Bayesian Analysis of Color Preferences: An Application for Product and Product Line Design

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Received 6 February 2015; revised 3 June 2015; accepted 3 July 2015

Abstract: When choosing which colors to offer in their product lines, firms often rely upon consumer preference models that do not account for the heterogeneity of their target market and do not consider the trade-offs consumers are willing to make for different color options. For this research we used visual conjoint analysis to assess preference for backpack color and then modeled respondent utilities with a Bayesian hierarchal multinomial logit model. This provided counter intuitive results in which product line color options are not additive but each color changes depending on the number of options the firm is willing to offer and that colors which seem to dominate secondary preferences within a target market may not be the best colors to choose for product line expansion.

Col Res Appl, 41, 445–456, 2016; Published Online 26 August 2015 in Wiley Online Library (wileyonlinelibrary.com). DOI 10.1002/col.21982

Key words: color preference; visual conjoint analysis; utility; product line design; Bayesian hierarchal multinomial logit model

INTRODUCTION

The popular press commonly points to aesthetics as key to the success of a variety of products from companies such as Apple, Harman/Kardon, Microsoft, and Nike.[1–3] It has been clearly demonstrated that the acceptance and adoption of new products are highly dependent upon aesthetics design.[4,5] Product aesthetic can make up 40 to 90% of a consumer's purchases decision.[6] Product color is one of the key factors in product aesthetics; color's strong influence on purchase decision and its relatively low cost to vary in a product makes color an important driver for profitability of a product.

In light of the importance of color to product design and purchase decisions, which affect market share and profits, manufacturers rely upon industry associations, such as the Color Marketing Group, to provide expert direction towards upcoming color trends. For example, the Pantone Fashion Color Report for Fall 2014 projected the yellow shade of Misted Yellow (14-0837) and a different shade called Custard (13-0720) for Spring 2015. Often, because the meaning of colors changes by context, companies employ color consultants to aid further in making specific color decisions for their product lines. A product line is a set of identical products, make and model, that change only in dimension to account for physical differences between consumers. For example, while the iPhone 5c is available in five different colors, they are all the same make and model. Color consultants typically rely on design heuristics, current trends, and their own intuition and experience to make recommendations about a product's aesthetics.[7] These creative experts start by proposing an initial set of colors based on available information and insights, and then they conduct market research on this initial set of colors to determine the sales potential of each tested color. The manufacturer then uses the result of the market research to either retest a different set of colors or determine product color choice.

Since product color is typically chosen from the limited number of tested colors from the market research, the firm can easily miss out on an untested color that would have been even more popular than any that were tested. The research we present in this article demonstrates that a company can improve on the product color insights derived from the market research by exploiting the

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continuous nature of color. Companies using the methodology presented in this article can more accurately determine an optimal set of consumer-preferred colors for a given product line.

Manufacturers often offer products with multiple color options. As long as costs of different colors are nontrivial, firms do not offer every person their own favorite color shade, but instead provide multiple colors with the goal of offering alternatives that approximate preferences over the population. Therefore, the optimal set of colors for a product not only depends on the favorite colors of consumers, but also depend on their utility for alternative colors. The following example illustrates the fact that choosing product colors in a product line based on popularity of each individual color can be suboptimal. Suppose the market consists of three customer segments in descending order of size. The firm conducts market research to with the intent of choosing two final color options. The firm tests three colors: dark blue, light blue, and red. Segment 1 likes dark blue the most and also likes light blue. Segment 2 prefers light blue but also likes the product in dark blue. Segment 3 strongly prefers red, with steep declines in utility for other colors. If applied to this example, the current color research practices would reveal that dark blue is the most popular color, while light blue would rank second, and red third. Should the firm choose to offer the product in dark blue and light blue, based on the popularity ranking, the firm would lose the sales to segment 3 who have very strong preference to red. This stylized example illustrates a case where the existing approaches are suboptimal. The optimal two color offerings would be dark blue and red, because there will be little loss of sales to segment 2, which still likes dark blue even though they prefer light blue to dark blue. This simple example demonstrates the need to consider utility among color alternatives in deciding optimal color offerings in the product line decision.

To address this issue, we developed a choice model that exploits the continuity of colors and demonstrates the potential of leveraging this model for color choice in both single and multiple color options scenarios. We use a multinomial logit model with a non-linear utility function over a continuous color space, incorporating consumer preference heterogeneity through random-effects specification in a hierarchical Bayesian model. A hierarchical Bayesian model with random effects coefficients can represent consumer heterogeneity better than alternative methods such as latent class model.[8] Using the posterior draws from the estimated choice model, we integrate over preference distributions to determine the optimal color options that maximize aggregate expected consumer utility in the target market.

The contribution of our research is twofold. First, our research develops a choice model that exploits the continuity of colors and demonstrates the potential this color continuity has over the discrete color swatch approach in industry practice. Second, our research combines the choice model literature and product line design literature and demonstrates that this integrated approach allows manufacturers to understand consumer color preference better, and therefore can determine optimal color combinations when offering multiple color options within a single product line.

LITERATURE

Research on color preference has primarily focused on determining the universal preference of color ordering, and the relationship between color preference and demographic factors such as gender or age group. Eysenck and colleagues conducted surveys with 40 adults and showed blue as the most preferred color universally and that gender has a small association with color preferences.[9] Guilford and Smith conducted further studies and documented a universal ordering of preferences for over 300 colors.[10]

The bulk of color-related research over the past 40 years has focused on how consumers assess color,[11–14] how consumers respond emotionally to color,[15–17] and color preference heterogeneity via segmentation.[18–22] The extant findings on consumer reaction highlight the importance of product line decisions in regards to color. Our research focuses not on the consumer reaction but on the firm's best decision with regard to color selection.

Ou *et al*. linked color preference to a subjective description of color (e.g. color emotions and color appearance).[23] Because this work was conducted in the context of understanding universal preferences for colors, their findings do not provide insight on the heterogeneity in individual color preference nor on how to measure these individual preferences for the purpose of product design.

