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# DENTIFYING PREFERENCES THROUGH MOUSE CURSOR MOVEMENTS – PRELIMINARY EVIDENCE

*Research in Progress*

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## Abstract

*Identifying customers' preferences is a challenging task with significant practical implications for online shopping. Current methods often put considerable burden on the customers through such methods as questioning, so the process could benefit from a more accurate and less intrusive estimation of how customers weight product attributes, particularly in the initial purchasing phase. Our goal is to derive attribute weights automatically by recording and analyzing cursor movements. We conducted an experiment to confirm the suitability of the proposed design, and found a highly significant correlation between the time people spend investigating a product attribute and their self-reported importance rating. Our proposed Web page design might also reduce the risk of information overload.*

## 1 Introduction

Online shopping has become a major part of overall economic activity. In the United States alone, online retail sales totaled more than US$395 billion in 2016, accounting for 8.1 percent of total retail sales (DeNale and Weidenhamer, 2017). However, as online customers cannot experience products physically while shopping online, they often rely on product recommendations, such as provided by recommendation agents that facilitate decision making (e.g., Xiao and Benbasat, 2007). For example, McKinsey et al. (2013) reported that 35 percent of Amazon.com's sales are recommended products. Especially for complex products, how detailed product information is presented is an important factor in purchasing decisions (e.g., Franke et al., 2009; Hong et al., 2004; Mandel and Johnson, 2002).

When making purchase decisions, online customers typically follow a two-stage process (Häubl and Trifts, 2000). First, customers consider a large set of candidate products on one or more Web pages that they narrow down to a smaller subset of alternatives that seem to meet their needs. Then customers assess this subset in more detail through comparisons across products based on desirable attributes before choosing the product that best matches their needs (Ahuja, 2003).[1]

Customers and their preferences must be well understood in order to provide the best (most relevant to the customer) recommendations and support for the decision process (Xiao and Benbasat, 2007). In multi-attribute decision-making it is common to compute the value of an alternative by adding together each of the product's attributes multiplied by their weight (Barron and Barrett, 1996; Hwang and Yoon,

[1]The decision process can change in the presence of prior knowledge of the product (Karime et al., 2015) and recommendations, where customers might follow a process more akin to choosing from a set of predetermined alternatives (Dellaert and Häubl, 2012).

1981; Stillwell et al., 1987), so an important part of understanding customers' preferences is understanding which product attributes customers consider more or less important (i.e., attribute weightings).

However, in contrast to sales clerks in physical retail stores, who can infer preferences when interacting with a customer or by observing his or her appearance or behavior, online retailers often have limited opportunities to infer customers' preferences, particularly when a new customer has not viewed any of its products before (often referred to as the "cold start problem"; e.g., Bobadilla et al., 2013; Lam et al., 2008; Zigoris and Zhang, 2006).

In this research-in-progress paper, we propose a novel method for identifying customers' attribute weightings using a novel Web site design and recording and analyzing cursor movements. In particular, we argue that cursor hovering time correlates with attribute importance. In the next section, we discuss the process of obtaining preferences from customers. Subsequent sections present our method, experimental evaluation, and results.

## 2 Identifying Customer Preferences

Providing recommendations that are relevant to online customers is challenging, as their preferences are influenced by many factors (e.g., Holzwarth et al., 2006) and may not be stable over time (Holzwarth et al., 2006; Kramer, 2007). Even the retailer's choice of attributes to include when seeking to extract preferences from the consumer influences the consumer's preferences (Xiao and Benbasat, 2007).

The process of eliciting consumers' preferences is typically based on product features or the customer's needs (Xiao and Benbasat, 2007). In feature-based elicitation of preferences, the customer specifies the features he or she is seeking, and the retailer uses this information to reduce the choice set and to recommend suitable alternatives. Needs-based elicitation of preferences requires that customers provide input about themselves and how they intend to use the product.

