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ABSTRACT

Most mobile consumers make a decision about the product in a split second. The decision making in the mobile environment is surely faster than in front of the desktop. This paper claims that the decision-making in the mobile shopping is highly depending on the product's first impression and their visual preference. By predicting the human's visual preference based on the image processing model of perceived colorfulness and perceived visual complexity, this study tested an S-O-R path model from visual preference to consumer's bookmarking and purchase intention via age and gender as moderators. With the controlled laboratory experiment, we substantiated our predicting image preference model. Further, a plan for a real data based analysis is proposed to validate the congruity of our model with the Korean mobile shopping company later.

Keywords: Visual preference, First impression, Product bookmarking, Image processing, Colorfulness, Visual complexity

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INTRODUCTION

In the early 21[st] century, we entered the information society, and along with the 4[th] industrial revolution that is underway, we live in an era where big data can be analyzed. Despite the abundant information, we are stuck in a situation where we should give up some of our precious values. Even before the computers were introduced in 1971, a Nobel Prize winning psychologist, Herbert Simon predicted that people's attention would significantly decrease when they access to richer information. As more information becomes available, the decision maker's attention becomes poorer, and people are forced to make difficult choices. Indeed, his prediction seems to have been realized, as can be noted through the adverse effects of information overload in the online and mobile environment (Schwartz, 2004). In a situation where attention is limited, many people do not have any choice but to rely more on instinctive factors when they make a decision.

The online shopping mall experiences are an example of decision-making that depends much on the first impression, an instinctive element. Much research has been conducted on the first impression. Ingrid Olsen found that people evaluate their first impression in 13 milliseconds (Olsen, 2005). Previous studies have also shown that it takes 14ms or 100ms to make a decision based on the first impression (Locher *et al*., 1993), but the key fact that all studies share is that the first impression is pre-determined for a short period of time earlier than the people understands what it means through the eyes. In fact, a very high correlation has been found between preference evaluations for the website after viewing it for 0.5sec and for 10sec (Tractinsky *et al*., 2004). In other words, we evaluate the product in a split second through the eyes, but even if a long time is given, this evaluation does not change easily. It means that we instinctively make a decision, regardless of whether it is good, before we realize what we have seen.

As we mentioned earlier, several researches have noted that many businesses now are considering the fact that consumers make decisions faster through decreased attention when in front of a computer or a mobile screen. Shopping malls are likely to affect consumers' purchase decisions by showing different product price ranges, depending on whether they are shopping on a desktop computer or shopping on a smartphone. For example, Home Depot, a home-building material supplier, offers mobile customers products with much higher price through their product display page (Hannak *et al*., 2014). Businesses use this strategy because people pay less attention to the mobile screen rather than to the desktop screen, which often results in impulsive buying.

In this way, in front of the online or mobile screen, we evaluate a product at a faster pace, and the factor of first impression plays an important role in the process. What constitutes the first impression of product then? Which variables make us decide quickly with only brief visual experience? First impression is truly a visual experience. Our immediate decision making depends heavily on our intuitive perception. For many years, many studies have attempted to solve the mystery of this beauty using various landscape photographs or websites (Datta *et al*., 2006; Desnoyer & Wettergreen, 2010; Reinecke *et al*., 2013).

LITERATURE REVIEW

Halo Effect

The halo effect is a representative cognitive bias theory that refers to making inadequate inferences about unknown features of an object with only a few pieces of information known as important but fragmentary. This is the first concept published by Edward Thorndike (Thorndike, 1920). A number of studies have explored the connection between first impression and halo effect (Asch, 1946; Crano, 1977; Hendrick & Costantini, 1970). In psychology, the halo effect refers to individual's first impression formation or performance evaluation, and it is mainly mentioned in the consumer's attitude toward a specific product or the context of brand image evaluation in marketing field. Indeed, it has been found that aesthetic evaluation of a product based on visual information has a profound effect on the perceived usefulness of the product (Sonderegger & Juergen, 2010). Related studies have shown that aesthetically beautiful products are perceived not only as useful (Lindgaard *et al*., 2011; Reinecke & Bernstein, 2011), but also as more credible (Lindgaard, 2007).

Primacy Effect

The primacy effect is also a cognitive bias theory, similar to the halo effect. The theory suggests that the information based on the first impression has a stronger influence on the overall impression formation than information, which is obtained later (Alba & Amitava, 1991; Haugtvedt & Wegener, 1994; Hovland & Wallace, 1957;). The primacy effect refers to the serial position of information effect, which states that the aspects of information that are presented at the beginning (primacy) and at the end (recency) of a string of items pertaining to this information are easier to recall, as in Atkinson and Shiffrin (Atkinson & Shiffrin, 1968). This theory is consistent with the attention decrement theory, which suggests that the middle part of the list of memories are recalled at a slower rate compared to the earliest (primacy) or latest (recency) information.