Many quantitative methods have been developed in the context of product design but are limited in providing guidance for colors. For example, the Quality Functional Deployment, or House of Quality provides a means to translate customer needs to measurable technical requirements that designers can then attempt to maximize, minimize, or target to specific values.[24] However, customer needs are specified in subjective factors such as "visually appealing." Affective design methods, such as Kansei,[25] assess consumer qualitative preferences through the use of Likert scales and attempt to translate these into design directions and constraints. While these methods have generally found success, it has primarily been within the context of ergonomics and product form gestalt.[26] Methods like Kansei involve specifying color subjectively, treating colors in emotional qualities (e.g. "comfortable" or "dramatic") and perceptual attributes (e.g. "warm") instead of objective characteristics (e.g. "hue" or "luminance").[27–30] Specifying colors in subjective factors complicate the task of measuring color preferences from market research because each consumer may have different perception along these subjective dimensions.[31]

Our research is built on the new product development literature that uses utility functions to specify product preferences. Utility models have long been used to capture product preferences and product design decisions,[32] because such models make it possible to understand the relationship among attributes and identify worthwhile trade-offs.[33] Generally, when color is included in utility models, it has been included as a discrete variable.[34] The resulting measures simply reflect preferences among just those colors that have been rated, equivalent to the color swatch research currently used by color consultants.

Despite often being represented with indicator variables in discrete choice models, colors fall on a continuous spectrum. The continuous variable representation of color in utility models allows preference measurement of colors outside of a discrete set of colors shown to respondents, an important step forward for color research. Psychologists have long posited that color perception can be represented in three dimension where colors that appear similar in human perceptions are located close to each other in the three dimensional space.[35,36] One widely used color representation is the CIELAB color space (also known as LAB color space), in which each color is represented by its lightness, red–green, and blue–yellow.[37,38] Like other color representations, the CIELAB color space produces over 16.8 million possible colors. This incredibly large space makes it virtually impossible to explore effectively consumer color preference using indicator variables in choice models or qualitative verbal representations. This is the primary scientific motivation for the research we present in this article.

Figure 1 graphically shows how the color changes along the three dimensions of the CIELAB color space. One of the advantages of the CIELAB color space is that the red–green and blue–yellow dimensions are orthogonal.[37] CIELAB is based upon the natural perception of color in that red and green perception is distinct from yellow and blue perception in the same way that the human eye processes color trichromatically. Another advantage of the CIELAB color space is that a change of coordinates in the color space yields similar magnitude of change in color perception by human regardless of the coordinates.[35,36] The third advantage of the CIELAB color space is that this color space is device-independent. RGB color space is a well-known alternative to CIELAB color space, and is used widely in computer graphics. Each color in the RGB color space is defined by the additive combination of the red, green, and blue primary colors. The RGB color space is embedded in the CIELAB color space, and thus the CIELAB color space captures all the colors in the RGB color space and other colors outside of the RGB space. CMYK is another well-known color space primarily used in color printing. Each color in CMYK is defined by the amount of cyan, magenta, yellow, and black inks to be mixed. Similar to RGB color space, the CMYK color space is a subspace of the CIELAB color space. In fact, CIELAB color space can describe all the colors visible to the human eye and is one of the largest standard color spaces, representing more colors than other commonly used color spaces. One practical limitation of the CIELAB color space is that the

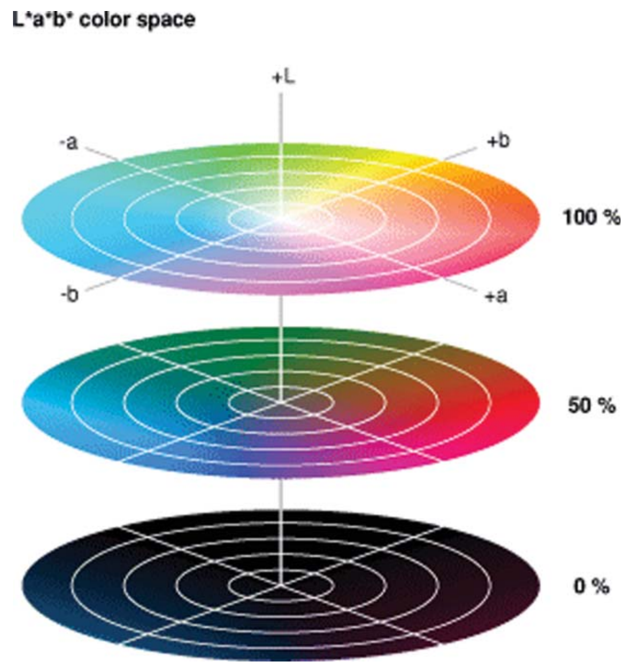

Fig. 1. Color representation of the CIELAB color space. The *L* dimension represents lightness; the *A* dimension represents redness/greenness; the *B* dimension represents yellowness/blueness. (Source of figure: https://developer.apple.com/library/mac/documentation/cocoa/conceptual/DrawColor/Concepts/AboutColorSpaces.html).

CIELAB color space includes nonphysical colors that cannot be produced by physical light source. Despite this limitation, the CIELAB color space is an important theoretical construct for analyzing human perception of colors. The CIELAB color space has been used in recent consumer research on color preferences.[39] The research we present models consumers' color preference over the CIELAB color space and focuses the analysis on the physical colors within the CIELAB color space.

