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HOW PRODUCT ATTRIBUTES AFFECT CONSUMER JUDGMENTS OF PREFERENCE AND DISTINCTIVENESS: ATTRIBUTE IMPORTANCE AND INDIVIDUAL DIVERSITY

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Abstract. *This paper investigates how product attributes affect consumer judgments of the preference and distinctiveness of a product. In an empirical study with 131 smart-phone users, we examine what attributes are the most important in judging preference and distinctiveness of a smart phone and analyze whether or not there is any difference between preference and distinctiveness judgments. We focus especially on the diversity of individual consumers. Random coefficient model is used to estimate both mean and variance of attribute importance weights. The survey results confirm a common belief that consumers may judge preference and distinctiveness of a product in different ways. We find, however, that some of this discrepancy originates from diversity of consumers, especially their heterogeneity in preference judgment. These results imply that manufacturers need to manage product preference and distinctiveness simultaneously and separately, and in order to improve both preference and distinctiveness, they should carefully consider both average and variable perception.*
Keywords: Consumer preference, Product distinctiveness, Product similarity

1. **Introduction.** With advanced technology, new products can be easily copied by competitors, and it becomes more difficult for manufacturing firms to keep a competitive edge in the market. In such a market with the prevalence of 'me-too' products, making a product distinctive is as critical as making a better product. Consumers want 'something innovative' that is significantly improved from previous models, and 'something different' that stands out from other competing products. It is not surprising to see that a new product is hit by severe criticism despite the state-of-the-art technologies because of its similarity to other products.

Although the importance of product distinctiveness has been noted by many researchers, the role of product design in improving product distinctiveness has not been researched in depth to date. In the design community, a greater focus has been given to the preference of a product (i.e., how much a product is preferred over other choices; the choice probability of a product) and what is the optimal specification of engineering characteristics to maximize the product preference. How specifications affect product distinctiveness has been rarely considered, as improving distinctiveness is regarded as identical to improving preference. Empirical studies, however, have suggested that "what is important to consumers when they judge the distinctiveness of products does not necessarily match what is important to them when they evaluate products for purchase [1]". Therefore, product distinctiveness needs to be managed simultaneously and separately from product preference, which requires a better understanding of the relationship between product specifications and distinctiveness.

Minjung Kwak and Changmuk Kang contributed equally to this work.

In this paper, we present an empirical study with an aim to better understand how product specifications affect the preference and distinctiveness of a product. A survey is conducted to investigate what attributes are the most important in judging preference and distinctiveness of a product, how attribute levels affect the degree of preference and distinctiveness, and whether there is any difference between preference and distinctiveness judgments. We focus especially on the point that the importance weight given to each engineering characteristic varies from individual to individual. To analyze individual diversity, random coefficient model is applied which enables to estimate both mean and variance of importance weights.

2. Background.

Many previous studies have been carried out about product preference and distinctiveness, which is often referred to as (dis)similarity, judged by consumers. They found that distinctiveness is as important as preference in making a buying decision. Suk (2008) [1] discovered that similarity negatively affects choice likelihood if a product is familiar to consumers, while it may positively affect if a product itself is unfamiliar. Lefkoff-Hagius and Mason (1993) [2] studied which attributes are more important in judging preference or distinctiveness than the others. Their founding follows that beneficial attributes are more important in judging preference while characteristic and image attributes are more important in judging similarity. In Creusen and Schoormans's (1997) [3] study, however, those hypotheses were only partially supported.

This study conjectures that the conflicting results may come from diversity of consumers and formulate a model to capture this diversity from consumer survey. Lefkoff-Hagius and Mason (1990) [4] also mentioned that there may exist diversity in consumer judgment. Walsh and Mitchell (2005) [5] categorized consumers based on their demographic information and discovered their diversity in judging similarity. Our model assesses intrinsic diversity of consumers by specifying survey respondents' judgment as a random variable.

3. Survey Framework.

This study proposes four steps of survey framework to gain knowledge for surveying judgment on preference and distinctiveness of smart phones, and analyzes the result by random coefficient model.

3.1. Step 1: Focus group interview.

This study conducted focus group interview (FGI) with nine smart-phone users aged from 24 to 28. The interview revealed five major attributes, which were display size, thickness, battery type, talk time (i.e., battery capacity), and rear camera, that smart-phone buyers mainly concern.

3.2. Step 2: Preliminary survey.

Next, a preliminary survey was undertaken to gain two levels for which consumers perceive similar degree of distinctiveness across different attributes. We collected attribute levels of recent two-year products from Apple, Samsung and LG brands, and selected minimum, maximum and medium values for each attribute as survey question questionnaires. Survey participants are 131 undergraduate students (81 male and 50 female) aged from 19 to 27. As a result of the survey, we chose attribute levels as presented in Table 1.

