Blue or Red?
How Color Affects Consumer Information Processing in Food Choice

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ABSTRACT:

Colors can carry specific meaning and have an important influence on people's feelings, thoughts and behaviors. This paper investigates the impact of blue versus red on how consumers process information in food choice. Results show color indeed influences consumer information processing and feature evaluation. Specifically, consumers spend more time and pay more attention to choice tasks in the red condition than in the blue condition. In addition, consumers are willing to pay more premium for certain feature on the red label than on the blue label.

KEYWORDS:

Choice experiment, Color, Information Processing, Willingness-to-pay

1. Introduction

Colors can carry specific meaning and have an important influence on people's feelings, thoughts and behaviors. Thus, marketers are using colors in various ways to attract consumers' attention and shape their perceptions. For instance, store interiors and window display use varied colors. Colors are integral in brand logos and ads. Moreover, similar products are sold with different colors of packaging. Although colors play an important role in consumers' daily lives, little is known about how color affects consumer information processing in food choice.

Research focusing on the physiological effects of color dates back over 100 years (Elliot and Maier, 2014). A majority of color research has contrasted the effects of blue with those of red. Blue versus red colors are chosen because blue and red are on opposite sides of the color spectrum and have a strong influence on behavior (blue is the coolest color while red is the warmest color). Blue is posited to be relaxing and to produce calm action, whereas red is posited to be stimulating and to produce forceful action. Thus, colors have a significant effect on cognitive performance. Some studies have found red enhances cognitive performance as compared with blue (Stone, 2003; Hill and Barton, 2005), but other studies have shown the opposite pattern (Elliot et al., 2007; Maier et al., 2008). Sequent research reconciles this discrepancy. Mehta and Zhu (2009) demonstrate that red (versus blue) can activate an avoidance (versus approach) motivation. Evidence shows that red enhances performance on detail-oriented tasks while blue enhances performance on creative tasks.

It is taken as an undeniable fact by marketers that color influences consumer behavior. One line of research focuses on atmospherics, design of buying environment.

Blue retail environment appears to be preferable to red retail environment, as blue-elicited relaxation that can induce more positive outcomes (Bellizzi and Hite, 1992; Gorn et al., 2004). Another focus is on the role of color in brand identity and recognition. The most frequently utilized logo color is blue (Labrecque and Milne, 2013), which conveys more competence than red (Labrecque and Milne, 2012). Recently, the role of color in influencing consumer evaluation has received attention. Bagchi and Cheema (2013) find that blue versus red background colors have a different influence on consumers' willingness-to-pay in auctions and negotiations. Red (versus blue) backgrounds elicit higher bid jumps in auctions and lower price offers in negotiations. This raises the question whether red (versus blue) backgrounds affect willingness-to-pay in choice.

Although many studies has been conducted on various aspects of color, little research has investigated the way in which color affects consumer information processing in food choice. We attempt to fill the gap in current literature by employing choice experiments. To examine the effect of different background colors, we designed two versions of choice experiments concerning fresh strawberries, one using a blue background and the other using a red background. Respondents were randomly assigned to complete one version of choice experiments. When consumers make choices, their choice time and attribute attention were recorded by online survey tools. Consumers' willingness-to-pay can be estimated using the Mixed Logit model. Therefore, we can compare consumers' choice time, attribute attention, and willingness-to-pay between blue and red backgrounds to determine the impact of color on consumer information processing and preference.

This research not only provides insights into consumer information processing in food choice, but also offers guidance for color use on food labels. A better understanding of consumers' attitudes towards color will help food markers to develop marketing strategies to offer cues about products and grab consumers' attention. For instance, if consumers are 'color-blind', black-and-white format would be an efficient but economical way of communicating information. But if consumers can be affected by colors, colorful format should be tailored to suit consumer preference.

The remainder of this paper is organized as follows: First, we describe the experimental design and sample data in Section 2 and explain econometric methods in Section 3. Then, we present the empirical results in Section 4 and offer concluding remarks in Section 5.