Manufacturers often offer multiple color options for a product, and our research addresses the product line selection problem while building on previous research in this area. Choosing the color options is in essence positioning a product line in a horizontal differentiation setting. Page and Rosenbaum demonstrated a product line redesign application in which the market share optimization was performed through simulation on consumer preferences estimated from conjoint analysis.[40] They focused only on the functional attributes of consumer kitchen appliances, not considering aesthetics. McBridge and Zufryden applied an integer-programming technique to find the product line selection that maximizes seller's return, also focusing on the functional aspects of consumer products while neglecting any aesthetic attributes.[41] Dobson and Kalish developed a heuristic for finding a product line that maximize profit or total welfare based on conjoint analysis.[42] There is much research on using various optimization method to derive the optimal product line.[43–45] When addressing the manufacturer's problem of product line design in the color setting, our research

Fig. 2. Example question from backpack color preference study.

focuses on accounting for the substitutability among product color in the consumer purchase decision. We do not model choice-set dependent effects nor assortment effects that may complicate the problem of product line selection.[46,47]

METHOD OVERVIEW

The method used in this research to determine consumer preference function for color can be generalized outside the specific context that we are using and is based upon commonly accepted quantitative consumer research methods. First, a choice study is created from a design of experiments. In our example, colors are separated into three variables which in turn produces a study with 25 different color combinations presented as 25 questions, each with three options. An additional set of questions, five in our example, is created for a hold-out sample to later test the validity of the derived utility function. The choice study for this research was presented digitally online but could just as easily been presented physically in person. After respondents finish their choice survey, their individual responses are analyzed using a hierarchal Bayesian multinomial logit model with splines, to be discussed in more detail later. The result of the analysis is a function that matches an individual's preference for color for the specific product line. This set of preference functions, one for each individual, is then aggregated to determine the optimum set of colors for the product line. The rest of this article will discuss the various steps of this method in detail within the context of a particular product line.

DATA

To provide context for this research, our model is applied to survey data about backpack colors. In our study, a hypothetical backpack manufacturer is interested in the color options to produce. This manufacturer conducts a study to elicit the color preference from the target market and make an informed design decisions about which color options should be produced for retail sale.

We chose backpacks to serve as the product domain for multiple reasons. First, backpacks can and do come in almost every conceivable color. This broadly existing design space eliminates external constraints that would complicate the design of experiments. Secondly, research has shown that color can play an even more important role in purchase decisions when competing product choices are not considerably different from one another on other dimensions,[48] as is the case with backpacks. In this experiment, color is the only differentiator between backpack choices provided. Third, the study was administered to students on a university campus; a high usage segment of backpacks. Fourth, the price of backpacks is nontrivial for the majority of students, increasing respondent level of involvement in the choice of backpack. Finally, given the variation of backpack colors in the marketplace, we expected that backpack color preferences will be heterogeneous.

Our research method used conjoint analysis to investigate the preference of colors in the context of aiding product design. A choice-based conjoint analysis study was presented to a sample of 291 students in a university freshman-level engineering class. Respondents were recruited verbally by the faculty at the end of a common course and respondents were compensated with a trivial amount of extra-credit for the course, 0.05% of their final grade. The advantage of recruiting college freshman is that most students participated in the study through campus computer labs that are managed. This helped to ensure that most respondents likely saw the same backpack images since campus lab computers all share the same hard-drive disc image and have the same hardware. This sample of respondents consisted of 215 men and 76 women and more than 90% of the respondents were between 18 and 21. Each respondent answered all 25 questions, where each question showed three backpacks, each with a different color choice, and the respondent was asked to choose the most preferred color in each question (Fig. 2).

The color choices in the 25 questions were chosen by a balanced, orthogonal fractional factorial design from 125 colors (Tables II and V). These first 125 colors were

TABLE I. Estimates of the population-level parameter color preference coefficients.

Population-level parameter	Posterior mean (95% confidence interval)
λ_1 coefficient to the 1st basis function representing lightness of color	0.244 (−0.260 to 0.748)
λ_2 coefficient to the 2nd basis function representing lightness of color	−31.732 (−37.755 to −25.858)
λ_3 coefficient to the 3rd basis function representing lightness of color	87.006 (71.175 to 103.053)
λ_4 coefficient to the 4th basis function representing lightness of color	−241.941 (−278.474 to −206.471)
λ_5 coefficient to the 5th basis function representing lightness of color	306.772 (260.157 to 354.064)
α_1 coefficient to the 1st basis function representing redness of color	1.940 (1.182 to 2.770)
α_2 coefficient to the 2nd basis function representing redness of color	3.329 (−1.588 to 7.944)
α_3 coefficient to the 3rd basis function representing redness of color	−260.85 (−305.014 to −218.953)
α_4 coefficient to the 4th basis function representing redness of color	317.770 (274.897 to 362.668)
α_5 coefficient to the 5th basis function representing redness of color	384.407 (329.707 to 441.748)
β_1 coefficient to the 1st basis function representing yellowness of color	−3.812 (−4.436 to −3.212)
β_2 coefficient to the 2nd basis function representing yellowness of color	62.103 (52.457 to 71.948)
β_3 coefficient to the 3rd basis function representing yellowness of color	−166.005 (−192.006 to −140.145)
β_4 coefficient to the 4th basis function representing yellowness of color	35.717 (20.000 to 50.272)
β_5 coefficient to the 5th basis function representing yellowness of color	129.425 (109.560 to 149.318)

The significant estimates have been marked with an asterisk, where the estimates are deemed significant when the 95% posterior interval does not contain zero.

determined by assigning five levels to each of the three color variables. This produced a set of colors that reasonably spanned the color spectrum and then a subset was statistically determined to be sufficient for a fractional factorial. The research method for determining consumer response involved each respondent answering the questions within an online survey. Since computers represent colors in the RGB color space, the set of colors were chosen in uniform spacing in the RGB color space. As stated previously, RGB is a subset of the CIELAB space, which was used for the utility preference analysis. All participants were given the same set of questions, but the order of questions was randomized for each participant so that fatigue or learning effects would not be confounded with specific colors. Even though incorporating prior estimates of consumer preferences in the design of choice experiments can lead to improve design efficiency and yield more accurate predictions,[49] we adopted the traditional experimental design because color preferences vary significantly across products and therefore color research studies discussed previously may not provide reasonable prior information to guide Bayesian experimental design.

TABLE II. Options for color study and their assigned RGB levels.