There are two principal methods for identifying or eliciting preferences from consumers: implicit and explicit. Implicit methods include visual observations of customer interactions (e.g., eye-tracking) and asking questions that are not directly related to preferences but still provide information about the customer (and his/her preferences), such as past product purchases. For example, Zdziebko and Sulikowski (2015) sought to predict users' product ratings using a large number of variables obtained from user interactions, including the time spent on a page and the distance covered by the user's cursor. Another way of eliciting preferences is to extract product features from customer feedback; for example, Popescu and Etzioni (2007) used text-mining techniques to identify product features and opinions in online reviews. However, the usefulness of implicitly elicited preferences has been debated (e.g., Zigoris and Zhang, 2006).

Explicit methods involve directly asking customers for their preferences. For example, given a product, customers might be asked to state for each product feature whether they prefer a product with a different value than that of the one shown (Pu and Chen, 2009) or a different product category (Kveton and Berkovsky, 2016). In this vein, online shops like eBay allow customers to filter available products by specifying values or ranges for attributes. Generally, explicit preference elicitation methods lead to better decision quality but require more effort than implicit methods do (Xiao and Benbasat, 2007). Therefore, an explicit method of identifying customer preferences that has minimal impact on the customer, seems preferable.

A variety of systems use either implicit or explicit methods, such as travel assistance systems, apartment rental support systems, or (virtual) sales clerks (Chen and Pu, 2004). In practice, large online retailers like Amazon, Walmart, and Alibaba seem to prefer non-intrusive, implicit methods in the sense that customers are not asked to specify product preferences. Instead, the retailers use various forms of recommendation systems (Bobadilla et al., 2013). For example, collaborative filtering is based on products in which a user was previously interested. This set of products is then matched using either other customers or other products. Matching products on a customer-to-customer basis involves finding

customers who have looked at a similar set of products and recommending the items the matched customers most frequently purchased (or viewed), based on the assumption that their tastes are similar. Despite its widespread use, this method suffers from an obvious shortcoming in that customers purchase the same products for different reasons, so basing recommendations only on matching customers' purchases (or interests) may lead to suboptimal recommendations. Matching products on an item-to-item basis relies on comparing attributes of items and recommending similar items (Sarwar et al., 2001). As, typically, not all attributes have the same level of importance, a weighted-distance metric to identify the most similar products (or nearest neighbors in the product attribute space) is commonly employed. However, the relevance of particular product attributes to a particular customer is not usually known, particularly if he or she has not purchased the product before or is a first-time visitor. Although in some cases information about a customer's demographics can help to guide recommender systems, more detailed information is usually needed to improve the relevance to customers of the recommendations provided (Bobadilla et al., 2013).

In order to address the shortcomings of current approaches, we develop a non-intrusive way of combining explicit and implicit methods of identifying customers' preferences. A long line of research has demonstrated the gaze-bias effect, which suggests that humans tend to shift their visual attention toward preferred alternatives (Lindner et al., 2014), and eye movement studies have indicated that higher-frequency fixation on a target can indicate greater interest (Armel et al., 2008; Krajbich et al., 2009, 2010; Jacob and Karn, 2003; van der Laan et al., 2015). Since eye movements and cursor movements correlate (Chen, Anderson, and Sohn, 2001; Rodden and Fu, 2007), it stands to reason that cursor movements can be used to infer the importance of a product's attributes.

Based on these findings, we hypothesize that *the time a customer's curser hovers over a product attribute correlates positively with the weight the customer gives that attribute.*

# 3 Method

To examine the relationship between *cursor hovering time* and *attribute weighting*, we mocked-up a Web page of an online shop and asked study participants to select products from the page and to subsequently weight the importance of the products' attributes.

## 3.1 Prototype

Products are generally characterized through a set of attributes that are often depicted in a list or grid (to facilitate product comparisons). These attributes include clearly measurable aspects of the product, such as weight, price, and customer ratings, but also less tangible aspects, such as product design. Prominent online stores like Amazon and BestBuy commonly present products using a list of these attributes, as shown in Figure 1. While this approach enables customers to compare products easily, information overload can be a concern, especially for complex products with large numbers of attributes, as illustrated in Figure 1, which shows part of an attribute-product comparison grid.