Schema Theory

In psychology, the theory of context effect extends the previously mentioned theory of primacy effect. This theory makes anchoring for judgments using the initially presented information. Here, anchoring refers to a context that serves as a guideline for processing new information and states that people receive information in their own context (Alba & Amitava, 1991). This theory can explain the fact that the desired information is actively recognized while the unwanted information increases cognitive dissonance with previous context. The overall context or knowledge structure based on the past experiences is also referred to as a schema in other academic terms, and this schema theory can explain the fundamental reason why people make different value judgments about the same stimulus (Brewer & Treyens, 1981). It is obvious that the evaluation of an object may differ from person to person because it is based on their own schema rather than on objective and accurate evaluation of the object (Axelrod, 1973). All three abovementioned theories try to describe the psychology of the consumer who wants to get the expected results through immediate and cognitive evaluation of the first impression, which can be interpreted from the perspective the expectancy theory.

Stimulus-Organism-Response Model

To explain the association of people's first impression and their consumption behaviors, this study adopts the Stimulus-Organism-Response(S-O-R) model. We wanted to prove that the first impression of products can ultimately affect the mobile consumer's bookmarking or purchasing behavior.

The Stimulus-Organism-Response (S-O-R) model is the expansion of the Watson's Stimulus-Response (S-R) model that considers behaviorist perspective. This model gives a great meaning to the role of the organism that acts as an intermediate mediator in that the external environmental factors stimulate the organism and the organism that accepts such stimuli produces the final reaction through the internal process (Shaver & Scott, 1991).

In the model, stimulus is a catalyst that can induce or strengthen human emotion. The cues of such stimulation include not only elements of color or design, but also those of fragrance, music, lighting, or spatial arrangement (Mattila & Wirtz, 2001; Spangenberg *et al*., 1996). The next mediator, organism, reflects the internal states of the emotions of the affected person through external stimuli. Here, not only human emotions, but also thoughts and values can be presented together (Bagozzi, 1986). The final step, response, is the result of external stimuli and the internal interpretation of the organism, which can include both human behavioral responses and attitudinal changes (Shaver & Scott, 1991).

Thus, the Stimulus-Organism-Response model is based on the assumption that the stimulus (S) from the external environment affects a person's internal emotional state (O), which can result in reaction (R) like approach or avoidance (Russel & Pratt, 1980). Various research attempts have tried to link these stimulus-organism-response models to the purchasing behavior associated with the consumer's emotions in the actual shopping process. Like we used in this study, several previous studies on stimulus-organism-response models used the color (Belizzi *et al*., 1983) and visual design (Eroglu *et al*., 2001; Kim & Sharron, 2013) as stimuli. Therefore, in this study, design elements, such as color factor and visual complexity that can form the first impression, were used as the external environment stimuli for the user. After forming first impression through the internal process, mobile consumers responded with behavioral or attitudinal change, which is in accordance with Stimulus-Organism-Response model.

Previous Research

Over the years, many efforts have been undertaken to extract the aesthetic elements of images in various image processing fields. Desnoyer and Wettergreen, for example, have shown that the computational methods of aesthetics based on the spatial composition, complexity, color, and contrast of the photographs are very similar to the actual preferences for the photographs they evaluate online (Datta *et al*., 2006). Ivory and Sinha have insisted that human experts' conclusions of the visual appeal of websites are similar with their proposed 11 predictor computations (Ivory *et al*., 2001). These predictors include, for instance, a number of word count, calculated size in bytes, or the types of fonts. They made 65% accuracy in predicting whether human expert conclusions will appraise a webpage positively or negatively. They acknowledged that it is unclear whether their computations completely reflect the opinions of the human experts. However, what is more important is the computations do not necessarily need a human's perception of a site, because they are based on information derived from HTML codes.

In terms of visual complexity, Zheng *et al*. evaluated the balance of perceived website layout using a computer calculation in terms of its structural symmetry or balance. They asked 22 people about visual preferences of 30 web pages (Zheng *et al*., 2009). Their study revealed that the computation and human response were highly correlated. More recently, Reinecke *et al*. found that color and visual complexity determine the aesthetic beauty of a web page and developed an algorithm that explains the first impression and pre-preference of a website based on these two visual variables (Reinecke *et al*., 2013). Now, compared to the previous works, our study expected to show that two visual factors, which are colorfulness and visual complexity, can fully explain the variance of the aesthetic first impressions of products in a mobile clothing business. Moreover, this research examined whether this leads to consumer's intention to purchase or bookmark a product. The computation metrics for each element of image in the previous research are introduced in detail in the hypotheses development part.

HYPOTHESES DEVELOPMENT

Research Model

In this study, the perceived color and perceived visual complexity were set as external environmental stimuli based on a study of online consumer purchase behavior of the stimulus-organism-response model (Kim & Sharron, 2013). Next, visual appeal through the internal process of the person who received the stimulus was formed. Finally, this study investigated whether the visual preference for the product leads to the intention to purchase or bookmark a product according to the following figure.