Table 1. Attribute levels for survey questionnaires

Attribute	Level 1	Level 2
Display size (inch)	4 inches	5.9 inches
Thickness (mm)	8.9 mm	6.3 mm
Battery type	Integrated	Removable
Talk time (hour)	8 hours	24 hours
Rear camera (megapixel, MP)	800 MP	1600 MP

3.3. **Step 3: Conjoint survey for preference and distinctiveness.** We conducted conjoint survey to find importance of each attribute with the above 131 test subjects and received 111 valid answers (72 male and 39 female). The preference survey asks to rank eight different products according to their individual preference. Meanwhile, distinctiveness survey asks to assign 0 (exactly same) to 7 (absolutely different) Likert-scale scores to each of eight pairs of compared products. For both survey, the presented alternatives were generated by fractional factorial design of five attributes with two levels.

4. **Analysis and Results.** From the survey on 111 respondents, we can estimate how important each attribute is in judging preference and distinctiveness of a smart phone. Whereas an ordinary least square (OLS) regression estimates the importance averaging out individual diversity, our analysis takes account of heterogeneity by a random coefficient model, which yields different understandings on consumer perception.

4.1. **Random coefficient model.** In an ordinary conjoint analysis, preference or distinctiveness of a product is represented as a linear combination of attribute levels and sensitivity coefficients, and a random error is added to the total preference or distinctiveness. If the subjects have individually diverse perception, their heterogeneity is embedded in the error term making it correlated within answers of a subject. Since the error term should be independent between observations, we adopt a random coefficient model that allows the coefficients to be random. The model is presented by Equation (1).

$$Y_{ij} = \mathbf{X'}_i(\boldsymbol{\beta} + \mathbf{u}_j) + \varepsilon_{ij}, \tag{1}$$

where Y_{ij} is the answer of subject j for question i, which asks judgment on preference or distinctiveness for $\mathbf{X}_i$ vector of attribute (indexed by k) levels or difference, respectively. The coefficient vector $\boldsymbol{\beta}$ with element β_k denotes fixed (or average) effect of attribute k, and $\mathbf{u}_j$ denotes random effect varying across subjects. The random effect $\mathbf{u}_j$ is assumed to be the same within a subject and follow $N(0, \boldsymbol{\Omega})$ where $\text{diag}(\boldsymbol{\Omega}) = \sigma_k^2$. Where this random coefficient model is specified, an estimate of vector $\boldsymbol{\beta}$ is equivalent with the estimate from an OLS regression model. The subject heterogeneity is captured by $\mathbf{u}_j$ for which covariance matrix $\boldsymbol{\Omega}$ is estimated.

4.2. **Analysis of preference judgment.** First, we analyze judgment on preference. Question i is coded in $\mathbf{X}_i$ with '0' and '1' denoting binary levels of each attribute. Generally preferred levels (5.9-inch display, 6.3-mm thickness, removable battery, 24-hour talk time, 1,600-MP camera) are coded by '1' for making all β_k positive, where their judgment is analyzed by OLS regression, and the model R^2 is only 29.1%, which implies substantial amount of undescribed variability. From the intuition that the variability may come from subject heterogeneity, we specify the above described random coefficient model and achieved the result of Table 2. The table shows estimated β_k (mean) and σ_k^2 (variance) values and the corresponding p-values (probability to accept H_0: $\beta_k = 0$ and H_0: $\sigma_k^2 = 0$).

TABLE 2. Random coefficient regression on preference judgment

Attribute	Fixed effect		Random effect	
	Estimated β_k	p-value	Estimated σ_k^2	p-value
Display size	0.3108	0.195	2.4294***	< 0.001
Thickness	0.5586***	< 0.001	0.9632***	< 0.001
Battery type	1.2117***	< 0.001	1.5388***	< 0.001
Talk time	1.7613***	< 0.001	1.2671***	< 0.001
Rear camera	0.9910***	< 0.001	1.1024***	< 0.001

Note. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Among the five attributes, only display size lacks enough significance to accept non-zero fixed effect. If we conducted OLS regression, which yields the same result of the fixed effect, display size would be considered as an insignificant attribute to attract customer preference. The random effect estimate, however, shows significant variance of display size. Since mean β_j is near zero, it can be interpreted that preference for display size is divided into positive (the bigger is better) and negative (the smaller is better) directions.

Other attributes achieve enough significance to accept non-zero fixed effect, and their magnitude is in an order of talk time, battery type, rear camera and thickness. Their random effect is also significant with very low p-values. While the variance estimates are not as much as display size, respondents also have heterogeneous preference on other attributes.

