

The moderating influence of source of product rating and product category on attraction and
compromise effects

By
Yunzhijun Yu
Division of Marketing, Leeds School of Business
University of Colorado at Boulder

Defense Date April 1st, 2015

Thesis Advisor:
Dr. Donald Lichtenstein, Division of Marketing, Leeds School of Business

Defense Committees:
Dr. E Christian Kopff, Department of Classics
Dr. Andrea Feldman, Program for Writing & Rhetoric

TABLE OF CONTENTS

I. Abstract -----	Page 3
II. Introduction -----	Page 4-7
III. Attraction versus Compromise -----	Page 7-11
IV. Horizontally versus Vertically Differentiated Product Categories -----	Page 12
V. Methods -----	Page 13-15
VI. Results -----	Page 15-18
VII. Discussion -----	Page 19-21
VIII. Reference -----	Page 22
IX. Tables -----	Page 23-25
XI. Figures -----	Page 26-34
XII. Appendix -----	Page 35-36

Abstract

Prior research has shown that the introduction of an irrelevant third choice to a two-choice set affects consumers' preferences between the preexisting two choices. In addition to compromise effect, which denotes that a choice gains share when it became the intermediate rather than extreme option in a three-choice set, attraction effect suggests that adding an unattractive dominated option enhances the attractiveness of the option it most resembles and increases that option's choice share. However, research has shown that attraction effect does not typically occur when one of the product attributes is not represented numerically. Furthermore, no research has looked into the source of numeric ratings (e.g., product quality ratings) and how that moderates such effects with different types of product category. This study examined how the factors of source of ratings (user vs. expert ratings) and product categories (horizontally vs. vertically differentiated product categories) moderate attraction and compromise effects with the cooperation of real-life experimental stimuli.

Keywords: attraction effect, compromise effect, decoy, product quality ratings, product category differentiation

Researchers and marketers have been long interested in understanding how consumers' preferences on product selection could be altered under different environmental contexts. In the past few decades, consumer behavioral research has shown many instances in which consumers' preferences are affected by the introduction of a third option to an original product set of two. The compromise effect suggests that an alternative would tend to gain greater choice share when it becomes a compromise or middle option in the set (Simonson, 1989). On the other hand, the attraction effect, sometimes called "decoy effect" or "asymmetric dominance effect" (Huber, Payne, and Puto, 1982), refers to instances in which the addition of an inferior alternative (decoy) to a choice set potentially increases the choice share of the option it most closely resembles.

Although such effects have been widely used in real-life marketing practices and advertising campaigns, a recent study (Frederick, Lee, Baskin, 2014) pointed out that the effect of attraction does not typically occur when consumers experience the product or when even one of the products attributes is represented perceptually rather than numerically. For instance, Frederick, Lee, and Baskin suggested that it is more likely to observe such effect when the attributes of the products are presented with numerous quality ratings rather than images of the products that indirectly imply the quality perceptually. Furthermore, Frederick, Lee, and Baskin argued that introducing an inferior alternative to a choice set does not only make the target alternative a dominating option but makes the inferior alternative a compromise option at the same time. This finding suggests that introducing an inferior alternative to a 2-choice set might generate the opposite effect of the desired effect. Therefore, it is important for marketers to understand the factors that could potentially moderate attraction and compromise effects before designing and launching campaigns.

One way to understand the role of this inferior alternative played is to understand consumers' perceptions of given products. Due to the rapid changes that internet has brought to communications during the past decade, more and more information has been made available to consumers to help them make purchase decisions. To communicate a product's quality to consumers, one of the most common practices is to present a form of quality rating scale (e.g., star rating, numeric rating, and so on) that is usually rated by peer users or professional rating experts/agencies. Recent studies suggest that almost all retailers nowadays provide consumer/user product quality ratings on their websites, and these product quality ratings are a significant driver of revenues across industries (Chevalier and Mayzlin, 2006; Loechner, 2013; De Langhe, Fernbach, and Lichtenstein, 2015).

Besides user ratings, there are product quality rating experts, such as *Consumer Reports*, that aim to provide credible, detailed ratings to the public. Compared with user ratings that are generated by peer consumers, expert ratings are more accurate and reliable indicators of product quality. However, no research has studied the issue of whether attraction or compromise outcomes could be moderated by the source of product quality ratings (i.e. user rating and expert rating). Moreover, research evidence also has shown that product category can influence how consumers perceive the quality of a given product, as quality is a multidimensional construct and could be defined in multiple ways. For vertically differentiated product categories, such as televisions and digital cameras, quality can be thought of in terms of objective performance. Product quality of a vertically differentiated product can be evaluated based on some objective standards that consumers find important (Tirole, 2003). Horizontally differentiated product categories, on the other hand, are those in which product rankings are primarily a matter of individual taste. Product quality of horizontally differentiated product categories, such as wines

or perfumes, is defined with more subjective elements of user experience and thus is harder to be measured with objective standards. This factor of product category brings a complication to the retailer and marketer's practice of presenting product quality ratings that helps the consumer to make purchase decisions. The presence of product quality ratings can be helpful and informative when consumers make selections on vertically differentiated products, but it could be problematic with horizontally differentiated products. This is because the evaluations of horizontally differentiated product qualities are becoming overwhelmingly subjective, and the quality measurements could vary on individual levels.

De Langhe, Fernbach, and Lichtenstein (2015) suggest the published expert quality ratings from *Consumer Reports* provide the most accurate indication of quality for vertically differentiated product categories. *Consumer Reports* is known for its independent corporate interest and is not allied in any way to any group of firms, and it applies scientific approach to analyze quality through blind laboratory studies that generates consistency and confidentiality in the testing results. On the opposite, due to the high subjectivity and relatively low level of reliability in quality measures, it is hypothesized that consumers are the least likely to rely on user ratings generated by peers to make purchase decisions on horizontally differentiated product categories.

This study is conducted to test the effects of the two types of ratings (user vs. expert) and the two types of product categories (horizontally differentiated vs. vertically differentiated product categories) on consumer purchase decisions. To test these effects and determine their relational directions, the model of asymmetric dominance (attraction vs. compromise effect) is applied to the experimental paradigm. Taking into account all the listed factors, it is hypothesized that:

H₁: A newly added alternative to a preexisting 2-choice set is more likely to be perceived as a decoy (i.e. attraction effect is observed) when consumers are making purchase decisions on vertically differentiated products with expert ratings as the product quality references.

H₂: A newly added alternative to a preexisting 2-choice set is more likely to be perceived as a compromise option (i.e. compromise effect is observed) when consumers are making purchase decisions on horizontally differentiated products with user ratings as the product quality references.

The effects of the other two product category-rating type combinations (vertically differentiated product categories with user ratings vs. horizontally differentiated product categories with expert ratings) are too ambiguous to make directional predictions due to the inconsistency of variable natures. A brief summary of the experimental hypothesis is outlined in Table 1.

In the next section, more detailed research theories regarding both predictions are presented and discussed. Then, the actual experiment (including design, sampling, and experimental procedure) is presented along with the study results and their interpretations. These interpretations are further explained in the discussion section, which also explores the drawbacks of the study and suggests future research directions.

Attraction versus Compromise

The Attraction Effect

Consider the following scenario: you are choosing between two TVs: TV A has a 32 inch screen with average performance, and is listed at \$389; TV B has a 65 inch screen with

excellent performance and costs \$1,699. Assume these TVs are equal on every other product attributes such as appearance and weight. Which TV would you choose?

Your choice is going to be a trade-off between the screen size/performance and price. Depending on how much you value the screen size and television performance, you might be willing to pay an amount of \$1,699 for TV B. Alternatively, you might believe that price is more important than the TV, which might end up sitting in the corner of your living room and get turned on once every month, and go for TV A. This is a classic scenario in consumer decision making and has no dominated alternative. One alternative is better on price, and another is better on quality.

Now, in the above 2-choice set scenario, a third alternative, TV C, is introduced. TV C has a 32 inch screen with average performance, and is listed at \$489. In this new 3-choice set scenario, TV C becomes a dominated option by TV A, because it is equal on all attributes but inferior on the price. Anyone who thinks rationally would probably not choose TV C. However, what is so interesting about TV C, is that it may produce an attraction effect and directs people's preference toward TV A by increasing the number of people who are choosing it (i.e. increasing the choice share of TV A).