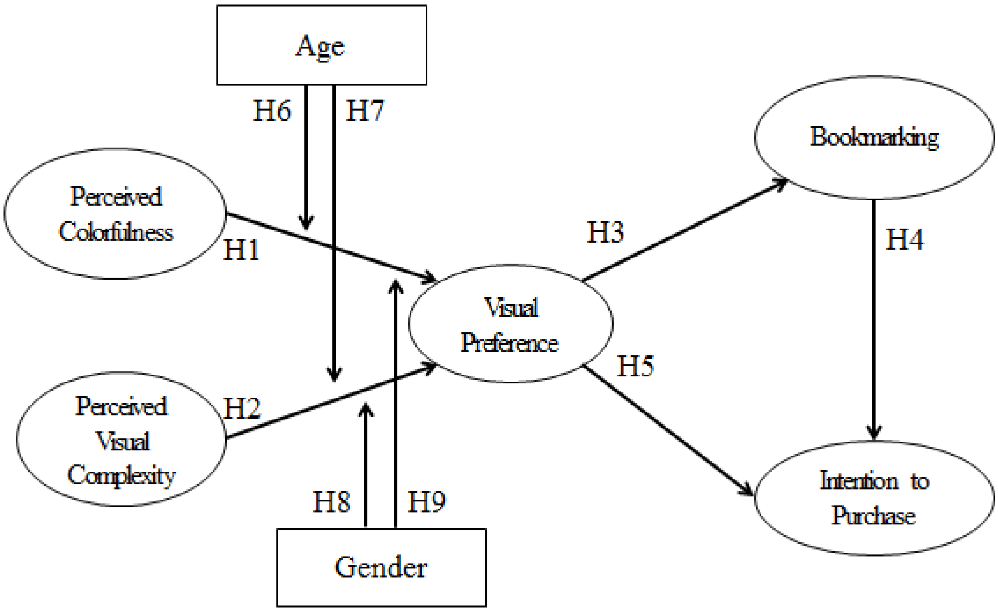

Figure 1: Research Model

Aesthetic Elements of First Impression

Perceived Colorfulness

In many studies, color has been found to be the best source of human emotional response (Coursaris *et al*., 2008; Cyr *et al*., 2010; Lindgaard, 2007; Moshagen *et al*., 2009). In addition, it has been found that the colors of products lead to the perceived reliability of products affecting customer loyalty and even purchase intention (Hall & Hanna, 2004; Kim & Moon, 1998). Humans perceive the color as the arrangement of multiple color elements and tiny components, like pixels. Typical examples of these elements are the hue (the purity of color) that appears in the series of red, yellow, and blue; the saturation that indicates the sharpness of the color; and the value that represents brightness of color. These three attributes of the color are best seen through the perceptual HSV model.

In fact, perceived color depends heavily on how the distribution of colors in the image and the neighboring colors. For example, if the complementary color is close together, the image will appear brighter (Reinecke *et al*., 2013). In addition to the various colors in the various images, you can increase the level of perceived colorfulness with the high level of brightness. Yendrikhovskij *et al*. found that the perceived colorfulness has a positive relationship between the mean saturation value extracted from a specific image and the standard deviation of the color chroma value (Yendrikhovskij *et al*., 1998). In his study, when eight participants were asked about the degree of color perception of 30 images, the perceived colorfulness obtained by the saturation computation described above was highly correlated with the response value of the participants. Hasler and Susstrunk also found a way to compare the Euclidean distances of RGB values between pixels as another way of measuring perceived colorfulness (Hasler & Suesstrunk, 2003). In their case, they asked 20 experiment participants about the perceived color of 84 images and confirmed that the correlation between the computer measurement result and the response value is very high.

According to some studies, colorful photographs are generally regarded as pleasurable (Solso, 1996). In addition, several studies have reported that the aesthetic preference of visual perception is higher as the perceived colorfulness level of images increases (Harrison *et al*., 2015; Hasler & Suesstrunk, 2003; Moorthy *et al*., 2010). Therefore, the first hypothesis was derived based on the above literature reviews.

H1: The perceived colorfulness will be positively related with the visual preference.

Perceived Visual Complexity

A great deal of research has been conducted on not only the color, but also the visual complexity that can affect visual preference (Michailidou *et al*., 2008; Pandir & Knight, 2006; Zheng *et al*., 2009; Tuch *et al*., 2012). Bauerly and Liu pointed out that the complexity of too many components in webpages took a toll on aesthetic evaluation, and research has shown that consumers rather favor moderate visual complexity (Bauerly & Liu, 2008; Geissler *et al*., 2006). This is consistent with Berlyne's theory that moderate level of complexity fosters positive impacts on visual excitements whereas a very low or very high level of complexity leads to a comparably low-level stimulation (Berlyne, 1974). According to his theory, there is an inverted U-shaped relationship between aesthetic evaluation and visual complexity, which means that high and low complex stimuli are less preferred than are moderate complex stimuli. On the other hand, Tuch *et al*. found an overall negative linear relationship between visual complexity and aesthetic preference (Tuch *et al*., 2012). Their study showed that participants had a much worse first impression of images with higher levels of visual complexity compared to lower levels of visual complexity.