2. Data

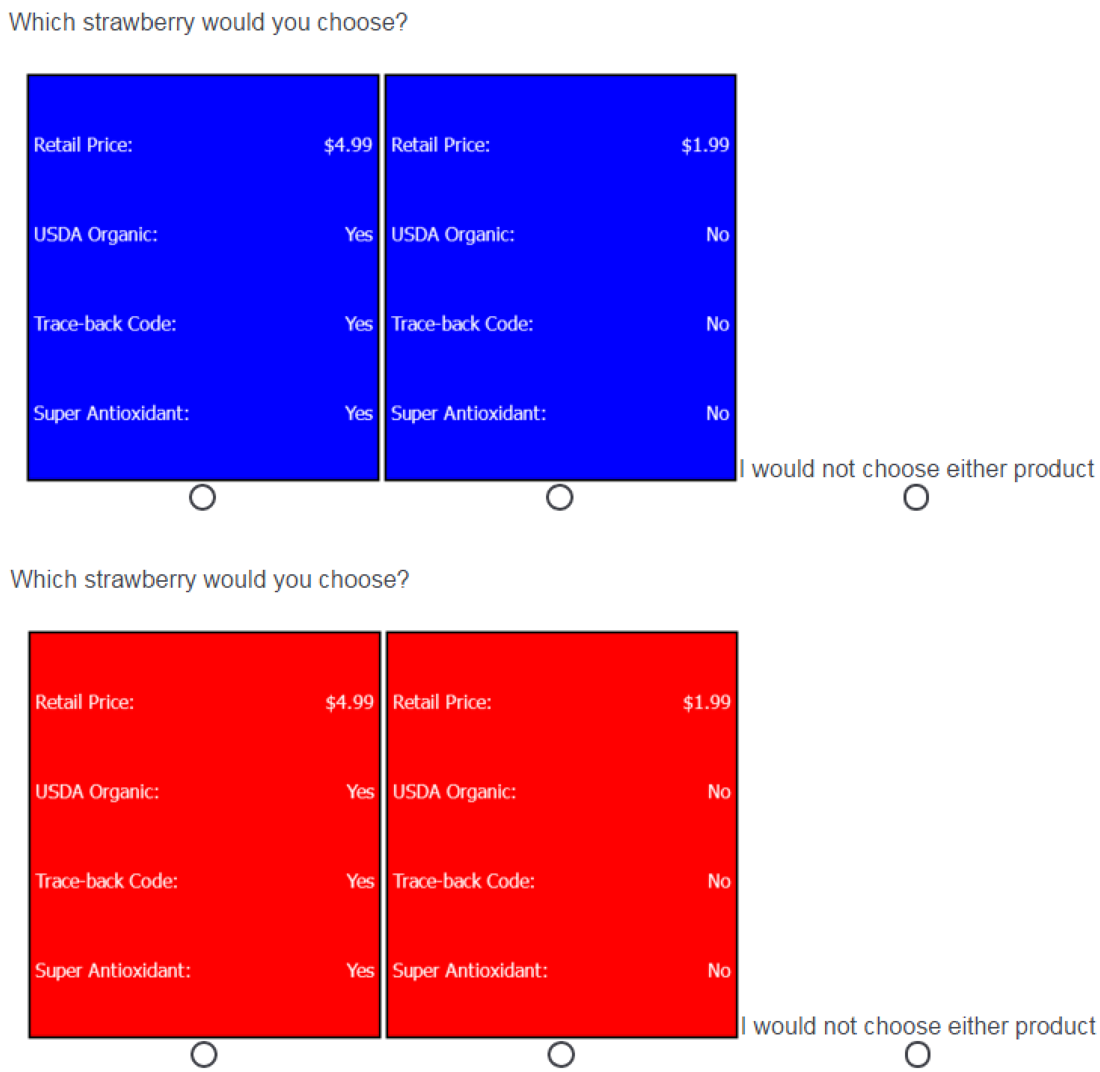
The data come from online surveys that elicit consumer preferences for a 16 oz. box of strawberries. The strawberries were described by a combination of attributes and levels: Retail Price ($1.99/box, $2.99/box, $3.99/box, and $4.99/box), USDA Organic (Yes or No), Trace-back Code (Yes or No), and Super Antioxidant (Yes or No). Except the price attribute was specified four levels, the other three attributes had two levels: Yes (with the claim) or No (without the claim). All attributes and levels, presented in Table 1, were identified from literature reviews and pilot surveys.