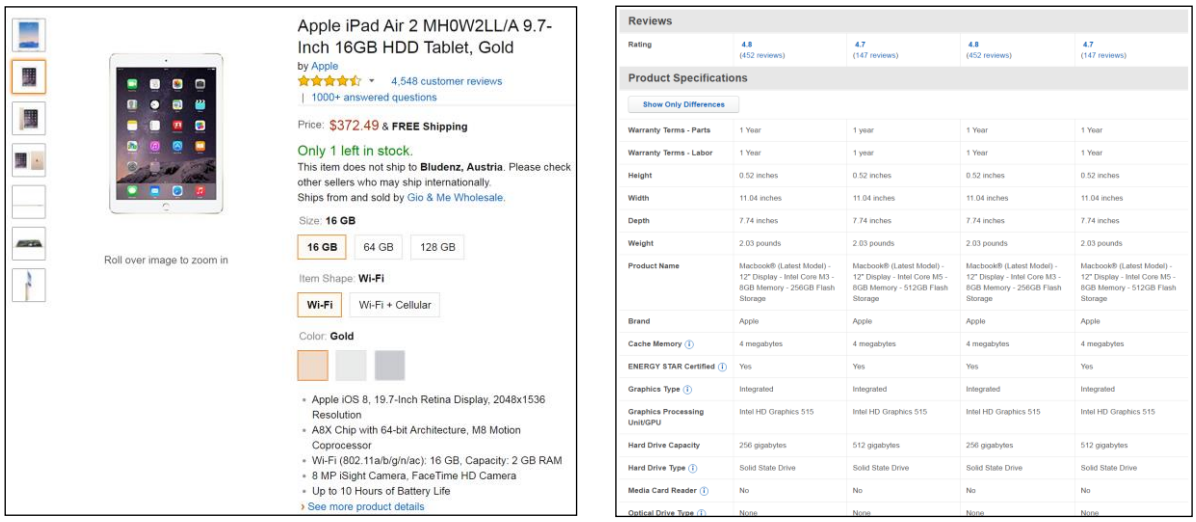


*Figure 1. Left: Typical structure of a product display for an online store (Amazon.com). Right: Attribute-product comparison grid (Bestbuy.com).*

We address the problem of inferring customer preferences by using a novel design for comparison grids that displays a certain product attribute only when the user's cursor hovers over the attribute for a set period of time.[2]

We argue that online customers' cursors hover over attributes that are important to them longer than they hover over attributes that are not as important, so we develop a design that collects and analyzes those times (*cursor hovering time*) to enable online stores to identify users' preferences. To this end, we modified the traditional attribute-product comparison grid to display the attributes' names only, and reveal the attribute values when a customer's cursor hovers over them (Figure 2). In other words, the attribute values are hidden and are revealed only when a user explicitly wishes to see them. The time users spend examining an attribute allows us to infer the attribute's relative importance.

The design was derived with the objectives that 1) the design should not require more user interaction than necessary, 2) the user's interaction must provide data that potentially allow to reveal his preferences, 3) the design should be simple, and 4) usage of the page should be simple. We tried to address Points (1) and (2) by relying on tracking mouse cursor movements only rather than requiring the user to perform selections, e.g., based on clicks on specific elements. Points (2) and (3) are considered by hiding relevant information (i.e., attribute ratings); the information is only revealed if the user moves the mouse cursor over the attribute ratings. Thus, by hovering over an attribute, a user provides data that can be used to infer the importance of the attribute. Regarding Point (3), the design is as simple as ordinary Web sites as we do not introduce any additional elements like buttons or text fields but only hide content. Furthermore, revealing information upon hovering on an area on the screen is common on webpages as well as standalone software. For example, "tooltips," i.e., contextual information, are commonly displayed upon positioning the mouse cursor on a menu icon. Thus, users should quickly learn how to interact with the page.