The relatively controversial experimental results between this visual complexity and aesthetic preferences make it necessary to know clearly, which components in a real photograph can represent human’s perceived visual complexity. According to Wood (Wood, 1986), people feel more complexity in information as it is denser and more inconsistent. From a similar point of view, Rosenholtz *et al*. examined various elements, such as color, brightness, size, and shape, to calculate the clutter and complexity of the maps (Rosenholtz *et al*., 2007). In particular, they found that visually perceptible clutter increases when maps have a large number of colors or when the distance from one color to another color has a wide distribution (large difference in hue).

In addition, several studies have suggested that perceived visual complexity can be approximated by the pixel-by-pixel texture or distribution of colors and by how finely it is possible to divide an image into smaller elements that can be clearly distinguished (Bauerly & Liu, 2008; Bucy *et al*., 1999; Ivory *et al*., 2001). Among them, Zheng *et al*. divided the image into small pieces of several units using a quad-tree decomposition method to compare how much information is contained in one website screen (Zheng *et al*., 2009). The analysis showed that images segmented into more quad-tree fragments appear to be much more complex and seem to be less professional compared to images with smaller numbers. Therefore, in our study, the number of quad-tree decomposition leaves was also used to measure visual complexity. In addition, visual complexity is closely related to the arrangement of information (Bucy *et al*., 1999). In this study, we demonstrated the relationship between visual complexity and visual preference through the symmetry, balance, and central bias used to measure aesthetic elements in Gestalt cognitive model. Based on the above literature findings, the level of perceived visual complexity was expected to have a negative effect on visual preference. Therefore, we developed the following hypothesis.

H2: The perceived visual complexity will be negatively related to the visual preference.

Visual Preference, Bookmarking, and Intention to Purchase

Consumer Behavior according to the Visual Preference

The consumer bookmarking (or adding to favorites) in online and mobile shopping offers you a special function allowing you to instantly show your preference for a product by adding it your list of favorite sites or products. This mechanism is similar to the internet bookmark (favorites) or e-cart usage. The concept of the wish list, which can be said to be the most similar to the product bookmarking, has been found to be a function of the web shopping cart for the purpose of organizing and managing information systematically (Close & Kukar-Kinney, 2010; Vachon, 2011).

In addition, several studies have identified there is a utilitarian motivation using shopping carts in Internet shopping. Utilitarian motivation is using it for the purpose of organizing and storing the items of interest as described above. This includes further motivation to narrow down the scope and evaluate information at a higher level. In the study of Close and Kukar-Kinney, utilitarian motivation was found to have a positive effect on shopping cart use (Close & Kukar-Kinney, 2010). Since this utilitarian motivation, which is arranging the palatable items to find them easily, can be induced by one’s preference of the product, high visual preference is expected to have a positive effect on shopping cart usage.

In terms of functions similar to favorites in internet, Lin’s research showed that the preference for a particular website indicates how interesting the website is, suggesting that it has a positive effect on the revisiting intention (Lin & Lu, 2000). In addition to this, his study also found that the intention to revisit the site increases the intention to bookmark, so that finally, the site's preferences have a positive and significant effect on the intention to bookmark the site.

Additionally, in the case of consumer's bookmarking, the conversion rate could precede actual purchase in online shopping. Therefore, the visual preference for the product photographs will lead to the preference for the product due to the halo effect, and such product preference appears to lead to the real purchase (Thorndike, 1920). Moreover, according to a research, among the various product attributes, increasing the aesthetic appeal of the product and promoting its features can increase the consumer's loyalty towards that product, which leads to the purchase intention (Martin, 1998). Based on the above literature results, the following hypotheses were drawn.

H3: The visual preference will be positively related to the consumer's bookmarking
H4: The visual preference will be positively related to the consumer's purchase intention

Bookmarking as a Mediator
As mentioned above, one of the biggest concerns for those who run malls in online and mobile environments is the conversion rate, which is directly related to the conversion of a shopper to a buyer. Monetate Ecommerce's Quarterly Research Statistics show that worldwide purchase conversion rates were 2.5% in the third quarter of 2016, and the add-to-cart rate, which corresponds to the number of items in the shopping cart compared to the product detail page view, was 8.7% in the same quarter. For this reason, online shop operators are constantly worrying about how they can drive a consumer's series of actions involving search for products, collection of information, and comparison with other products, all of which lead to final purchase. Indeed, many studies have shown that online shopping and online purchasing are different actions. The main motivation for using online shopping is the physical inconvenience of not being able to visit the store directly (Rohm & Swaminathan, 2004; Seider *et al*., 2000; Wolfinbarger & Gilly, 2001; Wolfinbarger & Gilly, 2001). In addition, recent research has shown lack of evidence for the relationship between hedonic factors of online cart use, such as joy and stress relief, and actual online purchasing (Bridges & Florsheim, 2008). Utilitarian factors are more important for final purchase. Moreover, according to Close and Kukar-Kinney who have been studying shopping cart use, the frequency of purchase increases as the frequency of shopping cart usage increases (Close & Kukar-Kinney, 2010). Based on the literature findings, the following hypotheses could be derived.