Table 1. Attributes and Levels in the CE

Attributes	Levels
Retail Price	1.99, 2.99, 3.99, 4.99 $/16 oz. box.
USDA Organic	Yes, No
Trace-back Code	Yes, No
Super Antioxidant	Yes, No

Based on the selected attributes and levels, a so-called ‘’Optimal Orthogonal in the Differences’ (OOD) design was adopted to generate choice profiles. The OOD design attempts to maximize the differences in the attribute levels across alternatives, and hence maximize the information obtained from respondents answering CE surveys by forcing trading off of all attributes (Street and Burgess, 2005). The Negene software package was used to aid the design. The OOD design resulted in 12 pairs, with a D-optimality of 90.8%. An ‘I would not choose either product’ option was added in each choice set in case that respondents were not satisfied with either profile. To examine the effect of different background colors, we prepared two versions of CE, one using a blue background and the other using a red background. During the survey, respondents were randomly assigned to complete one version of CE which included 12 choice tasks. Sample choice tasks are shown in Figure 1.

Figure 1. Sample Choice Tasks



The final survey consisted of four sections. A screening section identified primary grocery shoppers who were over 18, not color-blind and had purchased fresh strawberries within the last month. Before the choice tasks, the warm-up section contained questions about color preference and attribute knowledge. In the choice experiment section, respondents were randomly assigned to complete 12 choice tasks under the condition of blue or red backgrounds. After the 3rd, 7th, and 12th choice task, respondents were also asked which attributes they paid attention to. When respondents were answering choice questions, the online survey tool recorded the amount of time that respondents spent on each choice task. After completing choice tasks, respondents rated the importance of various strawberries attributes using a 5-point Likert scale. A final section comprised socio-economics questions.

The online surveys were delivered by Survey Sampling International to its representative consumer panels in June 2015. A total of 411 completed questionnaires were collected. The 411 respondents were primary grocery shoppers who were over 18, not color-blind and had purchased fresh strawberries within the last month. As advised by Gao et al. (2015), this survey used a validation question to screen out mindless respondents who did not read the question carefully and randomly selected an answer. Results show that 397 respondents has passed the validation question. In addition, the online survey tool (Qualtrics) provides a series of time measures about the online survey process. Because consumers' information behavior is the aim of this study, we used click counts, number of a respondent clicks on a page, to exclude respondents whose choice processes could not fully captured by the online survey tool. The final sample includes 380 valid responses, with 197 responses to the blue background and 183 responses to the red background. Table 2 compares the social-demographic characteristics of the eligible respondents with the 2010-2014 American Community Survey 5-year estimates.

Table 2. Summary Statistics for Survey Respondents

	Blue Background	Red Background	U.S. Population
Age (Median)	38	38	37.4
Gender (%)			
Male	46.19	44.81	48.6
Female	53.81	55.19	51.4
Education (%) (Population 25 years and over)			
Less than high school	0.00	1.09	13.6
High school	20.30	19.67	28.0
Some college	24.87	24.04	21.2
Associate’s degree	13.71	8.74	7.9
Bachelor’s degree	26.40	32.79	18.3
Graduate or professional degree	14.21	13.12	11.0
Annual Household Income (%)			
Less than $14,999	6.60	2.73	12.5
$15,000~$24,999	7.61	10.93	10.7
$25,000~$34,999	15.23	13.11	10.2
$35,000~$49,999	12.69	13.66	13.5
$50,000~$74,999	22.34	18.58	17.8
$75,000~$99,999	13.20	19.67	12.2
$100,000~$149,999	10.66	7.65	13.0
$150,000~$199,999	3.05	6.01	5.0
$200,000 or more	2.03	2.19	5.0
Household Size (%)			Average household Size
1~2	43.88	44.81	2.63
3~4	41.33	44.26	
5 or more	14.80	10.93	
No. of respondents	197	183	

Note: The chi-square tests cannot reject the null hypothesis that these two groups share the same social-demographic characteristics.

