CAPTURING INTERACTIONS IN DESIGN PREFERENCES: A COLORFUL STUDY

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ABSTRACT
Many engineering and marketing tools exist to help a designer optimize quantitative attributes of a product, such as height, weight, volume, or cost. However, these methods cannot effectively take into consideration attributes for which there is a significant interaction between the product attributes with respect to the consumer's preference, such as aesthetics.
This research has begun the work of developing this necessary functional relationship for product attribute interactions and has created a methodology for further research. To accomplish this, this study considered consumer preference for product colors. Colors were represented by their red, green, and blue light components, and preference information for each of these attributes was gathered by presenting individuals with a small sample of colors, applied to backpacks, in a short choice survey.

Keywords: Preference modeling, utility function, aesthetic design

1 INTRODUCTION
With the emergence of internet retailers and competition from global suppliers, it is increasingly necessary for companies to design and manufacture products that meet consumers' wants and needs on every level. Tools such as the Quality Functional Deployment [1] have helped engineering designers to translate customer needs into product functionalities, giving designers a means to understand the inherent trade-offs involved in a design and to develop one or more functionally optimal products. However, these methods cannot effectively take into consideration interactions between product attributes, or any other attribute for which there is no understood mathematical relationship between the attribute's potential values and the consumer's preference. For this reason, aesthetic design decisions are typically left up to creative experts who rely on a combination of design heuristics, current trends, and educated intuition when making decisions about a product's aesthetics [2]. Without any kind of proof to validate these choices, engineers are unlikely to give aesthetic attributes fair consideration when products must be redesigned to reduce costs or increase manufacturability. However, product aesthetics can make up 40 – 90% of a consumer's purchase decision [3], and these aesthetic compromises can create failures out of functionally acceptable designs.
Product aesthetics can be composed of any attributes that engage the five senses, though the sense of sight is often the dominant sense used for evaluating consumer products. Visual cues such as form, color, and sheen produce either a positive or negative reaction within the consumer. While many technical features, such as volume, are easily quantified and discretized, aesthetic attributes are not so easily separable. The various aesthetic attributes interact to create an overall gestalt that is pleasing, or not. The interactions between the various attributes that compose general aesthetic properties is not easily quantifiable and thus not usable for generating novel, customer preferred designs.
These issues are particularly prevalent when it comes to determining a product's color. While much research has been done on the subject of color preferences, the focus has been almost entirely on determining the universal preference order of colors, and how those preferences change for different genders, cultures, or age groups. The need exists, then, for a method that can quantifiably represent consumers' color preferences with respect to measurable color attributes. This can be done using utility functions, where the measurable color attributes are the red, green, and blue light components that combine to create colors in the visible spectrum. Optimization techniques can then be applied to these equations to generate the product color most preferred by any given individual.

2 BACKGROUND

2.1 Preference and Utility

Identifying customer needs and preferences and accurately translating them into a product's features and functionalities is essential to successful product design. Although many valuable methods exist to aid the designer in this part of the process, none of the currently available methods is fully able to incorporate qualitative preferences (such as those for aesthetics or usability) due primarily to their non-numeric nature.

For example, the widely used Quality Functional Deployment, or House of Quality [1] provides a means to translate customer needs to measurable technical requirements which designers can then attempt to maximize, minimize, or target to specific values. In this method, however, customer needs such as "be visually appealing" are difficult, if not impossible, to incorporate into this model without measurable methods for representing factors, such as color or form, that contribute to visual appeal.

The issue of translating and interpreting customer needs is further complicated when the needs of the customer cannot even be articulated objectively [4]. The words people use to describe affective attributes can vary considerably from person to person [5], so the task of determining optimal product colors from this kind of consumer feedback is reduced to educated guesswork at best.