H5: Consumers' bookmarking will be positively related to their purchase intention and has a mediating effect on the relation between the visual preference and the purchase intention

Age as a Moderator
It is intuitive to think that the age of a person is related to the perception of color and the information processing associated with visual complexity. In a related study, Saito conducted a questionnaire study on the color preference of the people in Asian countries, including Japan, Singapore, and other countries (Saito, 1996). The results of the questionnaire showed that the age and gender of the participants in the experimental group had a significant effect on color preference. In addition, many studies have indicated that age is a significant variable in the cognitive process and preference formation of color (Child *et al*., 1968; Dittmar, 2001; Garth & Porter, 1934; Katz & Breed, 1922 Saito, 1996).

From the perspective of visual complexity, several studies have shown that the more complex the processing visual information, the greater the effect of age. Strong evidence suggests that visual complexity can change with age. Horberry *et al*. found that older motorists were more susceptible to visual disturbances that had a more negative effect on driving ability (Horberry *et al*., 2006). The following hypotheses can be derived from the literature reviews.

H6: Age will moderate the effect of perceived colorfulness on visual preference. Specifically, the effect of perceived colorfulness on visual preference will be stronger for young people than for old people.
H7: Age will moderate the effect of perceived visual complexity on visual preference. Specifically, the effect of perceived visual complexity on visual preference will be stronger for old people than for young people.

Gender as a Moderator
So far, many studies have suggested gender differences in the decision-making process. Although many researches have shown that different preferences for perceived colorfulness and perceived color distribution depend on gender (Hurlbert & Ling, 2007; Silver *et al*., 1988; Sorokowski *et al*., 2014), in this present study, we will control for gender when assessing the effect of the degree of perceived colorfulness on visual preference because gender preferences for color vary across countries and cultures (Sorokowski *et al*., 2014; Al-rasheed, 2015).

Moreover, in the case of perceived visual complexity, Meyers-Levy and Maheswaran found a gender difference in processing and refining information (Meyers-Levy & Maheswaren, 1991). In their study, women processed more information compared to men and refined the accepted information better, which means that the marginal acceptance limits of women's visual complexity are higher than that of men. This is in line with the findings that women generally engage in additional information analysis processes that require more effort, such as comprehensive and item-specific identification (Darley & Smith, 1995). Therefore, the following hypotheses were derived based on the above literature studies.

H8: Gender will moderate the effect of perceived colorfulness on visual preference. Specifically, the effect of perceived

colorfulness on visual preference will be stronger for females than for males.
H9: Gender will moderate the effect of perceived visual complexity on visual preference. Specifically, the effect of perceived visual complexity on visual preference will be stronger for males than for females.

METHODOLOGY

Data Collection

We conducted a web-based experiment to assess the participants' first impression of fashion items in mobile environment. The participants were selected from online postings from the KAIST Graduate School of Management Engineering and the MBA students. A simulated online store with the main page showing the clothes was used to measure the participants' first impression of these products. To reduce the bias related to the style as much as possible, we diminished the categories of clothes to shirts and T-shirts. Additionally, to remove the bias related to price, items were selected from similar products costing 30,000 ~ 50,000 KRW in real shopping app.

Experiment Procedure

First, the participants came to the lab with their own mobile device. They read the brief description of the experiment and the purpose of the experiment first. The purpose of the experiment was to investigate the consumer behavior in mobile environment according to visual preference. After that, participants had 30 minutes to perform 2 stages of experiment, the visual preference experiment and the mobile environment experiment.

In the first visual preference experiment, the participant saw a product image of 30 clothes on the computer screen. The image comprised 30 pictures of male clothes and 30 pictures of female clothes. A photograph of a model wearing the product will appear on the screen for only one second and then disappear immediately. After that, the participant will answer three questions for each photo based on the first impression of the photo. (1) How colorful were the pictures (1:Not at all colorful, 9:Very colorful); (2) How complicated were the pictures (1:Not at all complex, 9: Very complex); (3) How much did you liked the pictures visually (1: Not at all appealing, 9:Very appealing) (Reinecke *et al.*, 2013). The preliminary test with 6 people was completed in about 10 minutes each.

Lastly, in the mobile environment experiment, the participants connected to a mobile shopping mock page, which was made in advance. This simulated mobile shopping page displayed same 30 items from 1st stage of experiment. The participants could freely choose their favorite products, as they do in the actual mobile shopping. To eliminate the effect of prices, all products were priced the same amount of 1$. After enough time to make decisions, we asked the participants what products among the 30 products they are willing to purchase.