3. Methods

Under the experimental design, we observed 3 attention counts, 12 choice time, and 12 choice outcomes for each respondent. Because the two versions of choice experiments are exactly the same except the background color treatment, we can compare the difference in choice time, attention counts, and willingness-to-pay between blue and red backgrounds to determine the impact of color on consumer information processing and preference.

When several measurements like attention counts or choice time are taken on the same respondent repeatedly over time, the measurements tend to be correlated with each other. This correlation can be taken into account by performing a Repeated Measures Analysis of Variance (Repeated Measures ANOVA). The Repeated Measures ANOVA not only tests hypotheses about the between-subject effects, but only tests hypotheses about the within-subject effects and the within-subject-by-between-subject interactions. With respect to choice time and attention counts, the effects of interest are as follows:

Between-subject effect: whether there are any difference in attention counts or choice time between blue and red backgrounds.

Within-subject effect: whether there are any difference in attention counts or choice time at all time points.

Within-subject-by-between-subject interaction: whether there are any difference in attention counts or choice time for background*time combinations.

Each consumer's willingness-to-pay can be estimated using the Mixed Logit model. A consumer i is assumed to choose among J alternative products, with a number of attributes of differing levels, in choice scenario t to maximize his/her utility.

Following Lancaster (1966), consumer utility associated with a product can be derived from the bundle of attributes. In our case, the utility of consumer i from choosing alternative j in choice scenario t can be represented as:

$$U_{ijt} = \beta_i' x_{ijt} + \varepsilon_{ijt} = \alpha + \beta_{i\_P} P_{ijt} + \beta_{i\_O} O_{ijt} + \beta_{i\_T} T_{ijt} + \beta_{i\_A} A_{ijt} + \varepsilon_{ijt} \qquad (1)$$

Where $\beta_i' x_{ijt}$ is the systematic component of utility and ε_{ijt} is the stochastic component of utility. β_i is a vector of unknown individual-specific taste parameters and x_{ijt} is a vector of observed attributes of alternative j. P_{ijt} represents the price of product j in choice scenario t, O_{ijt} represents the dummy variable of the Organic attribute, T_{ijt} represents the dummy variable of the Traceability attribute, and A_{ijt} represents the dummy variable of the Antioxidant attribute. In addition, α is a dummy variable which takes 1 for the opt-out option, and 0 for the alternatives A or B. The stochastic component ε_{ijt} are often assumed to be independently identically distributed with Gumbel distributions.

In the Mixed Logit model, β_i is specified as a random vector following density function $f(\beta_i|\theta)$, where θ are the parameters of the distribution. In this case, the coefficient on price β_{i_P} was estimated as a nonrandom parameter. The coefficients of the other attributes were defined as random parameters with a normal distribution, such as $\beta_i = \beta + \Gamma v_i$, where Γ is a lower triangular matrix and v_i is a normal random term $v_i \sim N(0, I)$. The population mean of the taste parameter β accounts for the mean valuation of attributes of all consumers. The individual-specific deviations from the population mean parameter Γv_i captures variation in preferences across consumers and correlations over attributes. The Mixed Logit model is estimated by maximizing the simulated log-likelihood function:

$$lnL = \sum_{i=1}^{N} ln\left\{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\frac{exp(\beta_i' x_{ijt})}{\sum_{j=1}^{J} exp(\beta_i' x_{ijt})}\right\} \qquad (2)$$

Where R is the number of replications.