A more objective means of working with consumer preferences can be found by using utility functions [6]. The amount of utility generated by a specific product can be represented as a function of the key attributes that define the product [7], making it possible to understand the relationship among attributes and identify worthwhile trade-offs [8]. Once utility functions have been determined for individual consumers, it is possible to apply clustering algorithms to the functional data to divide the population into market segments sharing similar preferences, allowing for optimal product designs to be developed for each market segment, thus increasing overall consumer satisfaction [9,10]

When gathering data on consumer, both rankings and ratings based conjoint provide a wealth of information to the researcher. It has been shown that the quality of data received can be greatly reduced when the consumer feels mentally fatigued by the complexity of the tasks being presented [11]. In addition, these methods have been criticized for their lack of resemblance to consumers' actual behaviors while shopping [12] It has been recently demonstrated that consumer preference for aesthetic form can be quantifies using choice based conjoint by atomizing the product attributes [13].

2.2 Aesthetic Preference

The aesthetics of a product are generally considered to be perceived in one of two ways. The gestalt of the product is the overall feel of a product, how the various attributes come together to form a complete picture that is independent of any of the individual attributes [14]. Whereas, atomization implies that as the individual attributes of a product can be separated and studied uniquely [15]. A combination of these unique attributes then creates an overall preference. In this work it is assumed that preference is generated through a combination of both philosophies. The consumer reacts to the overall gestalt of a product, which created through the interactions between the discrete individual attributes. This is similar to an orchestra where each instrument must play their part beautifully, but only together do you get the full auditory experience.

Previous research has considered primarily product shape and has only accomplished preference modeling by atomizing the products and assuming (a small number of) individual attribute preferences to be linearly independent [13]. While this may work sufficiently in academic experiments, real products are much too complicated to be represented in such a simplified manner. Real product have thousands of attributes, all of which interact with one another in ways that are still not completely understood.

2.3 Color

Research and experimentation in the area of color preferences has been going on since at least the 1890's, however the bulk of the research has focused on which colors are most preferred by each gender [16] or for a general population [17] as determined by the Munsell color system [18]. More recently, there has been moderate success in predicting color preferences, using both color "emotions" and color appearance factors as predictor variables [5].

Overall, the prior works in preference modeling have proven the applicability of utility functions and choice surveys for mathematically modeling consumer preferences. Additionally, the existing

research regarding color preferences provides support for the notion that preferences for color can be mathematically modeled as a function of measurable color attributes.

3 METHODOLOGY

3.1 Selecting a Product Domain

One of the limitations of nearly all existing color preference research is that subjects are asked to evaluate colors as stand-alone entities, separate from a product or application. This creates a rather significant logical problem, as one's preference for colors of automobiles, for example, is unlikely to be the same as his preference for kitchen appliances or sweaters [19]. In this study, backpacks were chosen to serve as the product domain for three reasons. First, backpacks can and do come in almost every conceivable color. This broad existing design space eliminates external constraints that would complicate the design of experiments. Secondly, research has shown that color can play a more important role in purchase decisions when competing product choices are not considerably different from one another [19], as is the case with backpacks. In addition, consumers are less likely to choose from a limited set of "typical" colors for these types of lower risk purchases because advertisements are unlikely to have created any learned color associations. In short, a student's choice in backpack color is significant enough to involve some thought and emotion, but not so significant as to be practically predetermined by social norms. Finally, backpacks are most regularly used by students, and since this research was conducted on a university campus, a ready supply of product consumers was available to serve as research test subjects.

3.2 Choosing a Color Model

For this research, it was necessary to first break the color one perceives into measurable components. This was done using the red, green, blue color model. The RGB color model is an additive model used to generate colors on electronic devices, such as televisions or computer screens. This model breaks perceived colors into red, green, and blue colored light components which can vary on an integer scale from 0 to 255. This model is called additive because darkness (that is, black) is produced when all three components are at their lowest level. In order to produce colors, light must be added, ultimately creating white when all components are at their highest levels (255). A shade of grey is produced when all three components are at the same level, and all remaining colors are produced by other combinations of level values.