Figure 2: Mock Mobile Shopping Application

Image Metrics Variables Selection

For the total 60 images used in the experiment, the factors corresponding to the colorfulness elements and the visual complexity can be obtained through the image processing method. We used JAVA OpenCV coding scheme to extract each factor from the product image and refer to the image metrics source code of earlier studies (Reinecke *et al.*, 2013).

Table 1: Image metrics variables

Variables	Description
Hue	The purity of a color with regards to the primary colors
Saturation	The intensity of a color
Value	The visually perceived brightness
Color distribution(aqua-white)	W3C: The percent of pixels close to one of 16 colors
Color1 (Yendrikhovskij *et al.*, 1998)	The sum of average saturation value and its std. deviation
Color2 (Hasler & Susstrunk, 2003)	Computation model of Euclidian distance between RGB pixels
XYLeave	A number of leaves by space based XY recursive decomposition

PercentLeave	The percent of XYLeave in the image
Nontxt	A number of leaves of non-text area in the image
Image	The percent of image area in the image
AvgDecom	Average decomposition level
MaxDecom	Maximum decomposition level
qtColLeave	A number of leaves with color based quadtree decomposition
qtIntLeave	A number of leaves with intensity based quadtree decomposition
Vbal	Balance for vertical axis
Vsym	Symmetry for vertical axis
Hbal	Balance for horizontal axis
Hsym	Symmetry for vertical axis
Equil	Evaluates whether the leaves mainly center around an image

RESULT

Sample Characteristic

A total of 61 participants participated in this experiment. Forty respondents (65.5%) were in their 20s, 20 (32.7%) were in their 30s, and one (0.02%) was in the 40s. Furthermore, 31 respondents were female (50.9%) and 30 were male (49.1%).

Hypotheses Verification

In this study, we used two stage hierarchical regression model as the stepwise regression model. In the first stage, we used a linear mixed effect model to consider the random effect of different variance for each participant and photo. This is mainly because the relationship between the visual preference, perceived colorfulness, and perceived visual complexity were generated by one participant responding several times which is the repetitive measures. The statistical package used for the analysis was the lme4 function package of R. Subsequently, we obtained the linear fitted visual preference value using the fitted function of R, which was finally used in the second stage of PLS path analysis. In PLS, the significance test was determined by obtaining the t-value using a bootstrap method with 1000 subsampling as recommended by Hair (Hair *et al*., 2012).

Table 2: Linear Mixed Effect Model Results (Random Effect)

Groups	**Variance**	**Std.dev**
Person	0.3378	0.5812
Pic	0.2443	0.4943
Residual	1.1706	1.0819

Table 3: Linear Mixed Effect Model Results (Fixed Effect) *p<0.05, **p<0.01, ***p<0.001

Variables	**Estimate**	**Std.Error**	**t-value**	
Intercept	2.477e+00	8.656e-01	2.862	**
Age	4.308e-02	2.994e-02	1.439	
Gender	-4.932e-01	2.540e-01	-1.942	
Colorx	8.697e-01	1.366e-01	6.368	***
Compx	-2.935e-01	8.763e-02	-3.349	***
Age:Colorx	-4.916e-03	4.716e-03	-1.042	
Age:Compx	-6.569e-03	3.036e-03	-2.164	*
Gender:Colorx	1.274e-01	3.804e-02	3.348	***
Gender:Compx	1.068e-01	2.737e-02	3.903	***

Table 4: Linear Mixed Effect Model Results (R squared)

	Marginal (fixed)	**Conditional (random)**	**AIC**
R squared	0.57026653	0.7129861	5751.661

The final results are shown in Figure 3. Our predicting visual preference model accounts for the 57% of variance in consumer's preferences. All hypotheses were supported except Hypothesis 4 and Hypothesis 6. As the perceived colorfulness level increased, the visual preference increased (Hypothesis 1), and as the perceived visual complexity increased, the visual preference decreased (Hypothesis 2). In addition, higher visual preference was associated with increased likelihood that the participants would bookmark that product (Hypothesis 3) and subsequently with increased intention to purchase the product (Hypothesis 5). On the other hand, high visual preference did not necessarily lead to purchase intentions (Hypothesis 4). Additionally, the bookmarking fully mediated the relationship between the visual preference and intention to purchase a product. In addition, the moderating effect of age on the relation between colorfulness and preference was non-significant (Hypothesis 6); however, it was confirmed that the negative influence of visual complexity on visual preference increased with age (Hypothesis 7). In addition, the perceived colorfulness had a greater effect on visual preference of females rather than males (Hypothesis 8), and visual complexity has less negative influence on visual preference of females rather than males (Hypothesis 9).