Option	Red	Green	Blue
1	1	1	1
2	1	2	3
3	1	3	5
4	1	4	2
5	1	5	4
6	2	1	5
7	2	2	2
8	2	3	4
9	2	4	1
10	2	5	3
11	3	1	4
12	3	2	1
13	3	3	3
14	3	4	5
15	3	5	2
16	4	1	3
17	4	2	5
18	4	3	2
19	4	4	4
20	4	5	1
21	5	1	2
22	5	2	4
23	5	3	1
24	5	4	3
25	5	5	5

In addition to the main survey, respondents were invited to complete a follow-up survey several days after completion of the main survey. All the respondents returned for the follow-up survey. In the follow-up survey, each respondent was asked five questions in the same choice-based conjoint format as the main survey. The purpose of the follow-up survey was to provide a holdout sample for model evaluation. Respondents were not allowed to take the follow-up survey immediately. The purpose behind the several day wait between the main survey and the follow-up survey was to reduce any bias from memory effect.

MODELING COLOR UTILITY

We used a hierarchal Bayesian multinomial logit model with splines to study the color preferences in the data. Multinomial logit modeling has been used widely in marketing literature[50,51] and the hierarchal Bayesian multinomial logit formulation enables a natural incorporation of heterogeneity and an improvement of coefficient estimates through pooling information from other observations.[52]

We use natural cubic splines to model the relationship between utility and color attributes which allows this relationship to be nonlinear and smooth. Natural cubic splines are piecewise cubic polynomials with continuous first and second derivatives at the knots. The function fitted from natural cubic spline is linear beyond the boundary knots. In other words, the surface fitted by natural cubic spline are smooth in the entire feature space. In contrast to our method's focus on a smooth function, the linear spline basis in Kim, Menzefricke, and Feinberg's conjoint analysis of bathroom scales data yielded a nonsmooth utility function over the features.[53] The color space is incredibly large and is composed of three different visual vectors acting simultaneously. While humans attempt to create discrete steps between different colors, in fact color is presented and perceived as continuous.[37] Our research leverages this perception and therefore requires a smooth utility function over color space. Because the change of color is continuous and not discrete, it is reasonable to assume that consumers to have a gradual and smooth change in utility over color. Mathematically, if color representation is a higher order mathematical function, it is unlikely that a dependent lower order preference function could be anything other than smooth and continuous, i.e. using a cubic function to represent a quadratic space will always result in a continuous function. To ensure smoothness, four interior knots were chosen for each color attribute. We explored alternative spline parameterizations as a robustness check. We modeled consumer heterogeneity with a multivariate normal distribution on the coefficients for the basis represented lightness, redness, and yellowness.

This model assumes the deterministic component of the utility for a color option to depend on the lightness, red–green value, and yellow-blue value of the color. As discussed earlier, these 3 components are the canonical coordinates of the CIELAB color space.

The random utility of individual i that chooses backpack j in question k is

$$U_{ijk} = f\left(L_{jk}, A_{jk}, B_{jk}\right) + \varepsilon_{ijk} \tag{1}$$

where L_{jk}, A_{jk}, B_{jk} is the lightness, redness, and yellowness of the backpack j in survey question k. Furthermore, the utility function specification should be flexible to allow diversity of color preferences over the CIELAB space. To allow for a smooth and flexible utility function, we modeled the function of utility in color space with an additive natural cubic spline representation of the lightness, redness, and yellowness.

$$\begin{aligned} f\left(L_{jk}, A_{jk}, B_{jk}\right) &= \sum_{q_L=1}^{Q_L} \lambda_{q_L i}\ N_{q_L}\left(L_{jk}\right) \\ &+ \sum_{q_A=1}^{Q_A} \alpha_{q_A i}\ N_{q_A}\left(A_{jk}\right) + \sum_{q_B=1}^{Q_B} \beta_{q_B i}\ N_{q_B}\left(B_{jk}\right) \end{aligned} \tag{2}$$

where Q_L is the number of knots for lightness, Q_A is the number of knots for redness, Q_B is the number of knots for yellowness, λ's, α's, β's are the set of coefficients to the basis represented lightness, redness, and yellowness, $N_q(\bullet)$ is the qth basis function of natural cubic spline defined as

$$N_1(x) = 1 \tag{3}$$

$$N_2(x) = x \tag{4}$$

$$N_{q+2}(x) = d_q(x) - d_{q-1}(x) \tag{5}$$

$$d_q(x) = \frac{\left(x-\xi_q\right)_+^3 - \left(x-\xi_Q\right)_+^3}{\xi_Q - \xi_q} \tag{6}$$

A notable feature of natural cubic spline is that the function outside of the two boundary knots is linear whereas the represented function inside the boundary knots is nonlinear. This feature helps alleviating the issue of erratic extrapolation of preference for color outside of tested color spaces.[54]

We selected the number and locations of knots through model selection, unlike the approach in Kim, Menzefricke, Feinberg where the number and locations of knots were estimated jointly with the model parameters.[53] Analysis of the model performance in our model selection suggests that the joint estimation approach for knot number and location is unlikely to yield substantial benefit in our data.

Heterogeneity in preference across respondents is captured by a random effects specification

$$\theta_i \sim \text{Normal}\left(\bar{\theta}, \Lambda\right) \tag{7}$$

where $\theta_i = \left(\lambda_{1i}, \ldots, \lambda_{Q_L i}, \alpha_{1i}, \ldots, \alpha_{Q_A i},\ \beta_{1i}, \ldots, \beta_{Q_B i}\right)'$

In other words, the individual parameters for the components of the color preferences are distributed normally from the population means with a covariance of Λ. This covariance matrix relates to the magnitude of heterogeneity of color preference across respondents.