3.3 Reducing the Design Space

Next, it was necessary to choose the specific colors for which preference data would be collected. In total there are 256^3=16,777,216 unique combinations of RGB values. Since this is clearly an unrealistically large number of sample products for an individual to evaluate, it was necessary to somehow reduce the design space to a more manageable without reducing the statistical reliability of the data that would be collected. To achieve this, a fractional factorial subset of the design space was used.

Red	Green	Blue	Swatch
0	0	0	
0	63	127	
0	127	255	
0	191	63	
0	255	191	
63	0	255	
63	63	63	
63	127	191	
63	191	0	
63	255	127	
127	0	191	
127	63	0	
127	127	127	

Red	Green	Blue	Swatch
127	191	255	
127	255	63	
191	0	127	
191	63	255	
191	127	63	
191	191	191	
191	255	0	
255	0	63	
255	63	191	
255	127	0	
255	191	127	
255	255	255	

Figure 1. Color Samples Used in Study

First, a smaller subset of evenly spaced values [12] were chosen from the entire 0 – 255 parametric range for each of the three color attributes. The goal being to fairly represent the entire color space

with as few samples as possible. This could be done with five evenly spaced levels per attribute, for a total of 5^3=125 colors in this reduced set. Thus, the levels used for the red, green, and blue color components were 0, 63, 127, 191, 255. These were then used to create a balanced and orthogonal fractional factorial design. The colors and their RGB values, are shown in Figure 1.

3.4 Selecting a Functional Form

Utility functions can take any form, such as linear, quadratic, or exponential. Prior works have suggested that a quadratic utility function will accurately represent individual preferences for most applications [20,21], including aesthetic form [13]. However, Guilford's work with color preferences [17] produced multiple local maxima for preferences regarding hue, suggesting that quadratic equations might not be sufficient. For this reason, cubic utility functions were used instead, as shown in Equation 1, where *x* is the level of a given color component and *a, b, c,* and *d* are the coefficients for cubic regression.

$$u(x) = ax^3 + bx^2 + cx + d \tag{1}$$

It should be noted that this assumption will not have the effect of distorting preferences that are truly linear or quadratic, however, as those types of equations can simply be represented with zero coefficients for any unneeded higher order terms.

3.5 Utility of Grey

One key area for improvement in the additive model is to take interaction effects into account when determining overall color preferences. Interaction effects refer to the effect that combinations of two or more different color component levels appearing together has on the overall utility function. This is most clearly seen in the following example. Shades of grey are represented in the RGB color scale by all three color components having equal levels (e.g. R=100, G=100, and B=100). If an individual has a strong preference for the color grey, but not necessarily for a certain shade of grey, their preference would not be for any specific color component levels, as long as the levels are all equal to one another. This interaction has no way of being captured in the current model because each color components are considered independently without consideration for the possible effects of such interactions.

One way to possibly account for this interactions would be to replace the additive utility function with a multiplicative utility function. To do this, we also considered the overall utility function to be a product of the attribute level utilities, rather than a sum, as shown in Equation 2**.** When this multiplication is carried out for the three attribute utility functions, interaction terms, and the corresponding coefficients, are created. A partial example of this new equation is shown for the domain of RGB color in Equation 3, where $a_1 - a_n$ are the coefficients, and *R, G,* and *B* are the numeric values of the red, green, and blue attributes levels.

$$U = \prod_{i=1}^{n} u(x_i) \tag{2}$$

$$U = a_1 R + a_2 G + a_3 B + a_4 RG + \square + a_n R^3 G^3 B^3 \tag{3}$$

Ideally, the utility function would be able to fully incorporate all possible interaction effects. However, predicting coefficients for interaction variables would first require that a larger fractional factorial, and therefore larger survey, be used [12], further increasing the risk of erroneous results due to fatigue.

The attempt was made to capture preferences for one of the more significant interactions, the one that results in shades of grey, in its own utility function. This interaction was chosen based on discussions with respondents from initial studies which indicated that these preferences make up a significant portion of backpack color preferences. Essentially, an additional "grey" utility function would be developed using the same method as the utility functions for the red, green, and blue color attributes.

