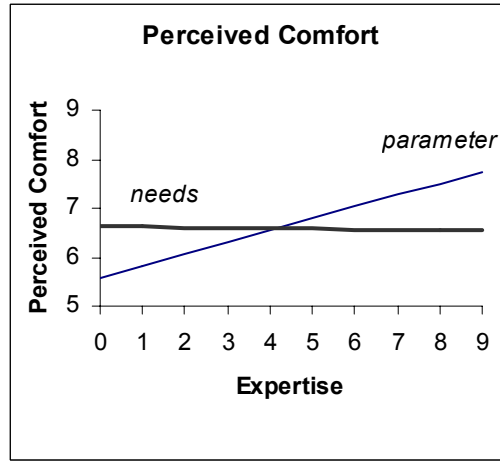
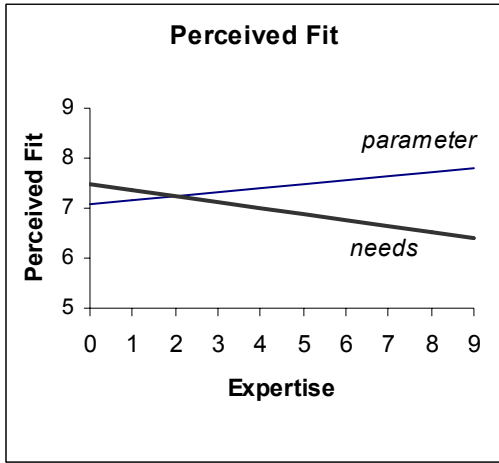


Figure 6: Graphical representation of estimated models for needs-based and parameter-based interfaces.

6. Discussion

The experimental results provide substantial support for our hypotheses. Novices are less comfortable with parameter-based systems and achieve better outcomes with needs-based systems. However, novices and experts alike perceive parameter-based systems as less biased towards the seller than needs-based systems. In this section, we discuss some limitations of our study, along with several issues related to application of needs-based systems in industrial practice.

Limitations of the Study

By including evening students and staff in our sample, we have attempted to create a sample that is more representative than a sample consisting only of young college students. However, our sample is still not fully representative for the overall consumer population, as college-educated consumers, especially business students, are over-represented. Therefore inferences about all consumers may not be valid. However, we conjecture that most consumers are in fact likely to be less well suited to parameter-based approaches than college students of business. Of course, there are segments such as information technology professionals in which consumers are likely to be better suited to parameter-based approaches than the subjects in our sample.

Our study focuses on a single product domain, laptop computers. We would expect similar results for other technology-based goods. Furthermore, although laptop computers are a relatively complex consumer purchase, they are built on a relatively modular architecture. That is, the mapping from design parameters to performance specifications is relatively simple (Ulrich and Ellison 1999). Thus, we expect that the advantages of needs-based systems would be even greater for products with more holistic customer attributes, such as fragrances or apparel. For simple domains, say the design of a sandwich or a pizza, or for domains in which even more modular architectures are prominent, we expect that parameter-based systems might suffer fewer disadvantages relative to needs-based systems.

Our results depend on the particular designs of the two interfaces we tested. The parameter-based system we tested is essentially similar to the actual Dell consumer website, although stripped of extraneous information. Nevertheless, it provides more information than many parameter-based systems including Dell's, in that it clearly displays the product performance

specifications associated with a particular design (e.g., how many CDs of music can be stored on the hard drive). There is substantially more discretion in how needs-based systems can be designed. Although we believe that the approach we have taken to the needs-based interface is good, improvements could probably be made to its design, in which case the relative advantages of the needs-based approach could be more pronounced.

What defines good performance of a design system?

We measure the performance of user design systems in terms of the fit of the resulting product with customer needs, consumer comfort with the purchase experience, consumer perceived bias, and time spent making a purchase decision. These are objectives framed from the perspective of the consumer. Although in the long run, these objectives are relevant to the seller because of their impact on customer satisfaction, they are not direct measures of profitability.

Perhaps one of the reasons that needs-based systems are perceived as more biased than parameter-based systems is that they offer an opportunity for the seller to more directly optimize profits. One could imagine a needs-based system in which seller's profit is part of the utility function used to recommend a product.

We also conjecture that in this phase of the industry lifecycle for laptop computers, sellers benefit in some cases from consumer ignorance. If a consumer simply does not know how much hard drive storage is required, he or she may opt for the most expensive and most capacious alternative. This tendency may support the parameter-based approach for optimizing profits. Note, however, that this potential benefit is balanced by the discomfort the same consumer may feel at being confronted by a decision about which he or she lacks sufficient knowledge.

Hybrid Systems

In testing our hypotheses, we chose to create a clear distinction between the parameter-based system and the needs-based system. Commercial systems need not adhere to this strict categorization. A hybrid system could offer the benefits and mitigate the weaknesses of each approach.

A simple hybrid system could offer the user the choice of a parameter-based interface or a needs-based interface. A more sophisticated hybrid system could allow the same interface to work in

both ways. That is, either parameters or needs could be directly manipulated. One such system would be equivalent to the needs-based system we developed, with the additional feature that any parameter (e.g., amount of memory) could be directly manipulated with the resulting impact on the customer needs shown immediately. We conjecture that a hybrid system would mitigate the bias issue to a large extent.