The survey questions required respondents to choose their favorite color among three color choices, and thus an outside option is not accounted for in this model. The "none" option essentially would enable the measurement of the difference between the utility of the outside option and the utility of the colored backpack. We explicitly excluded the "none" option in part because there was no outside option concept in this study, rather it was a choice of "best in set." The none option would be more relevant (more defined) in an experiment if prices for the colors were included, so that the "none" option would correspond to keeping the money instead of purchasing. As an additional consideration, this difference of the utilities, between the outside option and a colored backpack, depends on other attributes that may not be available in the color decision of product design phase. For example, when choosing color for a new product, the firm may not have yet decided on the selling price, the positioning, or even the list of features of the new product, and thus the comparison of the focal product with outside option is ill-defined.

ESTIMATION RESULTS

Model Selection

We used the data to estimate the proposed model and two alternative spline specifications. The proposed model is a multinomial logit model with a four-knot natural cubic spline representation of color attributes. The first

TABLE III. Log-likelihood and holdout hit rate of the three competing models.

	Proposed model	Alternative model with interaction	Alternative model with more knots
Spline basis	Natural cubic spline	Natural cubic spline	Natural cubic spline
Number of interior knots for each color attribute	4	4	5
Interaction between color attributes	No	2-way	No
Log-likelihood	−4334.8	−3624.0	−4202.2
Holdout hit rate (%)	65.9	63.3	60.6

Holdout hit rate suggested that the proposed model has the highest predictive validity.

alternative model includes two-way interactions in additional to the natural cubic splines. The second alternative model uses a five-knot natural cubic spline representation. Comparing the model performance of the first alternative model to the proposed model provides insight on the necessity of including interaction terms in modeling the color preferences; comparing the model performance of the second alternative model to proposed model enables a judgment of whether the proposed model is flexible enough to account for the nonlinearity of the color preferences.

We used a Markov chain Monte Carlo (MCMC) method for estimating the models. Sampling chain was run until convergence. We verified convergence using multiple parallel chains with different starting values.

For each participant, we asked five follow-up questions similar to the main survey. These questions and answers were used for out-of-sample prediction to verify the preference function. All models have holdout hit rates above 60%, which are significantly above 33% chance, the accuracy of random guessing. The proposed model, a natural cubic spline with four knots and no interactions between color attributes, has significantly higher holdout hit rate of 65.9%, as demonstrated in Table III, than alternative models with two-way interactions or with more knots. This suggests that adding interaction terms overfits the color preference function and four interior knots are sufficient to handle the nonlinearity of the color preference function. We concluded from the robustness check that the number of interior knots in the proposed model is sufficient and the main effect only specification is acceptable.

Utility of Color

With a clearly defined preference model for color, it is helpful to demonstrate graphically the utilities of color along the three dimensions of the color space. While it may be easier to represent the three-dimensional CIELAB color space mathematically, it is difficult to represent this complex color space and its associated utility preference. Because of this difficulty, each plot below shows the utilities across two horizontal dimensions, fixes the remaining color dimension at a chosen value, and uses the vertical dimension to represent utility. Respondent #2 is used for an explanatory example in Fig. 3. Figure 3(a) plots the utilities of colors over two of the three dimensions of the CIELAB color space. The redness value (A) is fixed at 0.4. The vertical z-axis represents the utility of a specific color. The x-axis on the left represents the yellowness (the B-dimension) of the color. The y-axis on the right represents the lightness (the L-dimension of the color). A more negative value on the x-axis (B dimension), that is further to the left of the plot, represents a more bluish color. A more positive value on the x-axis, that is further to the right of the plot, represents a more yellowish color. A larger value on the y-axis (L dimension), that is further to the left of the plot, represents a lighter color. A smaller value on the y-axis (L dimension), that is further to the right of the plot, represents a darker color. Each white contour line denotes the colors that give equal utility to respondent #2. From the contour lines in Fig. 3(a), we see that the utility slopes downward from the blue regions to purple regions and then flattens out in the red regions. This means respondent #2 prefers blue over purple and red, and is relatively indifferent between light purple and red.

Figure 3(b) is a similar plot to Fig. 3(a) except the redness value (A dimension) is fixed at -0.4 in Fig. 3(b) rather than at 0.4, where it was in Fig. 3(a). Again, the purpose of this plot is to help visualize the respondent's utility for particular colors. The contour lines in Fig. 3(b) show that the utility surface slopes downward gently from dark green to green and then falls off steeply from green to light green. From this plot, we interpret that respondent #2 slightly prefers dark green over green, and strongly prefers green over light green and light blue, which are equally not preferred.

Recall that a unit change in distance between two points in the CIELAB space lead to a constant change in relative differences in color perception. Figs. 3(a) and 3(b) show that in different regions of color the utility surfaces have different degrees of change. This varying degree of change over the unit distance across color regions supports the proposed flexible and nonlinear model specification.

To demonstrate the heterogeneity in color preferences, we analyzed the utility plots of different respondents. Figs. 3(a) and (b) show the color preference of respondent #2; Figs. 4(a) and (b) show the color preference of respondent #27; Figs. 5(a) and (b) show the color preference of respondent #30.