This new function would not be summed or multiplied with the other three to determine the overall utility of a color, however. Instead, overall utility would now be a piecewise defined function, as seen in the additive form in Equation 4, and in the multiplicative form in Equation 5. It should be noted that in the additive form of the equation, the grey utility is multiplied by 3 to account for the fact that it is taking the place of all three color components and must therefore be weighted accordingly. For the same reason, the grey utility is cubed in the multiplicative form of the equation.

$$U = \begin{cases} 3 * u(grey) & if\ red = green = blue \\ u(red) + u(green) + u(blue) & all\ else \end{cases} \tag{4}$$

$$U = \begin{cases} u(grey)^3 & if\ red = green = blue \\ u(red) * u(green) * u(blue) & all\ else \end{cases} \tag{5}$$

Table 2. Comparison of Partworth Utilities Using Different Grey Handling Methods

	Choice Totals				Partworth Utilities						
					No Grey Handling			Grey Method 1			
Level	**Red**	**Green**	**Blue**	**Grey**	**Red**	**Green**	**Blue**	**Red**	**Green**	**Blue**	**Grey**
0	6	6	6	3	0.400	0.400	0.400	0.400	0.400	0.400	1.000
64	6	3	8	2	0.400	0.200	0.533	0.400	0.200	0.533	0.667
128	5	5	4	2	0.333	0.333	0.267	0.333	0.333	0.267	0.667
191	3	7	4	2	0.200	0.467	0.267	0.200	0.467	0.267	0.667
255	5	4	3	2	0.333	0.267	0.200	0.333	0.267	0.200	0.667

	Choice Totals				Partworth Utilities			
					Grey Method 2			
Level	**Red**	**Green**	**Blue**	**Grey**	**Red**	**Green**	**Blue**	**Grey**
0	3	3	3	3	0.250	0.250	0.250	1.000
64	4	1	6	2	0.333	0.083	0.500	0.667
128	3	3	2	2	0.250	0.250	0.167	0.667
191	1	5	2	2	0.083	0.417	0.167	0.667
255	3	2	1	2	0.250	0.167	0.083	0.667

To develop the grey utility function, choices for greys could be accounted for in one of two ways. In Grey Method 1, these choices would be counted in addition to the regular choices for the red, green, and blue attributes. In other words, the red, green, and blue utility functions would be unchanged, and a separate function would be used to calculate the utility in the specific instance when all three color attributes existed at the same level.

In Grey Method 2, however, each choice in the survey is considered as a choice for a color *or* a choice for grey. This change in the way choices are counted affects the choice totals for each individual, and therefore results in different utility functions for all four of the attributes. For the sake of comparison, Table 2 compares the partworth utilities for one individual using both the grey handling methods.

The two new potentially beneficial changes to the functional form can be combined into a total of six different new utility functions, as follows: (1) Addition, (2) Multiplication, (3) Addition -Grey Method 1, (4) Multiplication - Grey Method 1, (5) Addition - Grey Method 2, and (6) Multiplication - Grey Method 2.

3.6 Generating Utility Functions

In most applications, the partworth coefficients are found by using software to apply a logit or probit model to aggregate consumer data [12]. However, it has been proved that while these aggregate methods can produce acceptable equations for predicting market demand, they are likely to generate erroneous preference models [22]. For this reason, it is necessary to evaluate utility functions on a consumer-specific basis. However, stable partworth coefficients cannot be found in a choice based survey logit or probit methods without aggregating results from many respondents [23].

In order to determine partworth utilities for individuals, then, it was necessary to use Luce's Choice Axiom [24]. This method is based on probability of choice, as shown by Equation 6, which states that the probability of an object being chosen is equal to the weight of that object (w_i) divided by the sum of the weights of all the objects from which the choice was made (w_j). In this case, the probability that a given color component level is chosen by an individual is equal to the number of times a design including that level is chosen in the survey, divided by the number of times it appeared.

$$P(i) = \frac{w_i}{\sum_j w_j} \tag{6}$$

In Figure 2, for example, if a respondent chose the blue backpack in the middle, the totals for Red 64, Green 0, and Blue 255 would each increment by one under the Addition method.