Huber, Payne, and Puto first examined and proposed the attraction (or asymmetric dominance) effect in 1982. It refers to the ability of an asymmetrically dominated or relatively inferior alternative, when added to a set, to increase the attractiveness and choice share (i.e. probability) of the dominating alternative. According to Huber, Payne, and Puto, an asymmetrically dominated alternative (also called decoy) is dominated by one choice in the set but not by another in a 3-choice set. As Figure 1 shows, the preexisting 2-choice set has two alternatives available: alternative A and alternative B. Alternative A is more attractive on

Attribute 1, but less attractive on Attribute 2. Alternative B, on the other hand, is more attractive to consumers on Attribute 2, but not on Attribute 1. This creates a classic tradeoff decision scenario for consumers. Alternative A and Alternative B are positioned so that neither dominates the other - each has an attribute on which it is superior.

The decoy is then a stimulus anywhere in the “Asymmetrically Dominated” regions of Figure 1 where it is dominated by either Alternative A or Alternative B but not both. For instance, if Alternative C is going to be added to the original 2-choice set that has Alternative A and Alternative B, adding Alternative C to region X1Y2 is going to make Alternative C asymmetrically dominated by Alternative A but not Alternative B. The Alternative C, which becomes the decoy to Alternative A, is hypothesized to increase the percent of choices to Alternative A. Similarly, if Alternative C is introduced to region X2Y1, Alternative B should be perceived as the asymmetrically dominating option, and an increased choice share of Alternative B is expected to be observed.

The Compromise Effect

Reconsider the TV-shopping scenario stated earlier: you are again choosing between TV A (32 inch screen, average performance, costs \$389) and TV B (65 inch screen, excellent performance, costs \$1,699). Assume these TVs are equal on every other product attributes such as appearance and weight. The same classic choice scenario is created again, and in order to make a decision, you need to trade-off between the price and quality of these two TVs.

Now, a new alternative, TV C, is once again added to this choice set. However, this TV C is different in terms of its price and quality. This new TV C has a 48 inch screen, decent performance, and is priced at \$989. Instead of becoming a dominated option/decoy and making

another TV more appealing, TV C stands out by becoming middle, compromising option in this 3-choice set. This triggers the compromise effect and directs people's product preference to TV C itself.

This compromise effect is firstly discussed by Simonson in 1989. He proposed that an alternative would tend to gain choice share when it becomes a compromise or middle option in a 3-choice set. Such an effect operates in an opposite direction to the attraction effect and would suggest that a product in a 2-choice set can gain choice share following the addition of an adjacent competitor that makes the product a compromise choice within the set. In Figure 1, within the original 2-choice set of Alternative A and Alternative B, adding Alternative C to region X1Y3 should make Alternative A a middle option and increase the choice share of Alternative A.

The Limits of Attraction

Although the attraction effect has been accepted as a stylized fact and widely embraced by industries and academia, Frederick, Lee, and Baskin (2014) believed that the truth is much less exciting than the story. Despite popular literature has promulgated the attraction effect, Frederick, Lee, and Baskin's research suggested a different conclusion as they found no evidence for this effect after 32 studies and 6 failed replications of past studies. During these 38 studies, Frederick, Lee, and Baskin were able to find significant attraction effect when all relevant attributes of products were numerically specified, but no instances of a significant attraction effect was found when the attributes of products were presented perceptually (see Figure 2 for an example of numerically represented and perceptually represented product attributes). Frederick, Lee, and Baskin claimed that there is a boundary condition for the attraction effect: numeric

representations. They further concluded that perceptual representations of products often elicit markedly different effects than numeric representations.

Another point Frederick, Lee, and Baskin argued is that introducing an inferior alternative to a choice set does not only make the target alternative a dominating option but makes the inferior alternative a compromise option at the same time. The preceding explanation for the attraction effect focused on the dominance relationship between alternatives, whereas the explanation for the compromise effect focused on individuals' psychological drive of compromising. However, these two effects together brought up a new ambiguous scenario: what happens to Alternative C when it is introduced to the boundaries of the attraction effect and the compromise effect? In other words, when Alternative C is introduced to an ambiguous region (see Figure 3), do other variables such as types of product categories or quality ratings influence which effect Alternative C generate?

The shaded regions in Figure 3 are an example of the possible locations for Alternative C to have ambiguous effects when it is introduced to the original 2-choice set of Alternative A and B. In the example, Alternative C is introduced to the marginal area of region X2Y2. Although it still lays within the region for generating compromising effect, it seems to make consumers to perceive Alternative A as a dominated option in the 3-choice set of Alternative A, B, and C. Note that the asymmetrically dominated relationship discussed earlier no longer applies to Alternative A and C, but it is interesting that Alternative A is still perceptually dominating with the presence of decoy Alternative C. This study, therefore, examines this ambiguity and aims to understand whether the representation of these alternatives (user vs. expert ratings) and the perception of consumers (horizontally differentiated vs. vertically differentiated product categories) will have an effect on determining the role of Alternative C plays in this ambiguous scenario.

Horizontally versus Vertically Differentiated Product Categories

The study takes the factor of horizontally and vertically differentiated product categories into consideration as they play crucial roles on how consumers interpret product quality ratings. Vertically differentiated product categories, as it discussed earlier, can be reliably ranked according to certain objective standards that consumers find important (Tirole, 2003; De Langhe, Fernbach, and Lichtenstein, 2015). For example, a water filter is a vertically differentiated product, because the majority of consumers would agree that a good water filter can be evaluated based on its ability to remove bacteria.

However, while evaluating the quality of a bottle of perfume, different individuals may have different preferences and tastes. Horizontal differentiation can be linked to differentiations in colors, shapes, and tastes. These subjective evaluating standards make a bottle of perfume a horizontally differentiated product, as the ranking and evaluation of product quality are primarily a matter of individual taste. Fashion waves often emerge in horizontally differentiated product categories as consumers' attitudes and preferences toward horizontally differentiated products can be easily influenced by cultural or societal forces.

Certain product categories could be characterized both by horizontal and vertical differentiation. For example, a woman's necklace has combined product attributes such as its shape, color, and material. Although the attribute of material can often be seen as a vertically differentiated factor, some other elements such as shape and color are more taste-dependent, or horizontally differentiated. To avoid possible confounds of mixed differentiation, it is very important to select experimental stimuli based on a standard, reliable measure that provides information on how each product category is differentiated.

Methods

Participants

A total of 200 adult participants were recruited from Amazon Mechanical Turk (MTurk) (see Appendix for a detailed distribution of participants' demographics). MTurk is a crowdsourcing Internet marketplace that allows individuals and businesses to coordinate the use of human intelligence to perform tasks, such as data collection that involves experimentation with human subjects. Participants were compensated \$0.50 for participating and completing the 5 minute study. Due to the use of images of alcohol in the study, participants were prescreened and had to be at least 21 years old to participate. Although the study was administered and completed online, all participants were U.S. residents and had no problem understanding the study instructions.

Materials and Procedure

As it mentioned above, MTurk allowed the questionnaire of the study to be administered online. Once the participants agreed to participate in the study, they were granted with the access to the questionnaire from their own computers. To ensure the quality of responses, participants had to finish the questionnaire in a limited amount of time (30 minutes). A consent form was first presented to the participants to inform them the nature of the study and the compensation terms. Once they agreed to the terms, they were randomly assigned to an experimental condition. This assignment was done without the participants' knowledge. After being assigned to a condition, the participants were taken to a new page and given an introduction on user or expert rating. The type of rating they saw would depend on the experimental condition they were assigned to. After reading about the ratings, the participants were asked to make virtual purchase decisions among

4 product categories choice sets (2 of which were horizontally differentiated product categories and the other 2 were vertically differentiated product categories). Depending on the experimental conditions, participants would either see 2-choice sets or 3-choice sets across all 4 product categories. They were also provided with the following key information that is necessary for purchase decision-making: a price, a numeric product quality rating (either user or expert rating), a product description, and an image depicting the product (see Appendix for a sample of the stimuli used).