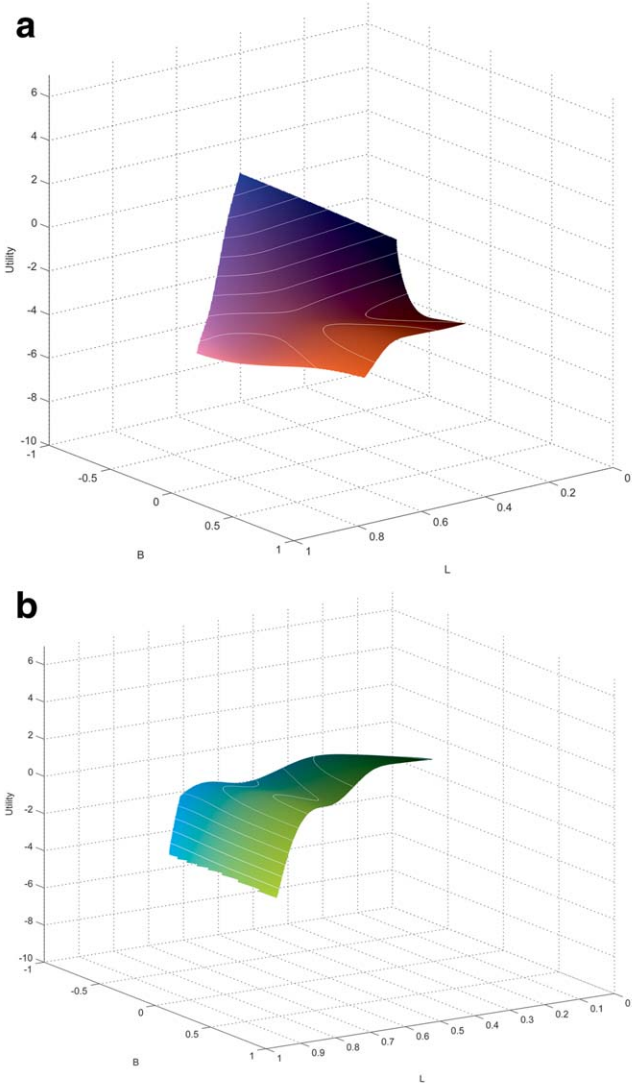

Fig. 3. (a) and (b) Utilities of colors along the yellowness (*B*) and the lightness (*L*) dimensions for respondent #2. Positive value on the yellowness (*B*) dimension represents a yellowish color; Negative value on the yellowness (*B*) dimension represents a bluish color. Larger value on the lightness (*L*) dimension represents brighter color; smaller value on the lightness (*L*) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (*A*) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (*A*) equal to −0.4. The plotted surface is limited to the subset of physical colors.

Figure 4(a) shows a group of valleys and peaks in the utility surface for respondent #27. This respondent primarily prefers red as this is the highest peak on the contour plot and also shows a strong secondary preference for blue. Purple and orange are located at level contours within the valleys, showing that they are equally preferred at a lower utility than either blue or red. Figure 4(b) shows that respondent #27 uniquely prefers green over teal and dark green, and likes light green the least among the variations in green colors.

The vast difference in the shape of the utility surface between Figs. 3(a) and 4(a) and Figs. 3(b) and 4(b) indicates strong heterogeneity in the color preference across respondents. The proposed model captures the preference heterogeneity through individual-specific coefficients. Furthermore, this model enables varying nonlinear shapes of utility surface because the model parameterizes the color space through a spline representation.

It should be noted that there are some potential limitations to such a simple preference model. For example, the backpack strap remains a constant color black. While this was intentionally kept constant to minimize interaction effects between the color of the strap and the color of the backpack it must be recognized that some colors may be more or less preferred due to the relationship between the color of the backpack and the strap. Future work will look into how the color preference model changes when more than one color is modified in a product line.

Favorite Colors of the Respondents

In the previous section we showed that the respondents have heterogeneous color preference. With this in consideration, it seems that the best approach is not to model a single utility function for the entire sample population due to the lack of homogeneity. Rather, in this section we explore the favorite colors of the individual respondents as predicted by the model. Figure 6 shows the predicted favorite color for each individual from the study in the CIELAB color space. The plots in Figs. 3 through 5 were a representation of ranges of colors with the vertical axis demonstrating peak utility. The axes for Fig. 6 are the three color coordinates (*L*, *A*, and *B*) with the color shown being the peak color from an individual's color preference plot. To phrase it another way, each point in the figure represents an individual and the color of the point is the color with highest predicted expected utility for that particular individual. Our model predicts that a substantial portion of respondents favor darker colors for backpacks, such as black (near the bottom of the scatter plot) and charcoal (in the center of the scatter plot). Many individuals favor blue, red, or green backpacks.

There is an additional point that should be considered. The sample population as described earlier is quite biased based upon gender (74% male), age (90% between 18 and 21 years), and professional inclination (100% engineering students). While that does mean the color preference results of this study are not translatable to the general population it does not minimize the effectiveness of the methodology. In fact, it would be expected that when firms use this methodology they would separate out respondents based upon their segmentation variables to determine whether distinct target markets have uniquely preferred colors for the product line. For example, a company selling backpacks to a small technical college may likely choose a set of colors very different from backpacks selling to a large liberal arts college.

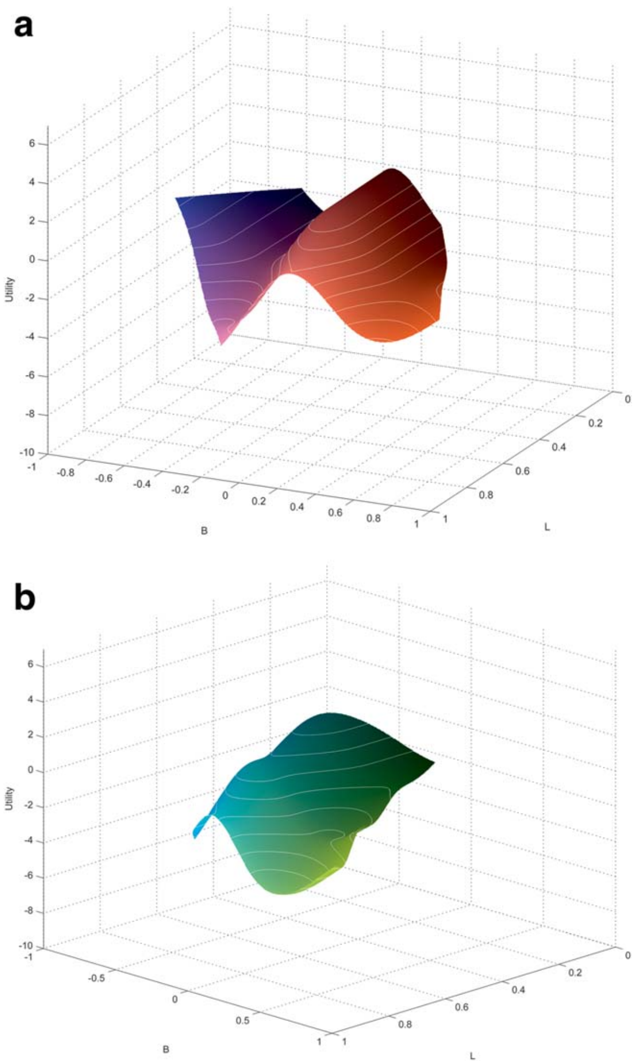

Fig. 4. (a) and (b) Utilities of colors along the yellowness (*B*) and the lightness (*L*) dimensions for respondent #27. Positive value on the yellowness (*B*) dimension represents a yellowish color; Negative value on the yellowness (*B*) dimension represents a blueish color. Larger value on the lightness (*L*) dimension represents brighter color; smaller value on the lightness (*L*) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (*A*) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (*A*) equal to −0.4. The plotted surface is limited to the subset of physical colors.