At the end of the process, a table similar to the one shown in Table 2 would be created. Dividing each of these totals by the number of times each level was seen, the partworth utilities are found. Each value represents the probability that the consumer will choose a design containing the corresponding level for that attribute. As a result, the partworth utilities can range from 0 to 1, with higher values indicating a higher preference.

Luce's Choice Axiom assumes that a consumer's overall utility is represented as a summation of his utility for the each of the individual attributes, as indicated in Equation 7, where $u(x_i)$ is the utility of an individual color component.

Figure 2. Example Survey Question with Color Component Levels

$$U = \sum_{i=1}^{n} u(x_i) \tag{7}$$

The advantage of this assumption is that it allows each attribute utility function to be optimized individually, meaning standard derivative based optimization can be used, without the need for more complex computer algorithms. However, this assumption is limited in that it forces the preferences for each individual attribute to be unrelated to preferences for any other attributes. Finally, these equations can be used to create high utility colors for each individual. Under these assumptions, the highest utility color is made up of each of the most preferred color component levels.

4 CONSUMER STUDY

4.1 Survey Distribution

In order to test the validity of these five potentially useful functional forms, a study was performed. A total of 291 students in a freshman-level engineering class participated in this research, and the demographic breakdown of this sample consisted of 215 men and 76 women, ranging in age from 18 to 40. More than 90% of the respondents were 21 or younger, and half were ages 18 and 19. The survey was distributed online to be completed by respondents in their own time, allowing them to take breaks as needed. In addition, the questions in the survey were presented in a random order to each individual, spreading any fatigue or learning effects evenly throughout the survey [25].

4.2 Follow-up Questions

In the follow-up survey used to validate whether the utility functions are accurate, one form of the utility function (a simple linear function of the cubic attribute utilities) was used to generate one multiple choice question for each individual, in which the highest, lowest, and neutral utility backpack colors were compared. All five potential forms of the utility function are tested using five questions for each, for a total of 25 questions. Using multiple questions for each method would decrease the impact of "false positive" responses and serve to better reveal the true success of each of the methods.

In practice, high utility colors were those that ranked within the top 10% of all colors generated. In other words, these colors had a utility of 90 – 100% of the maximum possible utility. Neutral utility colors were those with 45 – 55% of the maximum utility, and low utility colors had only 0 – 10% of the maximum utility. The range of 10% was chosen because it was a large enough window that it actually generated five non –identical colors within each range, but small enough that each of the three colors in a given question had distinctly different utilities. As illustrated in Figure 3, five colors were chosen at even intervals from within each of these categories. Additionally, the colors shown in each question were pulled from the same "slot" within each category, as indicated by the circled elements.

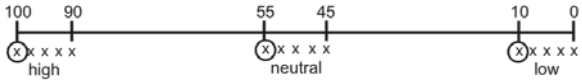

Figure 6. Utility Relationship of Colors Used in Follow-Up Questions

4.3 Results of Surveys

The individual-specific follow-up surveys were also distributed online and were completed by 256 of the original 291 respondents. The results of the survey are summarized in Table 3. As the table shows, both of the methods that did not incorporate grey handling performed essentially the same as one another, and superior to the methods that did attempt to take grey preferences into account.

Table 6. Percentage of Choices, by Utility Method

Functional Form	High	Neutral	Low
Addition	74.31	17.63	8.06
Multiplication	74.15	18.58	7.27
Addition (Grey 2)	70.36	18.42	11.23
Multiplication (Grey 1)	67.91	16.13	15.97
Multiplication (Grey 2)	67.67	16.84	15.49

Figures 7 – 11 contain this data graphically, including standard deviations. As seen in the graphs, below, only the values for the high utility choice are statistically significantly, as the standard deviation bars overlap for the neutral and low choice percentages in all of the methods.