Conclusion

User design offers tantalizing potential benefits to manufacturers and consumers, including a closer match of products to user preferences, which should result a higher willingness to pay for goods and services. However, the user design experience can suffer from a mismatch between preferences and the resulting product. Design defects can result from overwhelming confusion for novice users and daunting design complexity.

There are two fundamental approaches that can be taken to user design: parameter-based systems and needs-based systems. In parameter-based systems, users directly specify the values of design parameters of the product. In needs-based systems, users specify the relative importance of their needs, and an optimization algorithm recommends the combination of design parameters that is likely to maximize the user's utility.

Through an experiment in the domain of consumer laptop computers, we have found considerable support for the hypotheses that (1) outcomes for parameter-based systems degrade with the inexpertise of the user, (2) novice users achieve better fit using a needs-based approach, (3) novice users are more comfortable using a needs-based system than a parameter-based system, and (4) users perceive needs-based systems as potentially biased in their recommendations. The converse is also implied: experts appear to benefit from the speed and directness of parameter-based systems.

In practice, we believe that the strengths of the two approaches can be combined through the use of hybrid systems, in which either consumers select one of two systems to perform their user design, or a single system allows manipulation of both the design parameters and the user needs. The design of hybrid systems and the analysis of how users interact with them provides a first opportunity for future research. Specifically, it would be interesting to offer both design

approaches to the user and then observe the users' revealed preferences for using them. Second, we have only briefly touched on the impact that user design has on pricing decisions. On the one hand, user design offers substantial opportunities for price discrimination. On the other hand, consumers might perceive non-transparent pricing schemes, especially attempts to charge higher prices to consumers who are expected to be less price-sensitive, as unfair, which could lead to an erosion of trust.

Finally, many other domains offer promise for the application of needs-based user design systems. We are particularly intrigued by the possibility of such systems for selecting among hundreds of existing products, perhaps across the product lines of dozens of different manufacturers. At the time of this writing, a bewildering array of products confronts the consumer in the domains of digital cameras, automobiles, television sets, and home appliances. Thus, in addition to user-design, the needs-based approach offers the prospect of allowing consumers to more naturally navigate these large search spaces.

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Appendix I: Survey Questions for Assessing Expertise

1. How much random-access memory (RAM) does a typical laptop computer sold today have?
 - a. 64 KB
 - b. 2 MB
 - c. 256 MB
 - d. 20 GB
 - e. 128 GB
 - f. I don't know.
2. How thin is a thinnest laptop computer offered by leading brands (e.g. Dell, HP, Compaq, Toshiba) today?
 - a. Less than 1 inch
 - b. 1 to 1.25 inch
 - c. 1.25 to 1.5 inch
 - d. More than 1.5 inch
 - e. I don't know.
3. How much do the majority of laptop computers sold today weigh?
 - a. 8 to 14 pounds
 - b. 4 to 8 pounds
 - c. 2 to 4 pounds
 - d. 0 to 2 pounds
 - e. I don't know.
4. What is the minimum amount you would have to spend to buy a new laptop computer from a well known brand (e.g. Dell, HP, Compaq, Toshiba) that has a Pentium 4 processor and a 14-inch screen:
 - a. Less than \$1200
 - b. \$1200-\$1600
 - c. \$1600-\$2000
 - d. more than \$2000
 - e. I don't know.
5. Which of the following numbers indicates the screen resolution of an XGA display?
 - a. 1024 x 768
 - b. 1280 x 800
 - c. 1400 x 1050
 - d. 1920 x 1200
 - e. XGA does not imply a screen resolution.
 - f. I don't know.

6. What is the size of the largest screens that are sold on laptop computers with a Windows operating system?
 - a. Less than 15 inch
 - b. 15 to 17 inch
 - c. 17 to 19 inch
 - d. More than 19 inch
 - e. I don't know.
7. Which of the following hardware characteristics will lead to the biggest improvement in a typical laptop's ability to provide a great 3D video gaming experience?
 - a. Increasing RAM by 25 percent.
 - b. Increasing the processor clock speed by 25 percent.
 - c. Changing the graphics processor from an Intel Integrated solution to a processor from nVidia.
 - d. Changing from a Celeron to a Pentium microprocessor.
 - e. Doubling the capacity of the disk drive.
 - f. I don't know.
8. Assume you want to store a music collection consisting of 200 CDs on your laptop computer in MP3 format. Approximately how much space will this consume on the disk drive?
 - a. 1 megabyte
 - b. 10 megabytes
 - c. 100 megabytes
 - d. 1 gigabyte
 - e. 10 gigabytes
 - f. 100 gigabytes
 - g. I don't know
9. Microprocessors in Windows-based laptop computers sold today operate at clock speeds of
 - a. 0.5-3.0 Ghz
 - b. 3.0-5.0 Ghz
 - c. 0.5-3.0 Mhz
 - d. 3.0-5.0 Mhz
 - e. 0.5-3.0 Khz
 - f. 3.0-5.0 Khz
 - g. I don't know.