After the main task, each participant's price-perceived quality reference was measured by their responses to the following item (Lichtenstein and Burton, 1989): "On a scale of 1-7, with 1 being 'strongly disagree', and 7 being 'strongly agree', please indicate your level of agreement with the statement: 'The higher the price, the higher the quality'". This measure was designed to appear after the main task to avoid making participants actively think about their price-quality reference while making product purchase decisions. The participants then were asked to provide some demographic information about them (gender, age, and income). The questionnaire would be then completed. The participants were debriefed and compensated via MTurk. A copy of this questionnaire is attached in the Appendix.

This study includes both between-subject and within-subject variable and uses a 2 (two- vs. three-choice sets) * 2 (horizontally differentiated vs. vertically differentiated product categories) * 2 (user vs. expert ratings) design. The between subject variables are the number of choices available in the product choice sets, with the within-subject variable being the types of product categories. Therefore, a total of 8 experimental conditions are administered to the participants (see Table 2 for a brief presentation of variables included in each condition).

Stimuli: Vertically Differentiated and Horizontally Differentiated Product Category

The selection of product categories is very crucial to this study. Although the definition of each product category (vertically differentiated vs. horizontally differentiated) has been made clear, an objective measurement of the degree of verticalness and horizontalness is needed for the study to gain scientific validity. De Langhe, Fernbach, and Lichtenstein (2015) examined this factor across 260 different product categories (3,749 products) and identified the verticalness associated with these product categories. Among all product categories they examined, printers (inkjet models) and digital cameras were identified as the most vertically differentiated product categories, whereas wines and chocolate cookies were identified as the most horizontally differentiated product categories in consumer perceptions. In Figure 4, all four product categories (wines, chocolate cookies, printers, and digital cameras) are presented in a coordinate system that shows exactly where each product should be positioned in terms of their prices and product quality ratings.

Results

Descriptive Statistics

A total of 800 data points were collected from the 200 participants across 4 product categories. Table 3.1 and 3.2 show general frequency distributions of participants' responses for each experimental condition. The bar charts corresponding to each condition are presented in Figure 5(a) and 5(b). The Alternative C (listed in the middle between A and B) is the 3rd alternative introduced to the preexisting choice set of Alternative A and B. Thus, in Table 3.1., the frequency distribution of Alternative C in 2-choice sets is not listed (or always zero), because Alternative C is not present in these 2-choice sets. Although Alternative C seems to be gaining choice share for all product categories, it is unclear that whether this trend could be contributed

to the compromise effect, or it happened simply due to the introduction of a 3rd alternative. In other words, people might have chosen Alternative C because it was made available with Alternative A and B. It is unknown that whether alternative C was indeed perceived as a compromising option. This complication of data analysis interpretation is caused by a flaw of this study design, which is discussed with more details in the following Discussion section.

Despite the variable of rating types does not seem to have any particular effect on participants' product choices, expert ratings seem to shift participants' preference from low price/quality products toward medium-high price/quality products than user ratings. Table 4 illustrates the frequency distribution of participants' product choices when Alternative B and C are collapsed together. The variable "Low Price/Quality" represents the characteristics of Alternative A, and the variable "Medium-High Price/Quality" represents the characteristics of Alternative B and C.

Statistical Analysis

To further understand the interactions behind the descriptive results and test the hypotheses proposed earlier, multinomial logistic regression was chosen to answer the research questions because it provides an effective and reliable way to obtain the estimated product choice share; it is also a perfect fit for study designs that involve one categorical dependent variable (e.g., the purchase decisions participants made for the four product categories). According to the multinomial logistic regression model, participants' purchase decisions for these four product categories were affected by the number of choices available in a choice share (e.g., 2-choice set without the presence of an inferior alternative C, and 3-choice set with the presence of an inferior alternative C). There is a possibility for participants to choose Alternative C if it appeared in the

preexisting 2-choice set, regardless of its product categories (wines: $\chi^2 = 42.99, p < .0001$; chocolate cookies: $\chi^2 = 34.102, p < .0001$; printers: $\chi^2 = 15.553, p < .0001$; digital cameras: $\chi^2 = 15.553, p < .0001$). However, this interaction alone only indicates the presence of a third option split the choice shares of the preexisting two options and cannot be interpreted as a sign of any compromising effects. In order to make such comparison, the initial experimental design should include two sets of 3-choice sets (e.g., Alternative A, B, and C vs. Alternative B, C, and D). This design allows the statistical analysis to directly estimate the proposed attraction or compromise effects by comparing the incline or decline of choice shares of each alternative (Simonson, 1989). Nevertheless, this study failed to implement such experimental design, and thus, cannot reflect the proposed effects.

There is no main effect found between the types of ratings and participants' choices for wines ($\chi^2 = .327, p = .849$), chocolate cookies ($\chi^2 = .220, p = .896$), and printers ($\chi^2 = 1.425, p = .490$). A marginal significance was found with the types of ratings available in a choice set in participants' choices of digital cameras ($\chi^2 = 4.159, p = .125$). The observation was that participants were more likely to choose the medium-high price/quality alternatives (Alternative B & C) when they were presented with expert ratings. Similar directional observations were made and confirmed with the product category of printers (see Table 4). For the above reasons, a new hypothesis is proposed:

H3: Presenting vertically differentiated product categories with expert ratings help to stimulate and increase the choice shares for medium-high price/quality alternatives available in a 3-choice set.

To test this hypothesis, it is necessary to use a new mixed model because the analysis could account for both repeated measures as well as regression analysis. Instead of coding raw

data into the binary codes (buying or not buying) and weakening the statistical power, a mixed repeated measure regression model is proposed to capture the categorical nature of the dependent variable while obtaining good statistical power in the analysis. After controlling for participants with random effect, the interaction between the types of rating and the types or product category were examined. Unfortunately, there was no significant correlation found between expert rating and vertical product categories, which means that the presence of expert rating does not necessarily increase the choice shares for medium-high price/quality alternatives ($F(1, 799) = 0.974$, $p = .3298$).

Supplementary Analysis

The same mixed model was applied to examine the demographical factors: age, gender, and income (see Table 5 for a descriptive report of participants' demographical distribution). The analysis indicated that none of the demographical factors were good predictors of participants' product choices (age: $F(4, 790) = 1.293$, $p = .271$; gender: $F(2, 790) = .076$, $p = .927$; income: $F(5, 790) = 1.449$, $p = .204$). This suggests that the factors of age, gender, and income do not significantly affect participants' preference toward a particular product when they make purchase choice decisions regarding the four product categories. However, the factor of age and gender appear to have stronger directional influence than gender. Although the interactions were not significant, the directions suggested that the older or richer the participants were, the more likely that they were going to pay a higher price for better product quality.

Discussion

The results indicated that participants tended to evaluate user ratings and expert ratings equally when they used these ratings as references to make purchase decisions. Although there was a trend that participants were more likely to choose better products with higher prices, this trend was not statistically significant. This could be contributed mainly to the following reasons: 1) there was not enough statistical power due to a relatively small sample size. Lacking enough statistical power (or sensitivity of the proposed hypothesis test) made it harder to detect statistical significance despite of directional trend; 2) the choice of horizontally differentiated product categories was made poorly. Although wines and chocolate cookies were rated as the product categories with the slightest vertical differentiation, they could still be considered as “mixed” differentiated product categories, which are combinations of both vertically and horizontally differentiated product attributes. For example, although different individuals have different tastes for wines, their product quality can still be somehow evaluated based on objective standards such as the clarity of color, the concentration of fruits, and the manufacturers. Professional rating agencies such as *Wine Spectator* also are able to provide reliable, relatively objective ratings on wines. Product categories with more horizontal differentiation such as flowers and clothes were not evaluated in the study of De Langhe, Fernbach, and Lichtenstein (2014). In future studies, these product categories would probably serve as better horizontally differentiated stimuli.