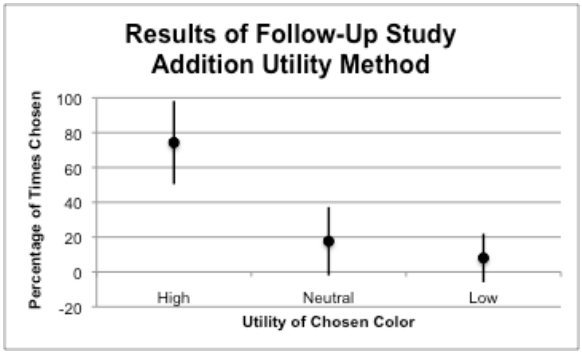

Figure 7. Follow-Up Results – Addition

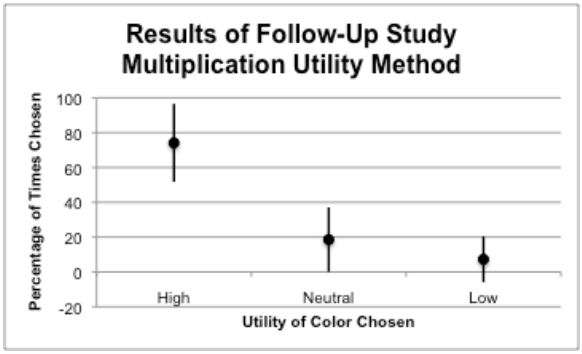

Figure 8. Follow-Up Results – Multiplication

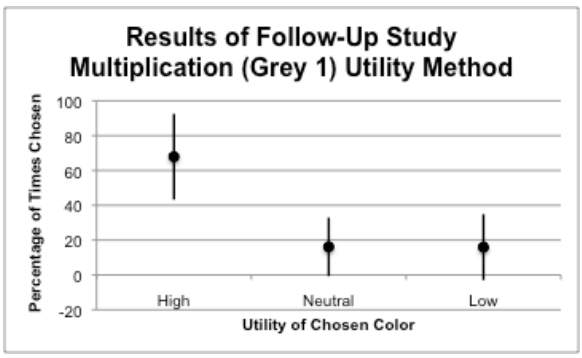

Figure 9. Follow-Up Results – Multiplication (Grey Method 1)

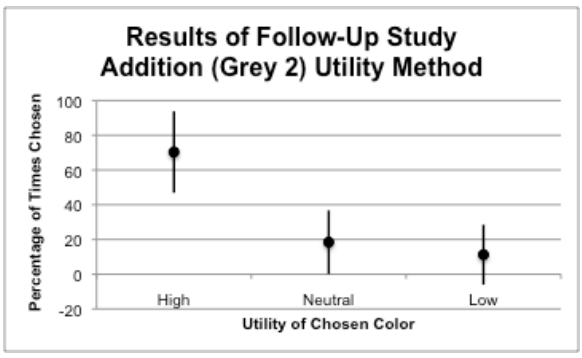

Figure 10. Follow-Up Results – Addition (Grey Method 2)

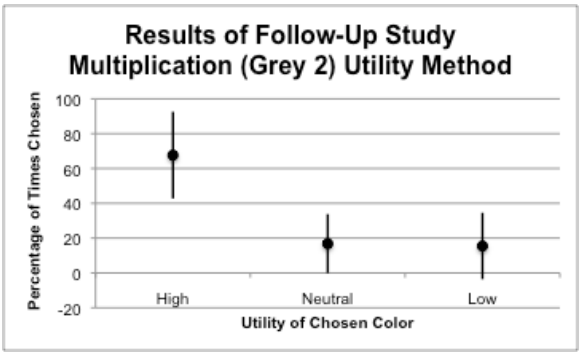

Figure 11. Follow-Up Results – Multiplication (Grey Method 2)

While none of the utility functions that incorporated grey handling methods performed better than the benchmark method, there was a surprisingly substantial variance in the performance of these methods from question to question. In particular, each of these methods performed exceptionally well in the questions where the highest utility color was one of the three options (i.e. the question that would be produced with the circled elements in Figure 6). A comparison of these results can be seen in Figure 12.