[2] Pages for mobile devices are often designed differently because of the reduced screen size and differences in the interaction technologies (e.g., touchscreens, rather than pointing devices). In this study, we focus on non-mobile devices.

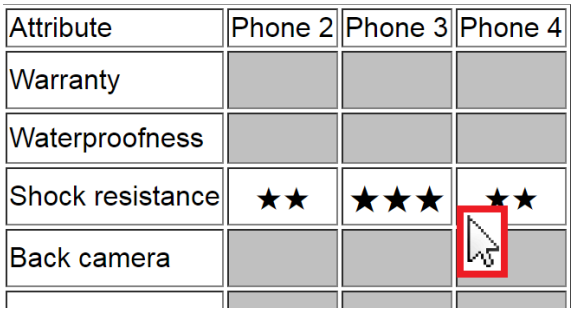


*Figure 2. Product comparison grid for three smartphone models. Attribute ratings are only revealed when the cursor hovers over an attribute.*

To implement the method, we could choose from a large range of data-collection frameworks from industry (e.g., Google Analytics) or academics (e.g., Zdziebko and Sulikowski, 2015). However, freely available tools like Google Analytics do not provide data on measures at a sufficient level of detail (as such mouse cursor movements), so their possibilities for in-depth analysis are limited. Therefore, we devised a Web page, data collection, and analysis system ourselves. As suggested by Weinmann et al. (2013) and Hibbeln et al. (2017), we used general-purpose Web design and programming tools like JavaScript, HTML, jQuery, and Python (and its libraries). HTML pages were generated by a server using Python. Because of the study's randomization requirements, unique pages that contained JavaScript that collected mouse cursor movement data and transmitted it to the server were generated for each visitor.

## 3.2 Experimental Procedure

We developed four scenarios in which participants made purchase decisions: two scenarios for smartphones and two for cars, each with either two or three alternatives. Table 1 provides an overview of the four scenarios, and Figure 3 shows the smartphone version. For each product, we chose eleven attributes that we found in the product descriptions of several online stores. To reduce the risk of decision fatigue (Tierney, 2011), which can result from having to compare multiple complex attribute values, we chose to provide star ratings rather than actual values (such as display sizes, camera resolution, or weight). We randomized the order of the attributes and the product characteristics for each scenario and participant as follows: Attribute order was randomized, and the rating of the attributes was assigned uniformly at random under the constraint that each product obtained the same number of attributes with one-, two-, and three-star ratings. (See Figure 2 for an example.) The first scenario was used as training to familiarize users with the interface, and we used the remaining three scenarios for data analysis. To obtain the attribute-weighting data, after participants completed Scenario 2 (i.e., smartphones) and Scenario 4 (i.e., cars), we asked them to provide a weight for each attribute. (Figure 3 shows the three steps for the smartphone experiment.)

| Scenario | Product type | Available alternatives | Number of Attributes |
|---|---|---|---|
| 1 | Smartphone | 2 | 11 |
| 2 | Smartphone | 3 | 11 |
| 3 | Car | 2 | 11 |
| 4 | Car | 3 | 11 |