Based on the individual specific estimates of β_i, each consumer's willingness-to-pay (WTP) for a non-price attribute k can be calculated as the negative ratio of the attribute coefficient to the price coefficient:

$$WTP_{i\_k} = -\frac{\beta_{i\_k}}{\beta_{i\_P}} \qquad (3)$$

Since the coefficient on price β_{i_P} was estimated as a nonrandom parameter, and the coefficients of the other non-price attributes were assumed to be normally distributed, then the willingness-to-pay were also normally distributed. Thus, the one-way Analysis of Variance (one-way ANOVA) can be used to tests hypotheses about the treatment effect: whether there are any difference in willingness-to-pay between blue and red backgrounds.

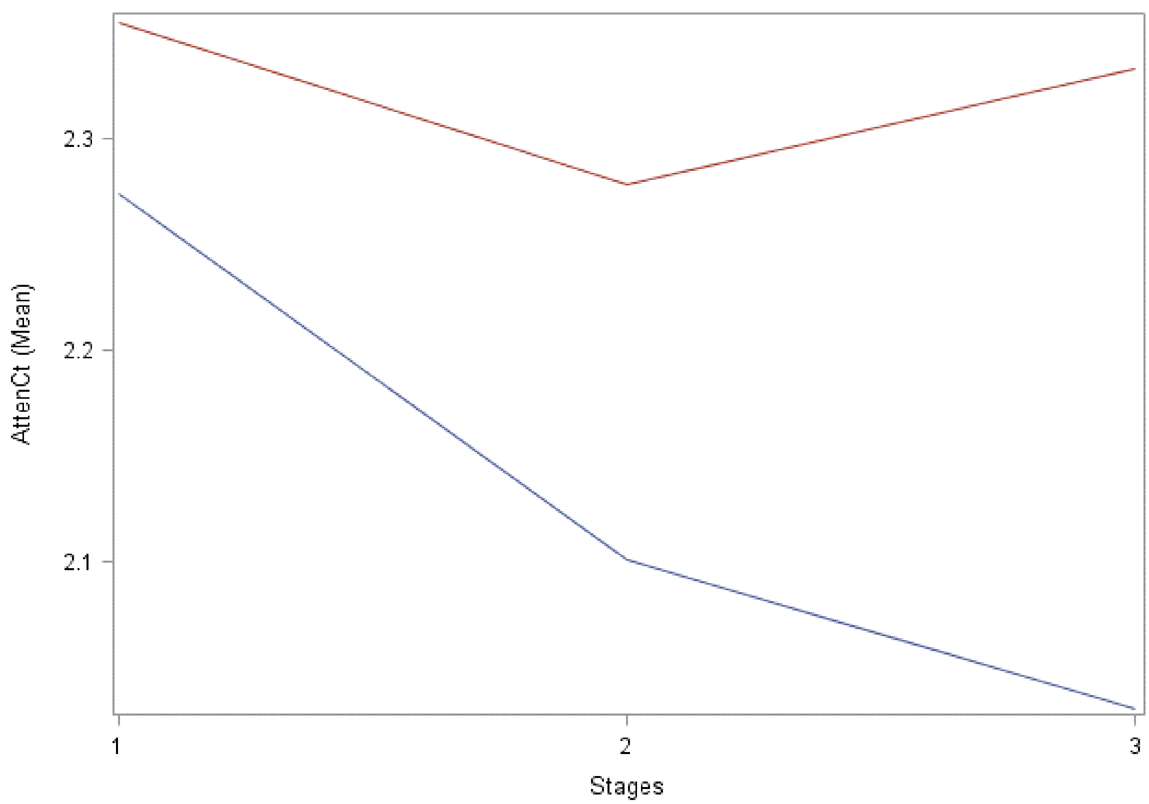
4. Results

Table 3 shows descriptive statistics of attention accounts and Figure 2 displays mean attention counts for the three stages. As indicated by the below table and graph, consumers in the red condition seemed to pay more attention to product attributes than those in the blue condition.