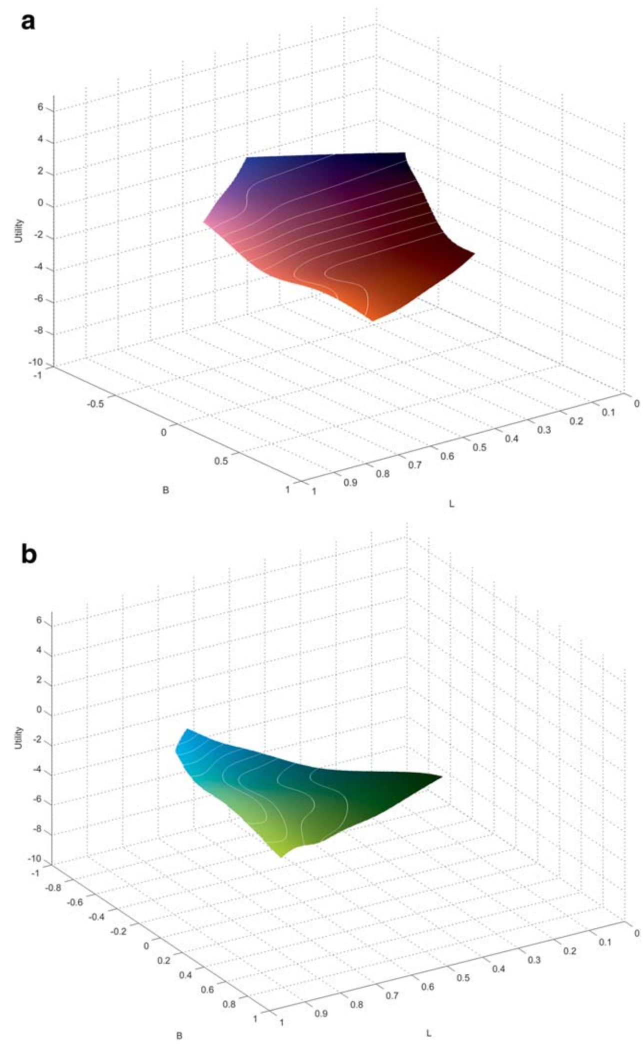

Fig. 5. (a) and (b) Utilities of colors along the yellowness (*B*) and the lightness (*L*) dimensions for respondent #30. Positive value on the yellowness (*B*) dimension represents a yellowish color; Negative value on the yellowness (*B*) dimension represents a blueish color. Larger value on the lightness (*L*) dimension represents brighter color; smaller value on the lightness (*L*) dimension represents a darker color. The figure on the left shows the utility of colors that have redness (*A*) value equal to 0.4; the figure on the rights shows the utility of colors that have redness (*A*) equal to −0.4. The plotted surface is limited to the subset of physical colors.

Optimal Color Options Selection

Figure 6 shows that there is a large variety of favorite colors among the respondents, and more generally, in the target market. This diverse color preference suggests that offering only one color option may not be a good decision for the firm. In fact, manufacturers often offer several color options for a product. For example, a consumer can choose among red, blue, grey, black, white, green, and an orange color for a 2015 MINI Cooper. Knowing the optimal set of colors to manufacturer is important—offering color options that are too similar to each other takes up production line and increases expenses but may not improve sales. When the firm decides to offer multiple color options, it needs to determine which colors to offer. To address this important product line design decision, we demonstrate the potential of using the estimated model in determining the optimal color options.

The primary focus of our research is on the problem of choosing the set of color choices conditional on the number of color options to be offered. We assumed that the firm has decided how many color options to offer based on considerations about manufacturing capabilities and expenses and the distribution channel. The number of color options is not endogenously modeled in this work because the decision of the quantity of color options would depend on information such as marginal costs in

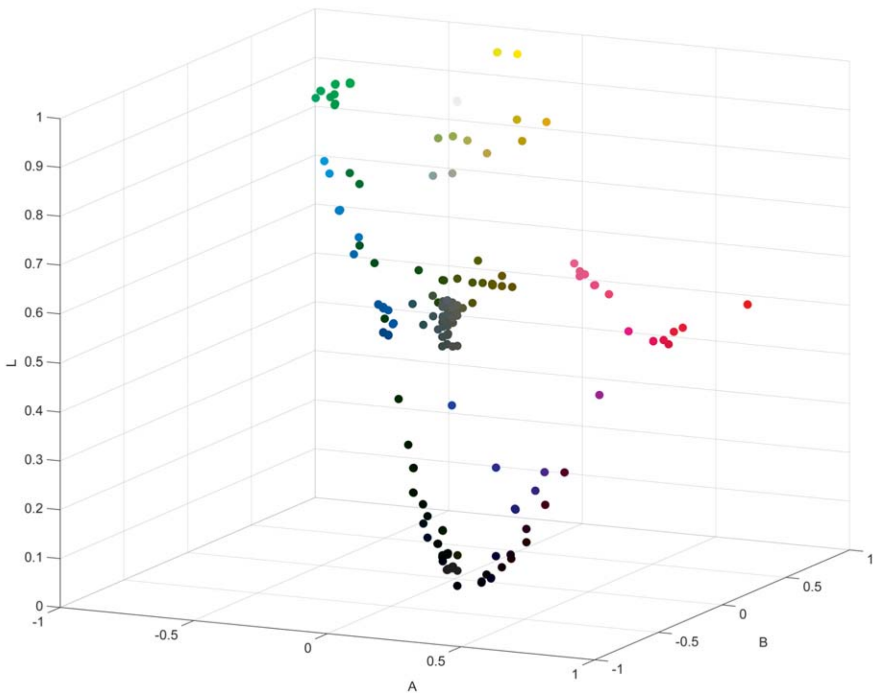

Fig. 6. Scatter plot of the favorite color of each of the 291 respondents as predicted by the model. Each dot shows the favorite color for one individual and the coordinates of that color in the CIELAB color space.