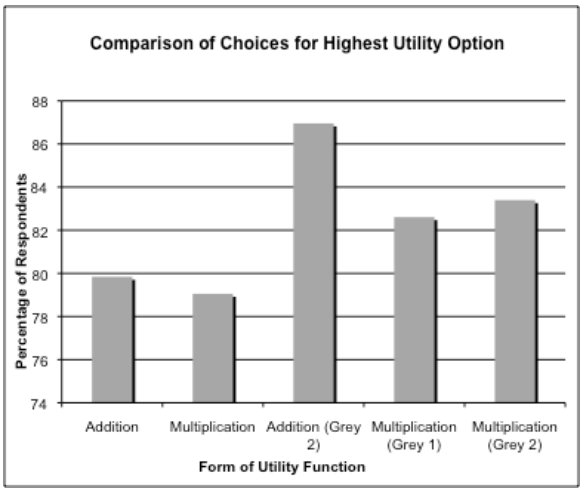

Figure 12. Comparison of Results for Questions Containing the Highest Utility Color

In particular, the addition functional form, using grey handling method 2 had the largest percentage of individuals choosing the highest utility option, as well as the smallest percentage of individuals choosing the low utility option. Why these methods failed to maintain this high rate of success in questions offering lower high utility options is unknown, but their success in this specific instance is not without merit. These results indicate that when it comes to determining *the* optimum color, a

method that accounts for grey preferences is essential. On the other hand, when a range of very good options is required instead, a method without grey handling is preferable.

5 CONCLUSIONS AND FUTURE WORK

While this study has developed a foundational methodology for representing product interactions with utility functions, this body of research can be enriched with additional work in any of several areas.

A valuable first step in future work would be to test this method using a different product space. It is possible that while backpack color preferences can be somewhat successfully represented by their red, green, and blue color components, preferences for other products might not follow suit. Additionally, the methodology has only been verified using a sample drawn from a relatively young, predominantly male population of engineering college students. It would be interesting to see if similar results are obtained using a more broadly representative sample of individuals.

Furthermore, the interactions that occur between colors are not necessarily indicative of all types of interactions between product attributes. Other aesthetic attributes, such as form, should be explored to determine whether the functional representation presented in this paper would equally account for other types of product attributes. This could be extended even to interesting aesthetics such as sound (a musical orchestra) and taste (a unique recipe).

Next, it will be necessary to accurately and fully account for all interaction effects in one continuous function. The partial success of the grey handling methods employed in this research indicates that interactions are important. However, these methods failed to produce superior results in any situation where the maximum utility option was not one of the available choices. A more reliable functional form must be developed, which will likely require that individual preferences be gathered through either a ratings or rankings based conjoint method, which have been successfully used for these purposes elsewhere [9,10,21]. In addition, the final utility form should be continuous, such that optimization methods can be applied for more efficient evaluation. Exhaustive enumeration is an acceptable academic approach, but it is too time consuming and computationally intensive to be used in real-world applications.

Finally, after these problems have been solved to some degree of completion, it would be pertinent to address product designs that involve multiple aesthetics, such as a set of colors. In the fairly simple product space of backpacks, individuals repeatedly commented that their actual favorite product color would be “red with black accents” or “black with blue and green stripes.” Prior research suggests that preferences for color pairings cannot easily be associated to preferences for individual colors [26], however it makes sense to resolve the simpler task before moving forward. Though the problem is different, the methods developed in this research on single color preferences could certainly be adapted to multi-color situations, and then combined with previously discussed form-preference work [13] to incorporate pattern preferences as well.

In conclusion, the translation of aesthetic preferences to objective functions is a complex task, and this research has responded by outlining a methodology and providing substantial preliminary verification to guide future researchers as they seek to refine and build upon the existing body of research.

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