Additionally, this study addresses a common concern in the market place, which suggests that learning about the average taste may not be useful due to its heterogeneousness. In response to this concern, some retailers (such as Netflix) have been providing a tailored average user rating that weighs certain ratings more than others (e.g., those by users deemed similar to the consumer based on transaction history). However, the finding of this study implied that the types

of product categories (e.g., horizontally differentiated vs. vertically differentiated product categories) might actually have no significant impact on how consumers chose the products. The factor of trust that consumers have toward peer recommendations and ratings could be a possible explanation. Smith, Menon, and Sivakumar (2005) found that consumers use the mere availability of peer recommendations as a decision-making heuristic, irrespective of the peer recommender's personal characteristics. Moreover, consumers' preference for user vs. expert recommendations largely depends on the specific nature of the consumer's shopping goal: utilitarian or hedonic. Smith, Menon, and Sivakumar argue that consumers who are shopping for hedonic shopping goal put less emphasis on the credibility and reliability of expert recommendations. Compared with utilitarian purchases, hedonic purchases are more likely to be heterogeneous. Therefore, consumers are likely to consider whether an opinion source shares their own preferences as a means of judging the quality of the recommendation or rating. In this study, all participants were asked to make purchase choice for themselves ("Imagine you are buying ..."), which set up a hedonic motive. This might explain why the types of ratings had no significant effect on participants' product preference, because despite the credibility of expert ratings, the participants believed user ratings were good indicators of quality due to the shared preferences. The factor of hedonic vs. utilitarian shopping goal could be incorporated into future studies by adopting the paradigm of Smith, Menon, and Sivakumar's experimental design. Participants would be asked to shop under one of the two scenarios: 1) to make purchases for themselves; 2) to make purchases for an important business conference or family meeting.

This study also failed to test for H1 and H2 due to the flaw in the experimental design. Although the current experimental design is very intuitive and direct, it lacks the numeric supports that could be generated by comparing a 3-choice set to a 3-choice set. This design also

complicates the statistical analysis approaches and limited the options of analysis to which could be applied. In Figure 6, adding a new Alternative D allows the study to monitor and analyze the change of choice shares of Alternative C and D by presenting participants with either a choice set of A, C, D, or a choice set of C, D, B. Future studies will implement this experimental design, which should generate meaningful insights into the attraction and compromise effects.

Reference

- Burton, S., Lichtenstein, D. (1990). Assessing the relationship between perceived and objective price-quality: a replication. *Advances in Consumer Research*. 17, 715-722.
- Chevalier, J.A., Mayzlin, D. (2006). The effect of word of mouth on sales: online book reviews. *Journal of Marketing Research*. Volume 43. 345-354.
- De Langhe, B., Fernbach, P., Lichtenstein, D. (2015). *Navigating by the stars: investigating the actual and perceived validity of online user ratings*. Working Paper.
- Frederick, Lee, Baskin. (2014). The limits of attraction. *Journal of Marketing Research*. Volume LI. (August 2014). 487-507.
- Huber, J., Payne, J.W., Puto, C. (1982). Adding asymmetrically dominated alternatives: violations of regularity and the similarity hypothesis. *Journal of Consumer Research*. 9 (1), 90-98.
- Simonson, I. (1989). Choice based on reasons: the case of attraction and compromise effects. *Journal of Consumer Research*. 16, 158–174.
- Slovic, P., Fischhoff, B., Lichtenstein, S. (1983). “The public” vs. “the experts”: perceived vs. actual disagreements about risks of nuclear power. *The Analysis of Actual Versus Perceived Risks*. 1, 235-249.
- Smith, Menon, and Sivakumar. (2005). Online peer and editorial recommendations, trust, and choice in virtual markets. *Journal of Interactive Marketing*. 19 (3), 15-37.
- Tirole, J. (2003). *The theory of industrial organization*. The MIT Press, Cambridge Massachusetts.
- Tversky, A., Kahneman, D. (1974). Judgment under uncertainty: heuristics and biases. *Science*. 185(4157), 1124-1131.

Table 1. This is a summary of the predicted directions of experimental hypotheses (H_1 and H_2) of this study.

	<i>Horizontally Differentiated Product Categories</i>	<i>Vertically Differentiated Product Categories</i>
<i>User Ratings</i>	H_2 : A compromise effect is predicted	Ambiguous
<i>Expert Ratings</i>	Ambiguous	H_1 : An attraction effect is predicted

Note: H_3 (please see Results section) is not included in this table.

Table 2. This table shows the specific independent variables that were examined under each experimental condition. The between-subject variables are the number of choices available in a choice set (2-choice set vs. 3-choice set) and the types of rating (user ratings vs. expert ratings). The within-subject variable is the product categories (horizontally differentiated vs. vertically differentiated product categories).

<i>Condition 1</i>	<i>Condition 2</i>	<i>Condition 3</i>	<i>Condition 4</i>
BS: 2-choice set; User ratings; WS: Product categories	BS: 2-choice set; User ratings; WS: Product categories	BS: 2-choice set; Expert ratings; WS: Product categories	BS: 2-choice set; Expert ratings; WS: Product categories
<i>Condition 5</i>	<i>Condition 6</i>	<i>Condition 7</i>	<i>Condition 8</i>
BS: 3-choice set; User ratings; WS: Product categories	BS: 3-choice set; User ratings; WS: Product categories	BS: 3-choice set; Expert ratings; WS: Product categories	BS: 3-choice set; Expert ratings; WS: Product categories

Table 3.1. Numbers of Available Choices in a Choice Set: Percentage of Participants' Product Choices. The original 2-choice set includes Alternative A and B; Alternative C is the newly introduced ambiguous alternative.

	<i>Wines (Horizontally differentiated)</i>			<i>Chocolate Cookies (Horizontally Differentiated)</i>			<i>Color Inkjet Printers (Vertically differentiated)</i>			<i>Digital Cameras (Vertically differentiated)</i>		
	A	C	B	A	C	B	A	C	B	A	C	B
2-choice sets	60%	-	40%	40%	-	60%	27%	-	73%	68%	-	32%
3-choice sets	38%	27%	35%	20%	18%	62%	17%	9%	74%	54%	23%	23%

Table 3.2. Types of Ratings: Percentage of Participants Product Choices: Percentage of Participants' Product Choices. The original 2-choice set includes Alternative A and B; Alternative C, again, is the newly introduced ambiguous alternative.

	<i>Wines (Horizontally differentiated)</i>			<i>Chocolate Cookies (Horizontally Differentiated)</i>			<i>Color Inkjet Printers (Vertically differentiated)</i>			<i>Digital Cameras (Vertically differentiated)</i>		
	A	C	B	A	C	B	A	C	B	A	C	B
User Ratings	50%	14%	36%	31%	8%	61%	23%	6%	71%	68%	8%	24%
Expert Ratings	48%	13%	39%	29%	10%	61%	21%	3%	76%	54%	15%	31%

Table 4. This table shows the choice share of low price/quality products and medium-high price/quality products across product categories.

	<i>User Rating</i>		<i>Expert Rating</i>		<i>Increase of choice share in Medium-High Price Quality with Expert rating</i>
	Low Price-Quality	Medium-High Price Quality	Low Price-Quality	Medium-High Price Quality	
Horizontally Differentiated	40.5%	59.5%	38.5%	61.5%	2%
Vertically Differentiated	45.5%	54.5%	37.5%	62.5%	8%

Table 5. Demographics of a total of 200 participants (gender, age, and household income range).

Gender	<i>Number of Participants</i>	<i>% Percent of Overall Population</i>
Male	123	61.5%
Female	77	38.5%

Age	<i>Number of Participants</i>	<i>% Percent of Overall Population</i>
21 – 30 years old	106	52.5%
31 – 40 years old	63	31.5%
41 – 50 years old	18	9.0%
51 – 60 years old	12	6.0%
61 or over	2	1.0%

Household Income Range	<i>Number of Participants</i>	<i>% Percent of Overall Population</i>
Below \$20,000	60	30.0%
\$20,000 - \$39,999	78	39.0%
\$40,000 – \$59,999	42	21.0%
\$60,000 - \$79,999	11	5.5%
\$80,000 - \$99,999	6	3.0%
\$10,000 - \$119,999	-	-
\$120,000 or more	3	1.5%

Figure 1. This figure shows the expected effect of an Alternative C based on the position it is introduced in relative to Alternative A and B. The X-axis and Y-axis represent two dimensions or attributes of the products. In this study, attribute 1 represents cost of the product (lower cost = more appealing), and attribute 2 represents the quality ratings of the product (higher cost = more appealing).