Table 3. Descriptive Statistics of Attention Accounts

Version	N	Variable	Mean	SD	Median	Min	Max
Blue Background	197	AttenCt1	2.27	1.08	2	0	4
		AttenCt2	2.10	1.06	2	0	4
		AttenCt3	2.03	1.07	2	0	4
Red Background	183	AttenCt1	2.35	1.15	2	0	4
		AttenCt2	2.27	1.15	2	0	4
		AttenCt3	2.33	1.21	2	0	4

Figure 2. Mean Attention Counts for the Three Stages



The Repeated Measures ANOVA results in Table 4 indicates that the treatment effect is significant at the 10% level and the time effect is significant at the 5% level. Despite the 10% significance level, there are significant differences in attention counts between blue and red backgrounds.

Table 4. Repeated Measures ANOVA for Attention Accounts

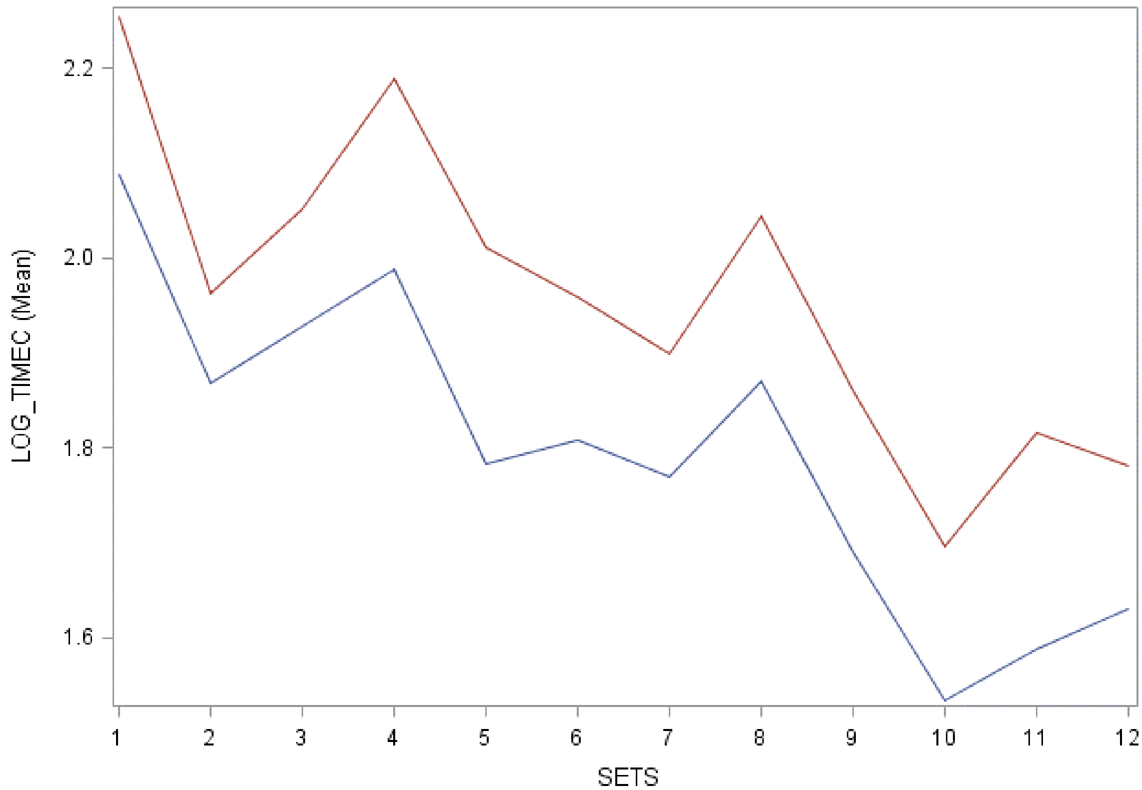
Source	DF	Type III SS	Mean Square	F Value	Pr > F
Background	1	9.95	9.95	3.15	0.0766
Time	2	4.20	2.10	6.71	0.0013
Background* Time	2	2.34	1.17	3.75	0.0239

With respect to choice time, our exploratory analysis suggests distributions of original choice time are positively skewed and there are some outliers. To make patterns more interpretable, we instead use log-transformed choice time. Table 5 shows descriptive statistics of log-transformed choice time and Figure 3 displays mean log-transformed choice time for the 12 choice tasks. The below table and graph reveal that consumers spent more time on red background than on blue background when making choices.