manufacturing additional color options and marginal costs in expanding shelf space in both warehousing and retail. The method we employed for arriving at the recommended set of color options is to find the set of color options that maximizes the total expected utility of the entire set of participants. We did not derive the optimal color options by maximizing market share. The rationale behind our choice of objective function is that the outside option is often ambiguous in the color decision stage of product design and the comparison of focal product to an outside option may depend on factors that are not finalized in the color decision stage. In summary, our work here uses the estimated color preference model to guide the manufacturer's process by searching for the best set of color options that maximize the sum of expected utility for a set of color options in the set of participants (Table I).

In Table IV, we show the optimal color options as a function of number of desired color options, derived from optimization over the total expected utility predicted by the model. Our model suggests that the firm should offer a charcoal backpack if the firm decides to offer only one color option. If the firm would offer two color options, charcoal and green would be the best combination. The best three color options combination is charcoal, green, and black. The best four colors options combination is charcoal, green, black, and magenta. Note that the shade of green in the best four color options is lighter from that in the best three color options. This shows that the optimal expansion of the color options is more than adding an extra color to the set of chosen color options in a stepwise manner. The reason is that the addition of the fourth color option allows the manufacturer to segment the market further. The fourth color option removes the need of

TABLE IV. Optimal color options and the predicted aggregate utility as a function of number of color options to be offered.

No. color options	Optimal color option(s)				Total expected utility
1	Charcoal				814.9
2	Charcoal	Green			1053.2
3	Charcoal	Green	Black		1121.0
4	Charcoal	Green	Black	Magenta	1176.4

TABLE V. Choice study design.

Question	Choice 1	Choice 2	Choice 3
1	19	6	15
2	1	17	8
3	2	25	18
4	6	2	19
5	23	17	5
6	20	7	14
7	10	18	12
8	25	16	12
9	15	9	22
10	16	22	14
11	18	2	11
12	25	8	12
13	5	21	14
14	7	23	11
15	24	20	11
16	10	19	1
17	13	9	5
18	8	17	24
19	4	20	13
20	21	10	3
21	15	3	16
22	4	23	6
23	9	3	21
24	1	24	7
25	4	22	13

Twenty-five total questions each with three options. Questions were presented to respondents in random order.

the firm to offer a darker shade of green that is moderately liked by a large number of target customers. Instead the expanded option enables the firm to offer colors, including light green and magenta, that better satisfy segments in the target market. A naïve method for choosing the optimal color options is to use popular favorite colors. Based on the insight drawn from Fig. 6 that illustrates the favorite color of each respondent, the manufacturer may naïvely decide to include blue in the multi-color options combination because blue is a color that is favored by a substantial proportion of respondents. However, this naïve decision is suboptimal because color popularity does not account for the relative utility level among colors for the individuals. For example, even though some respondents favor blue the most, they also like charcoal moderately whereas the respondents who favor green the most strongly dislike charcoal. In this case, offering green as the alternative color option to charcoal would satisfy more consumers than offering blue as the alternative to charcoal. Therefore, a green and charcoal backpack lineup would improve the aggregate utility in the market more than a blue and charcoal backpack lineup.

There are significant improvements in total expected utility if the backpack manufacturer expands the backpack offering from one color to two colors and from two to three, as shown in Table IV. As one would expect, adding color options increases the total utility because some consumers would be able to find a better matching product when there are more choices. On the other hand, the addition of the fourth color option does not improve the total utility as dramatically as the addition of the second and third options, suggesting diminishing marginal return for expanding the color options for the manufacturer. The number of color options the manufacturer chooses to offer should strike a balance between increasing demand by capturing the diverse color preference of consumers and increasing cost of manufacturing and carrying more color options. Our analysis suggests that manufacturers can use our proposed method to improve the quality of the decision-making for color options of their new products.

CONCLUSION

Color is an integral part of product design. In practice, manufacturers often have to make decision on not just one color, but multiple color options for their products. The research we presented in this article demonstrates empirically the advantage of combining a hierarchical multinomial logit model with constrained optimization to assist manufacturers in understanding the color preferences in the target market and optimizing the set of color options to put to market. If the consumers in the target market have more diverse color preference, it may be beneficial for the firm to expand its product line and offer more color options. Of course, the choice of color options for a particular product line is context and time dependent. To maximize their effectiveness, manufacturers should use this model to assess consumer color preference for each new product cycle. Firms should also not assume that consumer preference for a particular product, like backpacks, will automatically translate to color preference for other products, like automobiles, even within the same target market.

We found that consumers' color preferences for backpack are nonlinear, and the spline modeling approach was able to accommodate the nonlinearity. Furthermore, our analysis found heterogeneity in color preference in a backpack setting.

One future extension of research could investigate the difference in willingness-to-pay among colors. By including prices in the questions of the conjoint analysis, researchers would be able to draw inferences for how much consumers are willing to pay extra for their favorite colors or how much they might sacrifice in choosing colors of preferred, but secondary, preference. Another possible extension of this research would be to compare color preference between product domains for the same target market. This would demonstrate that while the model is accurate within a specific context, a complete understanding of a consumer's color preference requires a variety of product contexts to be explored. It may even demonstrate, in support of historical research, that there are some universal color preferences.

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