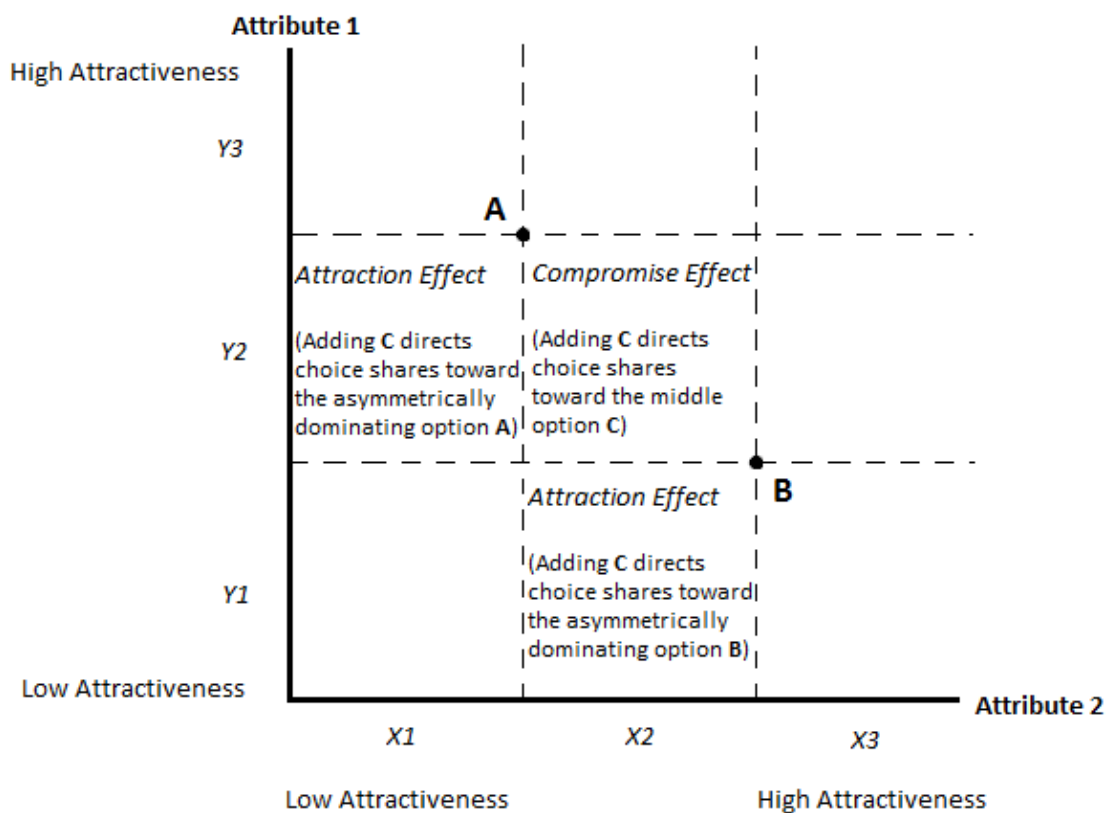


Figure 2. This is an example of how a television's picture quality is represented numerically and visually/perceptually. Although both (A) and (B) gave the information of price, the picture quality in (A) was represented by numeric ratings ("quality = 8.0/10") whereas the picture quality in (B) was represented by images that depicted the picture quality (three images were different in terms of contrast color range, color style, brightness, pixels, and so on).

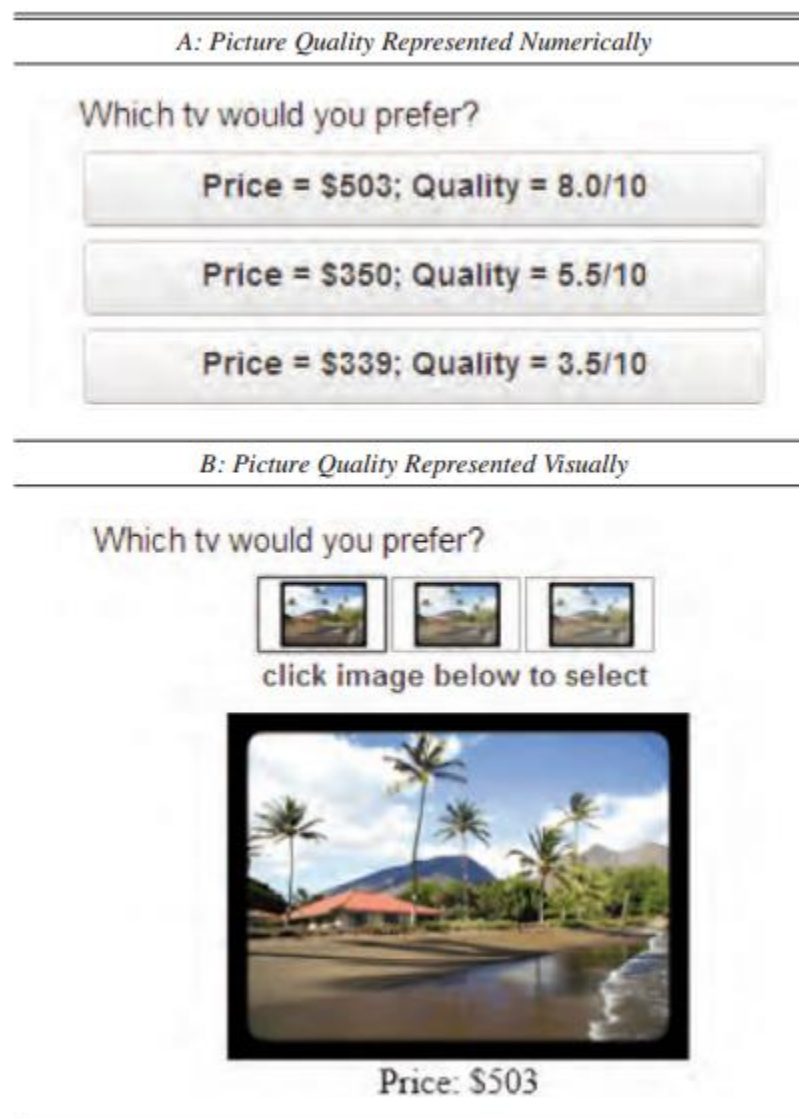


Figure 3. This figure is developed from Figure 1 and it shows the positions for Alternative C to be perceived as ambiguous. The shadowed regions represent these ambiguous positions. If Alternative C is introduced to a position within the shadowed regions, decision makers could interpret it as a decoy option or a middle/compromise option.