*Table 1. Overview of Scenarios*

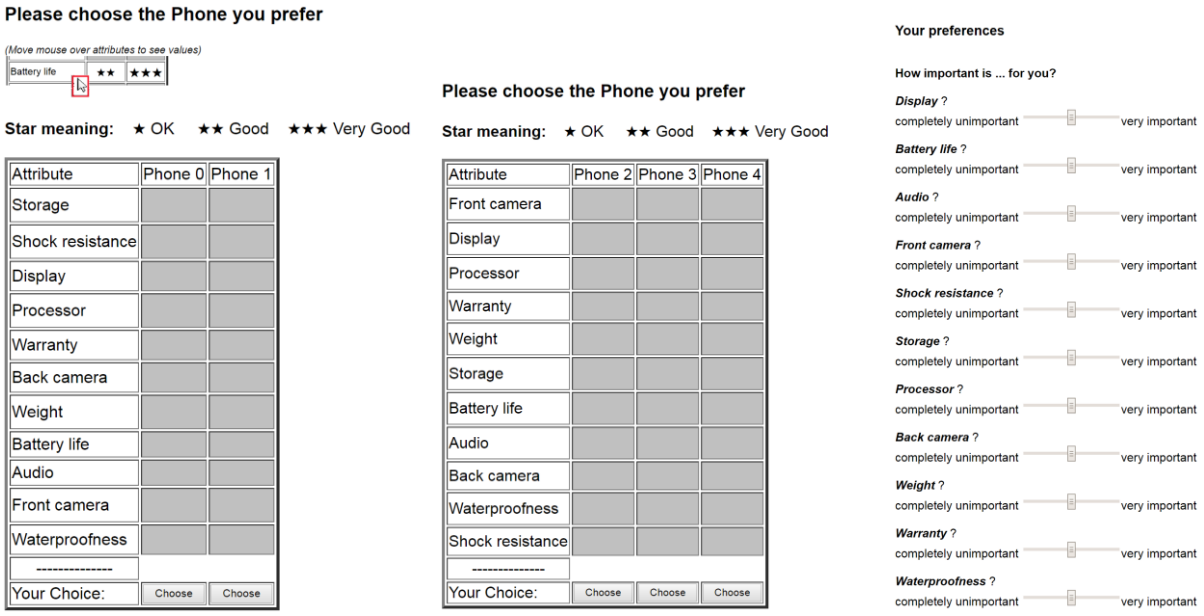


*Figure 3. Procedure: Left: Scenario 1, center: Scenario 2, right: attribute weighting*

### 3.3 Participants

We recruited fifty participants from www.prolific.ac. Forty-four percent were from the United Kingdom, 42 percent were from the United States, and the remaining participants were from various countries in Europe. Eighty percent were native English speakers, the mean age was 30.47 years, and 49 percent were women. Although our design might also prove effective on handheld devices, we focused on cursor movements, so we removed data from participants who used touch screen devices, leaving us with forty-three participants. We used a repeated-measures design, where each participant evaluated eleven product attributes in each of four scenarios, so we ended up with 1,806 attribute observations. For the final data analysis, we removed the first scenario, which was used to familiarize the participants with the interface, resulting in a final dataset of 1,333 attribute observations.

### 3.4 Measures

*Attribute weighting*. Participants used a slider to provide a weighting score, ranging from 0 to 100, for each attribute. (See Figure 3; right panel.)

*Cursor hovering time*. We captured a log of cursor events, with each event consisting of a timestamp, screen coordinates, and the name of the HTML element that resides at the specific cursor location. At post-processing we extracted the total hovering time for each attribute on which the cursor resided, that is, either on the attribute name or the rating of the attribute held by one of the products.

## 4 Results

To estimate the relationship between *cursor hovering time* and *attribute weighting*, we specified a linear mixed-effects regression model. As observations from the same participant or the same scenario might be correlated, mixed-effects models account for repeated measures (i.e., each participant evaluated eleven attributes) by allowing each participant and each scenario to have a varying intercept in the model. As such, the model accounts for unobserved between-subject heterogeneity—for example, as the experiment was conducted online, we could not observe individual environments—in addition to observed heterogeneity (e.g., age, gender). We specified the following varying-intercept model:

$$\textit{Attribute weighting}_{i[j]*k} = \alpha_{i[j]*k} + \beta_1 \cdot \textit{cursor hovering time}_{i[j]*k} + \gamma' \cdot \textit{Controls}_{i[j]*k} + u_i + u_k + \varepsilon_{i[j]*k},$$

where $i$ = 1,…, 43 participants; $j$ = 1,…, 11 attributes; and $k$ = 1,…, 3 scenarios. The subscript $i[j]*k$ indexes an attribute $j$, which is clustered within a participant $i$ (repeated-measures design), where $k$ is the number of scenarios. $\alpha_{i[j]*k}$ represents the individual intercept, $\beta_1$ is the effect of the cursor hovering time, $Controls_{i[j]*k}$ are the control variables Age and Gender, and $u_i$ and $u_k$ are random effects designed to capture the correlation between 1) attribute weights $j$ from the same participant $i$, and 2) attribute weights $j$ from the same scenario $k$.