Table 5. Descriptive Statistics of Log-transformed Choice Time

Version	N	Variable	Mean	SD	Median	Min	Max
Blue Background	197	Log_Time1	2.08	0.61	2.05	0.07	5.19
		Log_Time2	1.86	0.66	1.87	-0.08	5.09
		Log_Time3	1.92	0.72	1.88	0.04	4.66
		Log_Time4	1.98	0.65	1.86	0.58	5.14
		Log_Time5	1.78	0.64	1.76	-0.05	5.41
		Log_Time6	1.80	0.63	1.70	-0.15	4.68
		Log_Time7	1.77	0.69	1.68	-0.16	4.90
		Log_Time8	1.86	0.64	1.82	0.48	4.12
		Log_Time9	1.69	0.69	1.61	0.09	4.98
		Log_Time10	1.53	0.56	1.49	0.14	3.11
		Log_Time11	1.58	0.59	1.56	0.18	4.03
		Log_Time12	1.63	0.65	1.55	0.01	4.32
Red Background	183	Log_Time1	2.25	0.65	2.22	0.95	5.70
		Log_Time2	1.96	0.60	1.88	0.73	5.36
		Log_Time3	2.05	0.62	2.01	0.49	4.48
		Log_Time4	2.18	0.60	2.11	0.83	4.50
		Log_Time5	2.01	0.63	1.93	0.64	4.31
		Log_Time6	1.95	0.70	1.88	0.58	5.68
		Log_Time7	1.89	0.67	1.85	0.55	5.23
		Log_Time8	2.04	0.61	2.01	0.66	4.84
		Log_Time9	1.86	0.68	1.81	0.56	5.24
		Log_Time10	1.69	0.59	1.65	0.27	4.41
		Log_Time11	1.81	0.63	1.67	0.60	3.67
		Log_Time12	1.78	0.71	1.71	0.58	6.20

Figure. Mean Log-transformed Choice Time for the Twelve Sets



As indicated by Table 6, the Repeated Measures ANOVA results suggest that the treatment effect and the time effect are significant at the 1% level. Thus, there are significant differences in choice time between blue and red backgrounds.

Table 6. Repeated Measures ANOVA for Log-transformed Choice Time

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Background	1	31.04	31.04	12.39	0.0005
Time	11	111.31	10.11	43.61	<0.0001
Background* Time	11	1.69	0.15	0.66	0.7731

Turning now to the choice models, Table 7 reports the estimation results of the Conditional and Mixed Logit models. The estimates in both models are consistent for most of the variables in terms of signs and statistical significance.

Table 7. Utility Function Parameter Estimates

Version	N	Variable	Conditional Logit	Mixed Logit	
			Coef Estimate	Mean Estimate	SD Estimate
Blue Background	197	Price	-0.5693*** (0.0303)	-0.8096*** (0.0427)	
		Organic	0.6843*** (0.0509)	0.8434*** (0.1161)	1.3170*** (0.1099)
		Traceability	0.3009*** (0.0496)	0.4330*** (0.0723)	0.4691*** (0.0831)
		Antioxidant	0.3167*** (0.0499)	0.3647*** (0.0861)	0.8228*** (0.0897)
		None	-1.3774*** (0.1522)	-3.0844*** (0.2207)	
		Log-likelihood	-2011	-1742	
Red Background	183	Price	-0.6415*** (0.0329)	-0.8748*** (0.0459)	
		Organic	0.8530*** (0.0560)	1.0132*** (0.1069)	1.0910*** (0.1080)
		Traceability	0.3286*** (0.0539)	0.4297*** (0.0787)	0.5722*** (0.0901)
		Antioxidant	0.5632*** (0.0551)	0.6890*** (0.0958)	0.8887*** (0.1959)
		None	-0.8386*** (0.1631)	-2.3254*** (0.2244)	
		Log-likelihood	-1813	-1595	

Note: Asterisks *, **, *** denote variables significant at the 10%, 5%, and 1% levels, respectively.