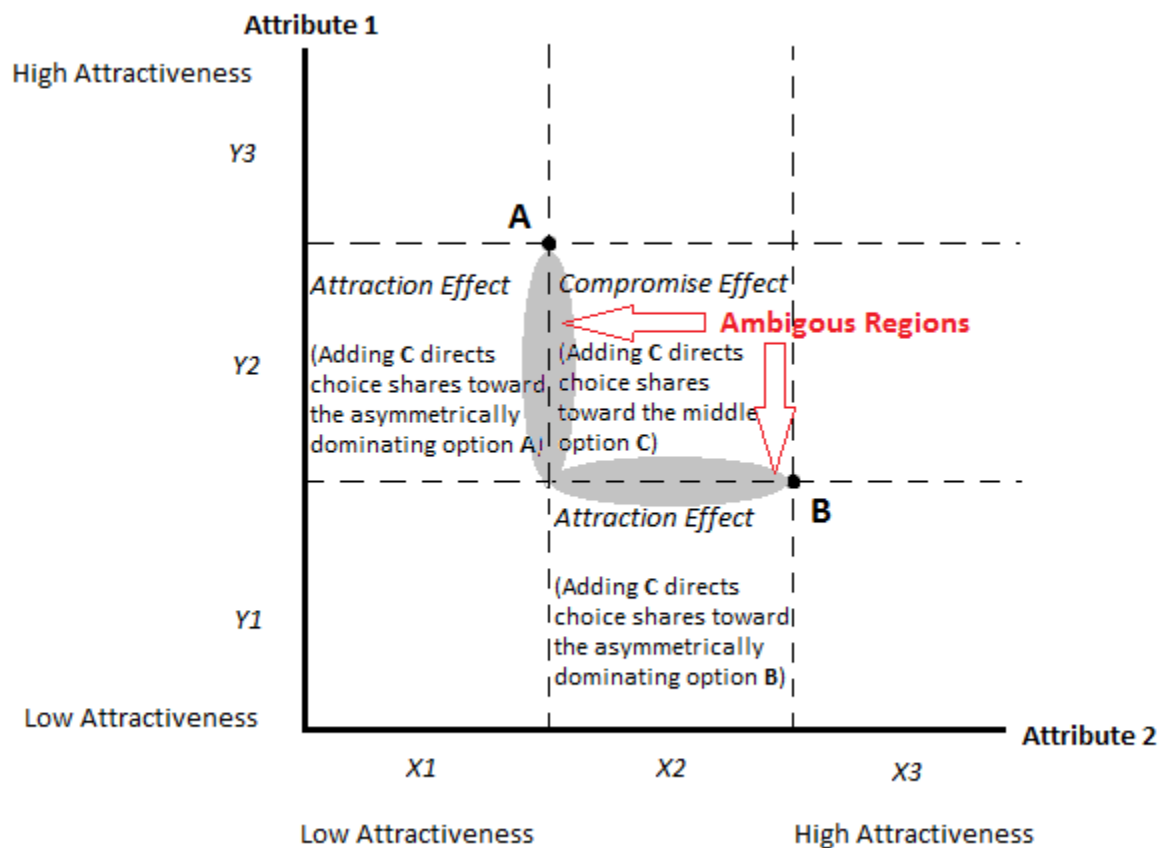
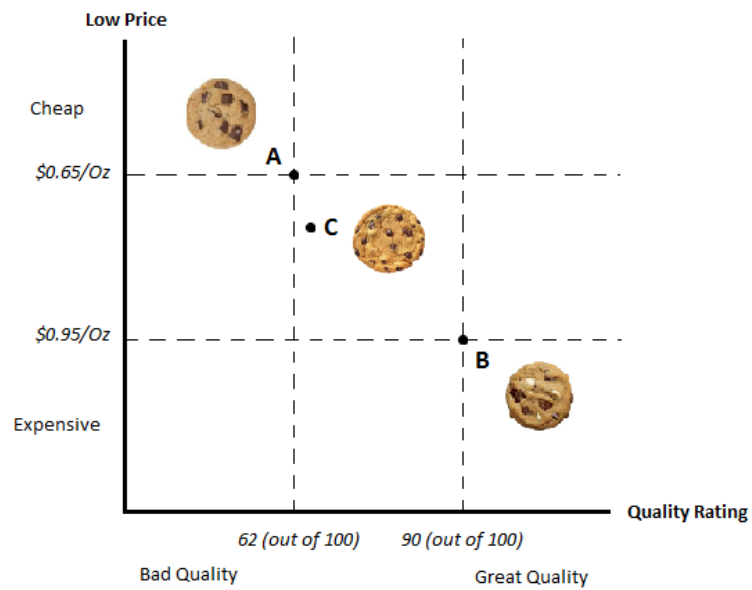


Figure 4. In this study, there were four product categories (wines, cookies, printers, and cameras) that were examined. The first two (wines and cookies) are horizontally differentiated product categories and the last two (printers and cameras) are vertically differentiated product categories. Their prices and quality ratings are positioned in a coordinate system to show the manipulation of adding an ambiguous Alternative C to a 2-choice set that included Alternative A and Alternative B.

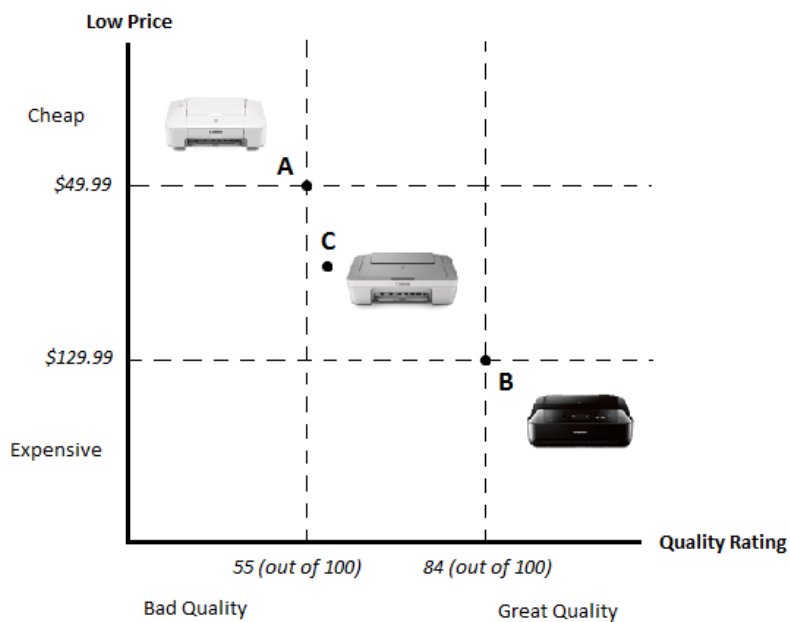
Wines



Chocolate Cookies:



Color Printers:



Digital Cameras:

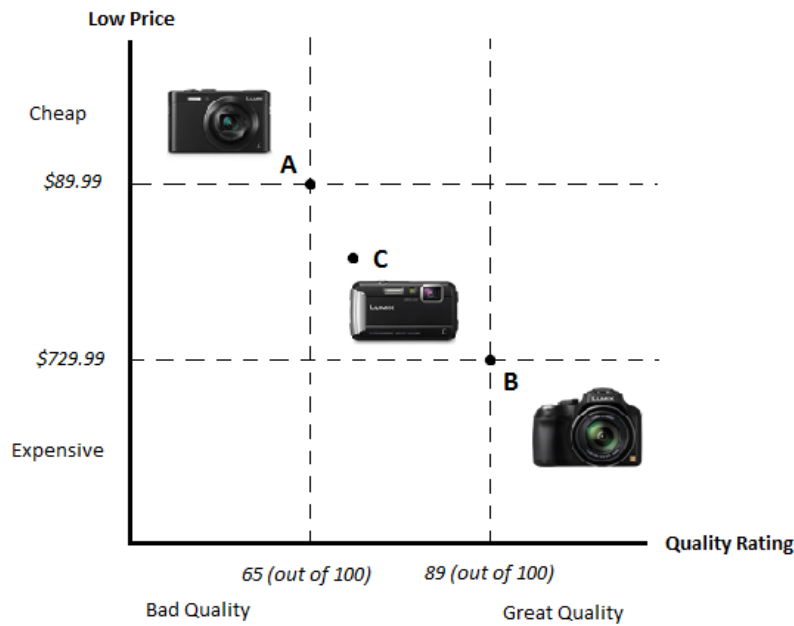
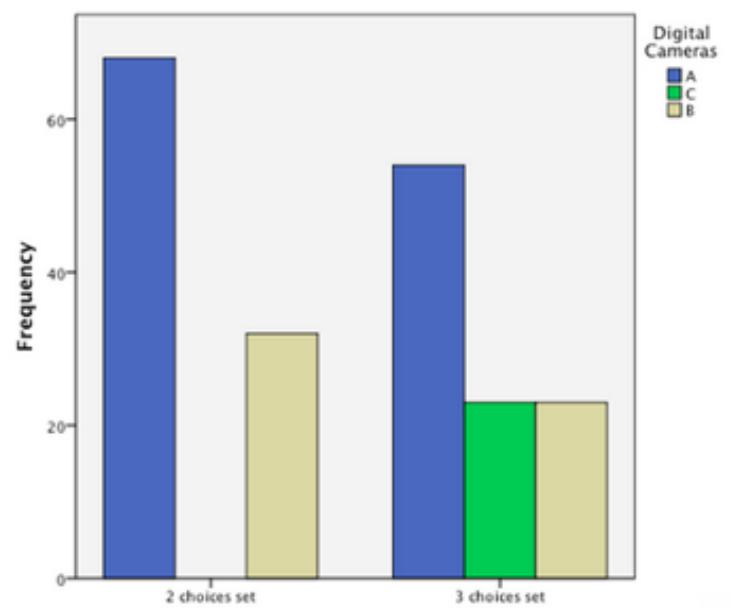
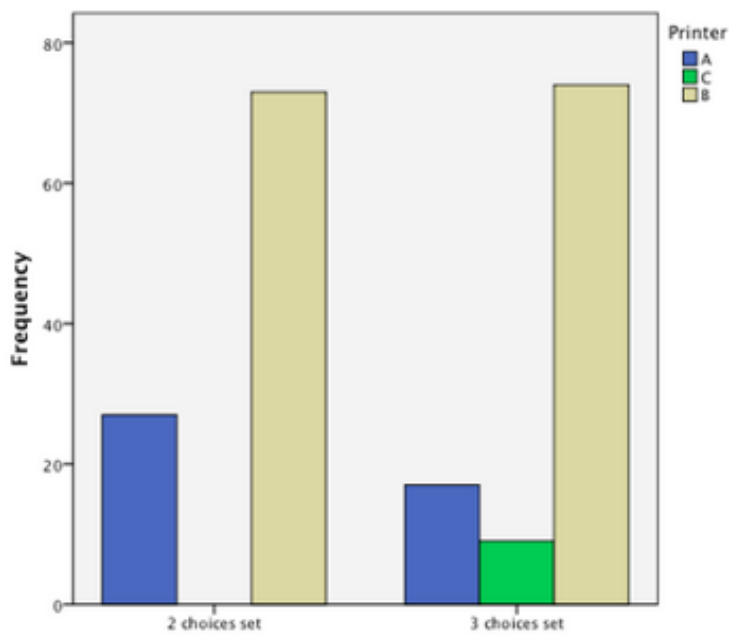
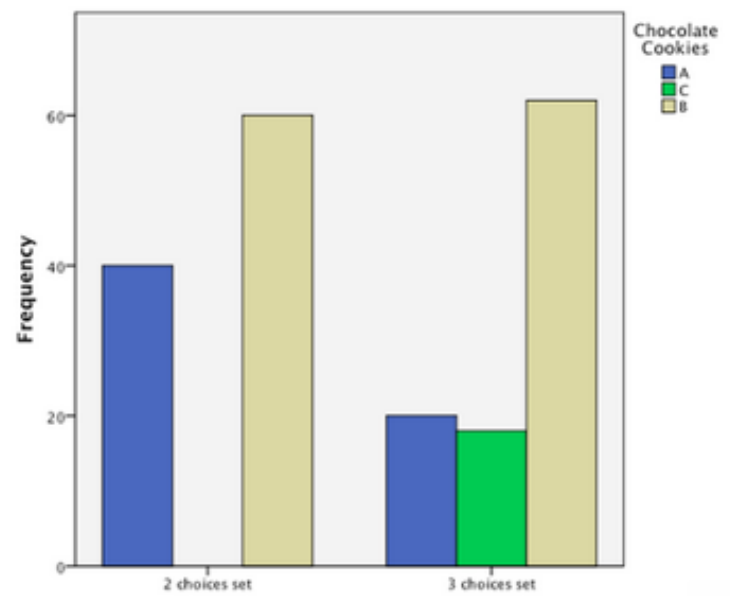
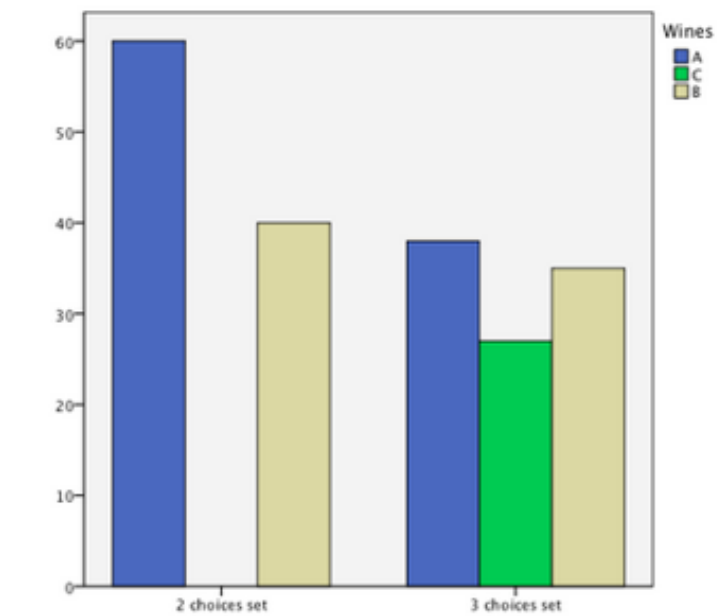


Figure 5(a) & 5(b). The figures in set 5(a) show the frequency distributions of participants' responses for the four sets of products when controlled for the types of product category. Set 5(b) shows the frequency distributions of participants' responses when controlled for the number of choices available in the given choice sets.

5 (a)



5 (b)