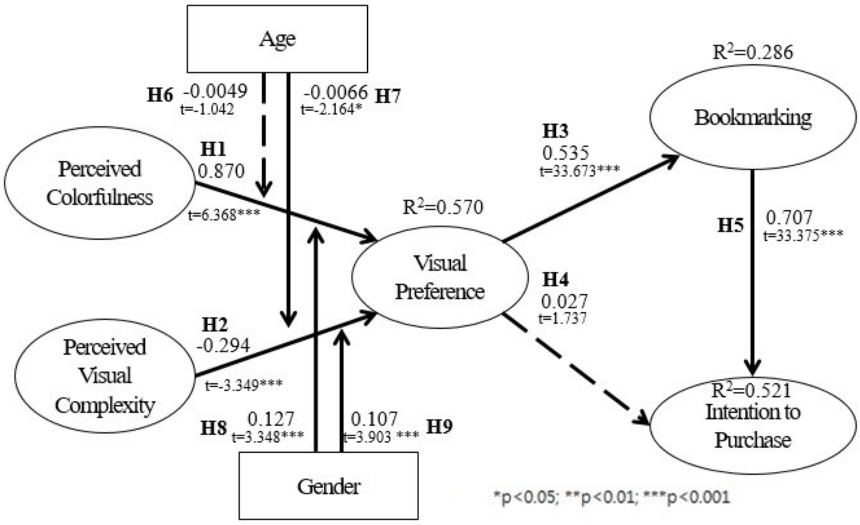

Figure 3: Research Model Results

Image Metrics Model Fitting

In order to fit the image extracted factors with participant responses of perceived colorfulness and perceived visual complexity, we used regression analysis of backward elimination method to obtain only the significant variables (Reinecke *et al*., 2013).

Table 5: Fitted Colorfulness Model

Colorfulness	**Coefficient**	**Std. Error**	**t-value**	
Hue	0.0066188	0.0012246	5.40	***
Value	-0.0196179	0.0035552	-5.52	***
Olive	2.579095	0.2421979	10.65	***
Purple	-2.454994	0.4079902	-6.02	***
Silver	0.1762292	0.0760695	2.32	***
Maroon	-1.488963	0.3619223	-4.11	***
Red	114.5419	23.0851	4.96	***
Teal	-1.110922	0.2482582	-4.47	***
Navy	-1.962866	0.4657411	-4.21	***
White	1.027144	0.3387236	3.03	***
Color1	0.0346175	0.0034305	10.09	***
Nontxt	-3.87e-06	2.96e-07	-13.07	***
qtColLeave	0.0001814	7.80e-06	23.25	***
qtIntLeave	-0.0001929	0.0000348	-5.55	***
Intercept	7.114859	0.6893575	10.46	***

**p<0.05, **p<0.01, ***p<0.001*

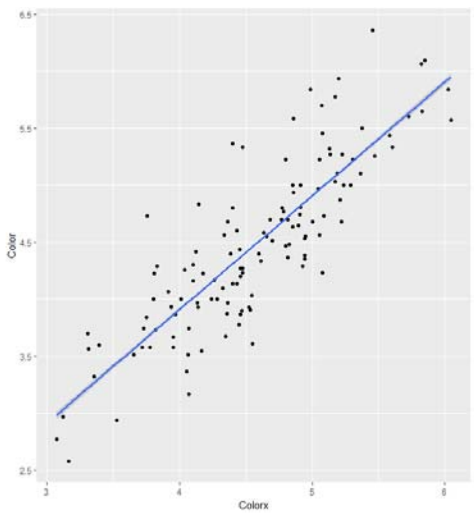

Figure 4: Plots for Fitted Colorfulness Model

Table 6: Fitted Visual Complexity Model

Complexity	Coefficient	Std. Error	t-value	
Saturation	-0.0022778	0.0005926	-3.84	***
Color2	-0.0122798	0.0011811	-10.40	***
XYLeave	-0.0587307	0.0051064	-11.50	***
Image	0.6279005	0.0421435	14.90	***
Avgdecom	-1.286829	0.1000463	-12.86	***
Maxdecom	0.6234014	0.0581353	10.72	***
qtColLeave	0.0001906	9.87e-06	19.30	***
qtIntLeave	-0.0001052	0.0000352	-2.99	***
Vbal	-0.4765928	0.1895131	-2.51	***
Vsym	-6.427793	0.3073217	-20.92	***
Hbal	1.319426	0.1862714	7.08	***
Hsym	1.883254	0.2541875	7.41	***
Equil	2.305275	0.6248061	3.69	***
Intercept	3.857306	0.6145904	6.28	***

**p<0.05, **p<0.01, ***p<0.001*

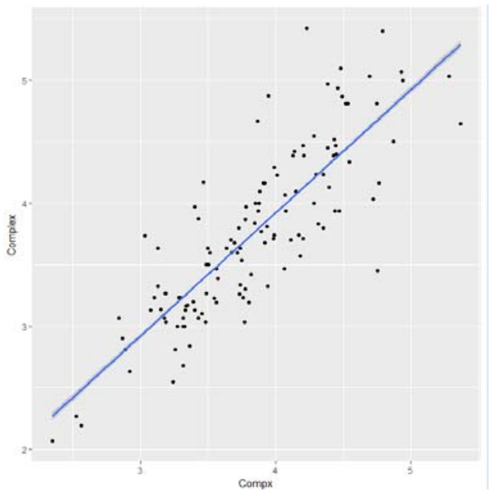

Figure 5: Plots for Fitted Visual Complexity Model

With the congruity of R square values (colorfulness: 0.8020; complexity: 0.7806), we concluded to use these two image driven factors for our predicting customer's preference model. Now, the image metrics model for colorfulness and visual complexity are set as independent variables on our new visual preference predicting model. In this model, we set dependent variable as participant's responded preference in the previous experiment. Though the visual complexity has a negative correlation with visual preference in total, we added 2nd order term for the visual complexity model as the inversed U-shape in Bauerly (Bauerly & Liu, 2008; Geissler *et al*., 2006)