Obviously, the Mixed Logit model exhibits a better fit to the data and provides richer information about heterogeneity in consumer taste. Therefore, the proceeding discussion will be based on the Mixed Logit model. In the Mixed Logit model, the mean and standard deviation estimates of all variables are highly significant. Except that the price coefficient is negative, the coefficients of other attributes are positive. The result implies that compared to strawberries without any claim, strawberries labeled with certain claim were more likely to be chosen.

Based on the individual specific parameter estimates in the Mixed Logit model, the calculated willingness-to-pay measures are presented in Table 8. According to Table 8, the preference ranking in the red condition is as follows: The Organic claim was the most valued followed by the Antioxidant claim, and last by the Traceability claim. However, the same ranking does not hold in the blue condition. Although the Organic claim was still valued most by consumers, consumers were not necessarily willing to pay more for the Antioxidant claim than for the Traceability claim. The one-way ANOVA results suggest the willingness-to-pay for the Antioxidant claim is significantly higher on the label than on the blue label ($F(1) = 17.78, p < 0.0001$).

Table 8. Willingness-to-pay Estimates

Version	**N**	**Variable**	**WTP**		
			Mean	SD	95% CI
Blue Background	197	Organic	1.04	1.45	[0.84, 1.25]
		Traceability	0.52	0.37	[0.47, 0.57]
		Antioxidant	0.44	0.77	[0.33, 0.55]
Red Background	183	Organic	1.16	1.03	[1.01, 1.31]
		Traceability	0..48	0.44	[0.42, 0.55]
		Antioxidant	0.78	0.80	[0.66, 0.90]

Note: WTP values are dollars for a 16 oz. box of strawberries ($/box).

5. Conclusion

In this paper, we have investigated the impact of blue versus red on how consumers process information in food choice. Results show color indeed influences consumer information processing and feature evaluation.

Our results demonstrate that consumers spend more time and pay more attention to choice tasks in the red condition than in the blue condition. Red, because of its association with danger, should make people more vigilant and attentive. In contrast, because blue is usually associated with peace, it is likely to make people more relax and careless. Therefore, the results meet our expectation that consumers are more engaged in the red condition. This results are also consistent with previous findings by Mehta and Zhu (2009), which suggested red enhances performance on detail-oriented tasks while blue enhances performance on creative tasks. Choice tasks are obviously detail-oriented tasks which require a lot of cognitive efforts.

Our findings indicate that consumers are willing to pay more premium for strawberries with the Antioxidant claim on the red label than on the blue label. One possible explanation is that the Antioxidant claim is taken more seriously on the red label. Compared to the preexisting Organic and Traceability claims, the novel Antioxidant claim was just introduced into the market. Given limited awareness of this novel claim, if consumers are less engaged in making choice, then they may not realize the importance of the Antioxidant claim fully. It is verified by the subsequent statistical test which suggests the importance rating of the Antioxidant claim is significantly higher on the red label than on the blue label ($R_{red} = 3.42\ versus\ R_{blue} = 3.15, F(1) =$

$4.53, p = 0.0339$). Thus, when the Antioxidant claim receives more attention on the red label, consumers will place more value on this claim.

Our research provides support for the marketing practice that have long used color to catch consumers' attention and shape their evaluation. Savvy marketers should customize colors on the basis of product characteristics. If a product have some novel or positive features, marketer should consider using alert colors like red to draw attention to these features. By contrast, if a product have certain plain or negative features, marketers should consider using black-and-white to save cost or using relaxing colors like blue to distract consumers from attending to such features. Thus, the decision to use which color may be an important one when tailoring messages to consumers. Our study also ring the alarm to researchers who conduct choice experiments. Because color can affect information processing behavior and stated preference elicitation, we should be cautious about color settings in choice experiments.

Nevertheless, more research is needed before a more solid conclusion can be drawn. First, further research could focus on how the change in information processing induced by color influences preference. Second, future research should consider using various product attributes to check the effect of color on willingness-to-pay. Last, future research might explore more color's (green, yellow, etc.) role in information processing and feature evaluation.

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