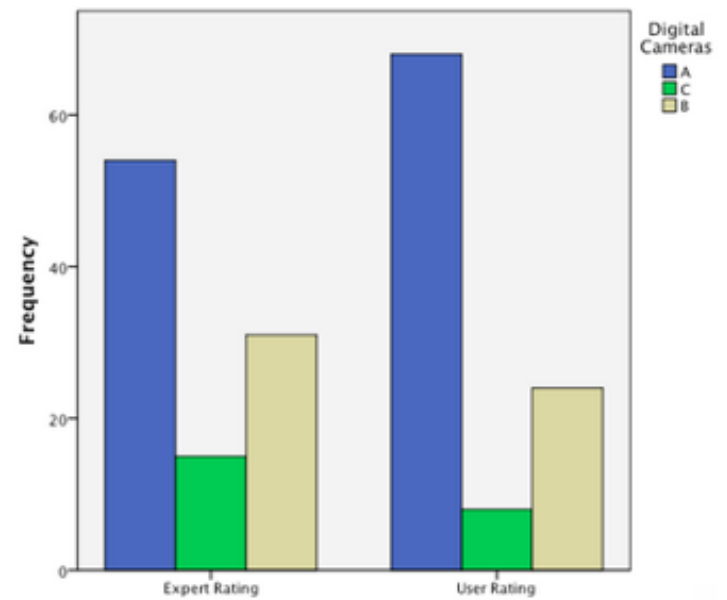
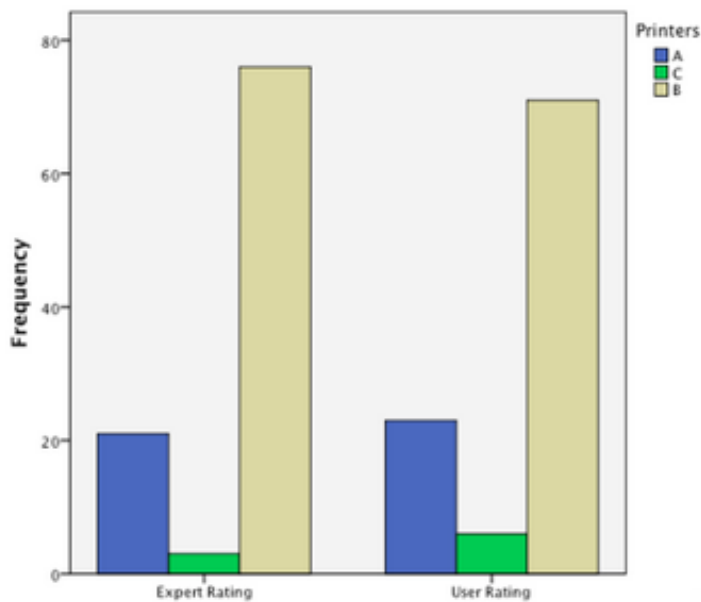
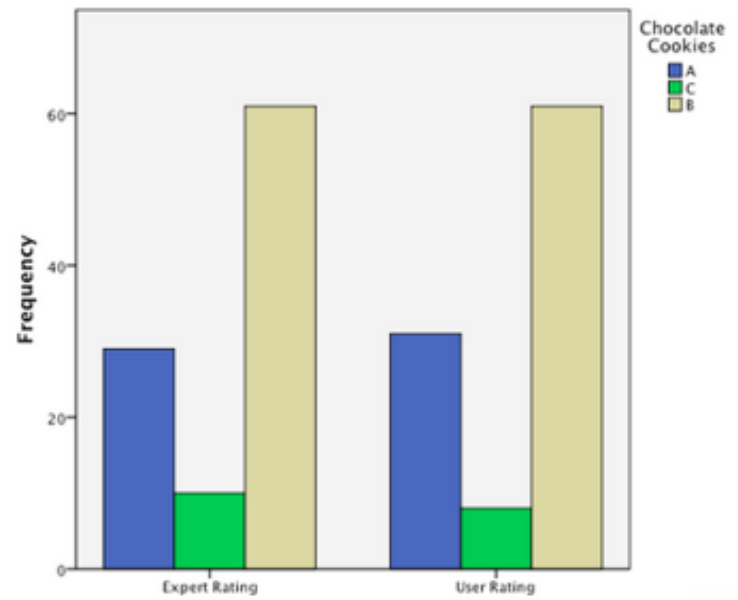
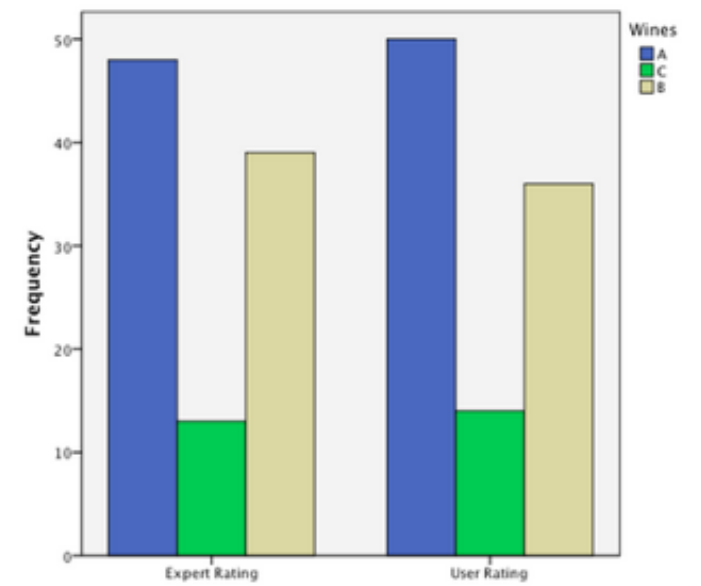
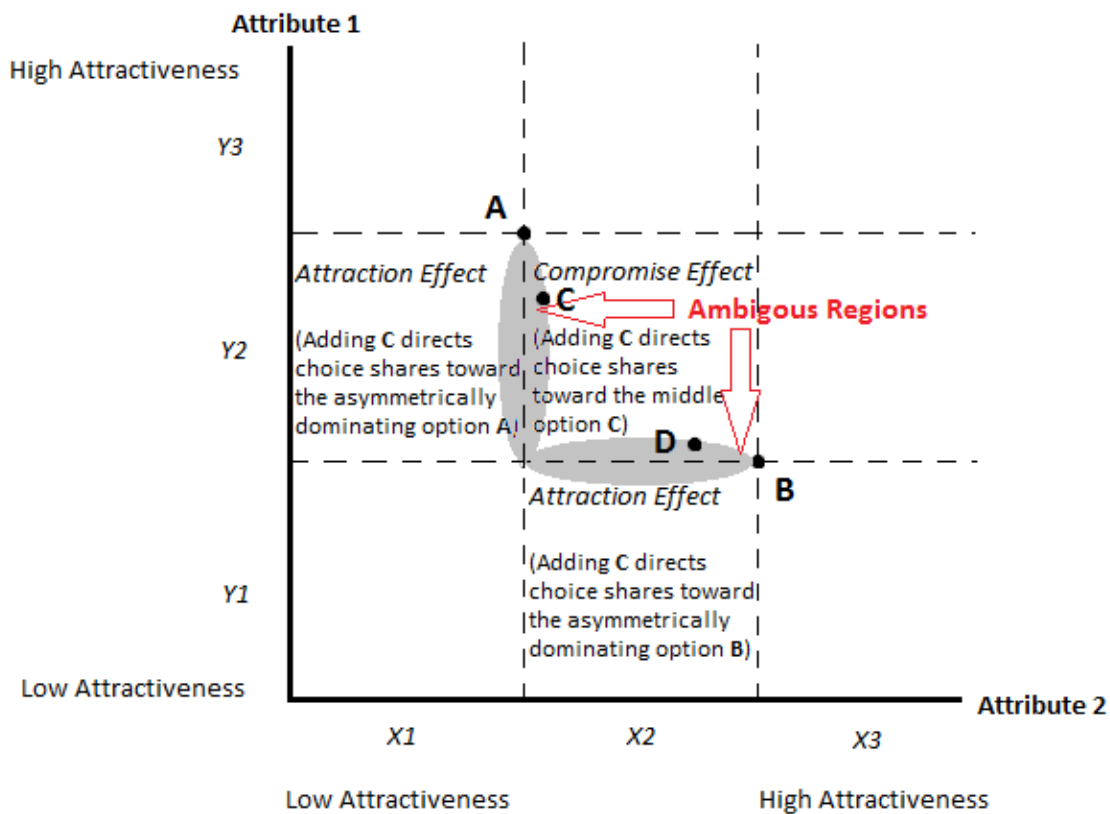


Figure 6. This figure illustrates the discussed new direction of experimental design for future studies. Instead of presenting a 2-choice set and a 3-choice set to participants, two 3-choice sets (A, C, D vs. B, C, D) will be presented. This design enables a direct statistical comparison of the choice share of C and D, which further allows researchers to analyze the compromise and attraction effects that could happen by introducing an ambiguous alternative of C or D.



Appendix

Appendix A: A sample of the online questionnaire that was distributed to participants on MTurk.

Note that this sample only included representative pages of the questionnaire due to the page limits.

Suppose you are buying a digital camera. Based on the information provided below for three digital cameras, which digital camera would you choose? (Please select one.)

- ☐ **Panasonic LUMIX DMC-LF1 12.1 MP 3.8X
Zoom Digital Camera**

Price: \$89.99

User Rating: 65 out 100



The MOS sensor enables shooting stills and video in low-lit scenes. Shares with smartphone or tablet via wireless feature.

- ☐ **Panasonic LUMIX DMC-TS25 Active
Lifestyle Touch Digital Camera**

Price: \$389.99

User Rating: 70 out 100



Go anywhere, any time with this rugged adventure camera that is waterproof. Features instant in-camera retouch and effects.

- ☐ **Panasonic LUMIX FZ1000K 4K QFHD/HD
16X Long Zoom Digital Camera**

Price: \$729.99

User Rating: 89 out 100



Experience the ultimate in 4K QFHD/HD hybrid photography with its integrated smartphone Wii or remote imaging control.

Appendix B. These are descriptions of Expert Ratings and User Ratings that were presented separately to participants.

Expert Ratings:

Please take some time to read the following instructions carefully:

General Instructions

In the next section, you will see four different sets of products. Within each of these four different product categories, we would like to provide you with three products that we would like you to compare. For these products in each of the four categories, you will be provided with the products' descriptions, prices, and how experts have rated the products. After looking at this comparative information, we would like for you to provide us with your preferred choice if you were going to purchase one of the three products.

What are expert ratings?

Expert ratings like those generated by *Consumer Reports* magazine are generated by engineers and technicians with years and sometimes decades of expertise in their field. They live with the products for several weeks, putting them through a battery of objective tests using scientific measurements, along with subjective tests that replicate the user experience. All models within a category go through exactly the same tests, side by side, so they are judged on a level playing field, and test results can be compared. Consumers that subscribe to the expert rating service such as Consumer Reports are then able to see and use these ratings in making their purchase decisions.

User Ratings:

Please take some time to read the following instructions carefully:

General Instructions

In the next section, you will see four different sets of products. Within each of these four different product categories, we would like to provide you with three products that we would like you to compare. For these products in each of the four categories, you will be provided with the products' descriptions, prices, and how users on a popular consumer website have rated the products. After looking at this comparative information, we would like for you to provide us with your preferred choice if you were going to purchase one of the three products.

What are user ratings?

User ratings are ratings generated by users who have purchased a product. After purchasing the product, they have the option to return to the seller's website (such as Amazon.com) and post a rating where higher scores (those close to 100, in our case) reflect more favorable ratings. Other users who visit the website are then able to see and use these ratings in making their purchase decisions.