$$Preference_i = \beta_0 + \beta_1 Color_i + \beta_2 Complex_i + \beta_3 Complex_i^2$$

Table 7: Preference Prediction Model (R^2=0.3051)

Variables	Estimate	Std. Error	t-value	
Intercept	-4.51930	0.74940	-6.031	***
Color	0.35603	0.03542	10.052	***
Complex	4.21709	0.42035	10.032	***
$Complex^2$	-0.54462	0.05478	-9.942	***

**p<0.05, **p<0.01, ***p<0.001*

DISCUSSION

Implications

This study can present a logical connection between visual preferences and favorable impressions of goods, bookmarking, and even the purchase intention.

First, this study quantifies the aesthetic beauty of a product wearing photograph. In the meantime, many research efforts have tried to quantify the abstract concept of beauty several times. They tried to measure the aesthetic beauty of ordinary landscape photographs by receiving visual preference responses to websites or info-graphic pictures. In this study, quantifying the aesthetic beauty of the pictures of shopping mall products, which is considered to be the crucial work for the manager in e-commerce, made it possible to make quantitative guesses without asking the customer directly about the first impression of the product. This will create a managerial implication that it is much easier for the marketing director to make decisions about which products to display. Most importantly, you can “automate” the shopping app layout and display strategy for the personalized first impressions. Based on this, managers are expected to be able to set their own strategies on how to take a picture of the product they want to sell and how to rearrange the images.

Second, since it is the era of smartphones, it is necessary to study the consumer behavior style in the mobile environment in real world. We systematically analyzed the meaningful path of how the first impression of the image leads to purchase in controlled mobile environment experiment.

Third, we conducted a meaningful study on the conversion rate, which is the biggest concern of those who run online or mobile shopping malls. In fact, scholars have presented many controversies about this issue or about the effect of the number of consumers bookmarking on the actual purchase. In this study, PLS path analysis showed positive correlation between the two.

Limitations and Future Research

First, in this study, we conducted an experiment to obtain 30 data points per person by recruiting 61 experimental applicants from 30 males and 31 females. Considering of the number of mobile users, this number seems marginal to represent whole mobile consumers. Likewise, 60 photographs of men and women wearing apparel were selected non-randomly among the millions and billions of product images registered in mobile shopping apps. In addition, although we chose photographs with similar variance metrics and showed a different set of clothes among two genders, the limitation of this study is that the set of photographs presented to male and female participants differed. Therefore, in future research, it is necessary to confirm whether the similar results can be achieved by replicating this research with far more extended data for purely female customers.

Second, this study measured only the influence of the first impression felt and received in a split of seconds. Thus, it can be said that it is not a suitable researches such as long-term effects of visual appealing. From a similar perspective, since some aberrant visual preferences of the images may change the first impression over time, this study needs to be expanded in terms of aesthetic preference and time shift relationship.

Third, to reduce bias of pricing factors, the photographs were limited to shirts, blouses, or T-shirts. As the design type was limited to relatively simple clothes, a limitation is that it is difficult to accurately reflect the weight of the evaluation of individual fashion style. Future research will broaden the product category so that it can be extended to a wide variety of clothing, accessories, and even shoes by collaborating with real shopping application.

Lastly, in the study, we analyzed the behavior of consumers using the bookmark function in mobile through experiments. However, this cannot fully explain the behavior of mobile consumers from the beginning to the end due to the gap between the real environment and the laboratory environment. To overcome these limitations, we scheduled to directly collaborate with real Korean company (Brandi: mobile shopping application business) to validate our prediction model.

Conclusion

This research fully explained the variance in people's visual preference in terms of perceived colorfulness and visual complexity. This visual preference expected to have a positive effect on both consumers’ bookmarking and purchase intention, but it directly influenced only bookmarking. In the study, a hierarchical regression analysis of the path analysis based on the stimulus-organism-response model was performed. In the first stage, a linear mixed effect model was applied and the perceived colorfulness and perceived visual complexity explained the variance in the visual preference. In the second stage of regression analysis, PLS path analysis was used to analyze how visual preference affects the number of product bookmarked and purchase intention. Through these empirical research tasks, several theoretical and managerial implications were made, which are expected to significantly contribute to the future study on mobile consumers’ behaviors and conversion rates.

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