Table 2 shows the estimated coefficients, standard errors, p-values, and confidence intervals of the fixed effects, as well as the variances of the random effects. The results indicate a significant positive relationship between *cursor hovering time* and *attribute weighting* ($\beta$ = 2.40; $p$ < 0.01; Model 1). The effect was robust when control variables were added in Model 2 ($\beta$ = 2.39; $p$ < 0.01). Thus, we found evidence for our hypothesis that cursor hovering time can indicate attribute weighting.

| **Dependent variable: Attribute weighting** | | | | | | |
|---|---|---|---|---|---|---|
| | **Model 1: without controls** | | | **Model 2: with controls** | | |
| **Fixed effects** | $\beta$ | p | CI | $\beta$ | p | CI |
| Cursor hovering time | 2.40 (0.38) | *** | 1.66 – 3.13 | 2.39 (0.37) | *** | 1.66 – 3.12 |
| Age | | | | 0.31 (0.12) | ** | 0.07 – 0.55 |
| Gender | | | | 5.43 (2.95) | | -0.36 – 11.22 |
| Intercept | 62.30 (1.80) | *** | 58.77 – 65.84 | 50.09 (4.69) | *** | 40.91 – 59.27 |
| **Random effects** | | | | | | |
| $\sigma^2$ | 509.96 | | | 509.97 | | |
| $\sigma^2_1$ (Participant; N = 46) | 86.52 | | | 70.51 | | |
| $\sigma^2_2$ (Scenario; N = 3) | 1.66 | | | 1.60 | | |
| AIC | 12,184.1 | | | 12,180.9 | | |
| BIC | 12,210.1 | | | 12,217.2 | | |
| Observations | 1,333 | | | 1,333 | | |

*Notes: * p < .05 ** p < .01 *** p < .001; standard errors are in parentheses.*

*Table 2. Mixed-effects regression models.*

# 5 Discussion and Conclusion

In this research-in-progress paper, we proposed a novel design for product comparisons that would reveal attribute values when a user's cursor is placed over an item. By analyzing users' cursor movements, we can infer the importance a user places on an attribute (i.e., attribute weights). Like any research, this study has limitations. First, our current design is somewhat artificial, so we intend to investigate in more detail questions related to privacy, information overload, and usability. We also focused on monitoring user behavior based on mice and trackpads, but touchscreens are the prevalent input method on touchpads and mobile devices. While it stands to reason that the method's underlying mechanisms apply regardless of the input method, future research could implement and test this method for mobile devices with touchscreens; likewise, future research could explore the potential of capturing and analyzing keystroke dynamics as an alternative way of extracting attribute weights. In addition, we have thus far tested our design with only a relatively small sample using simulated scenarios. In future studies, we intend to replace these scenarios and mock-up designs with conditions that involve actual purchases in a real shop in order to obtain better-tailored product recommendations. Although users could use our website with almost no introduction, it is unclear to what extent customers would perceive

being forced to move the mouse to see information as disturbing or inconvenient. Finally, the potential gains that can be won by avoiding the risk of information overload by displaying less information should be assessed in detail.

Notwithstanding these limitations, this study contributes to the extant research on identifying customer preferences by proposing a novel method for obtaining customer weights in an online shopping scenario that comes with little effort required from the customer. From a practical standpoint, this novel design can help to provide recommendations that are more relevant to the customer by leveraging insights about users' preferences. At the same time, this design can help to reduce information overload, especially for products with multiple attributes. As such, our research has the potential to have important practical implications for online retailers.

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