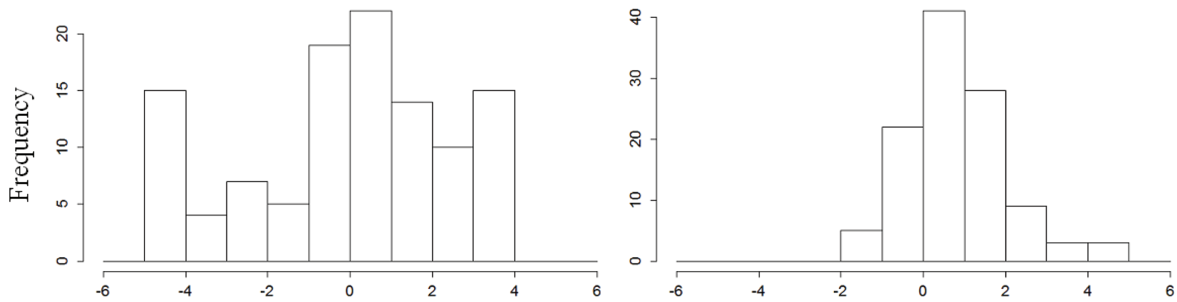
4.3. **Analysis of distinctiveness judgment.** The same analysis is conducted for distinctiveness judgment. In $\mathbf{X}_i$ coding, '1' denotes different attribute levels between compared pair of smart phones, and '0' denotes identical levels. Where judgment on distinctiveness was analyzed by OLS regression, the model R^2 is 54.7%, which is much higher than preference. The estimation result of the random coefficient model is presented in Table 3.

TABLE 3. Random coefficient regression on distinctiveness judgment

Attribute	Fixed effect		Random effect	
	Estimated β_k	p-value	Estimated σ_k^2	p-value
Display size	0.9730***	< 0.001	0.6101	0.123
Thickness	0.7477***	< 0.001	0.2903	0.875
Battery type	0.8423***	< 0.001	0.6350**	0.009
Talk time	1.3063***	< 0.001	0.7933**	0.001
Rear camera	0.6622***	< 0.001	0.2613	0.643

Note. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

All attributes are identified to have significant fixed effect. The order of magnitude is now talk time, display size, battery type, thickness and rear camera. In contrast, random effect of display size, thickness and rear camera is insignificant, which implies that respondents' judgment on distinctiveness is rather homogeneous. As an example, Figure 1 shows histogram of β_1 (for display size) values that are estimated by OLS regression for subject-wise subsets. Whereas distinctiveness coefficients are concentrated (Figure 1(b)), preference coefficients are distributed to positive and negative values (Figure 1(a)). Battery type and talk time have significant variances, but they are lower than those in the



(a) Judgement on preference (b) Judgement on distinctiveness

FIGURE 1. Histogram of β_1 (display size) estimated for individual subjects

preference judgment. These results show that judgment on distinctiveness is much more homogenous than judgment on preference, which is consistent with the previous studies.

5. **Discussion: How to Achieve Distinctiveness as well as Preference.** The first finding we got from this analysis is stronger heterogeneity in judging preference than distinctiveness. A manufacturer may have an opportunity to make a substantial distinctiveness with marginal loss of preference. Take an example of battery type. It is the second most important attribute in judging preference. It seems a foolish decision to make a battery-integrated smart phone for differentiating a product while it is the third most important attribute in distinctiveness. However, preference for battery type is largely diverse across consumers. Many people do not seriously care for it or some of them even prefer integrated phones. Then, integrating a battery is a reasonable option to make a new product seeming brand-new if an old product was equipped with a removable battery. For an instance, Samsung's new smart phone Galaxy S6 adopted an integrated battery for the first time in its series. While somebody worries about inconvenience, it succeeded at least in looking different from the previous models.

In an opposite way, low fixed effect in preference may disguise an attribute as an ignorable one. The display size attribute has a low preference but high distinctiveness coefficients. Then, it seems a good choice to design a new smart phone to have a smaller display for differentiation. As we all know, however, it is a risky decision to lose a substantial number of consumers who strongly prefer a bigger display. When we take account only of the respondents who have positive β_1 in histogram of (a) (76 respondents in total), the average β_1 is 1.717, which is the second highest among the preference coefficients. A portfolio approach is needed for such dichotomous preference.

Finally, the orders of attribute importance in preference and distinctiveness do not always coincide. As illustrated in Figure 2, only talk time and thickness are in the same rank of fixed effect. We have already interpreted mismatch of two attributes. Preference for display size is discounted by positive and negative preference offsetting each other. If we re-estimate β_1 with respondents who prefer larger display, the ranks of preference and distinctiveness coincide. Then, display size will move to the diagonal line in Figure 2. Battery type is a good candidate for a differentiator since the high preference rank is in fact blurred by diversity. A remaining attribute, rear camera is the third important in preference, but the least important in distinctiveness. When introducing a new model by improving such an attribute manufacturers should beware of failing to make enough

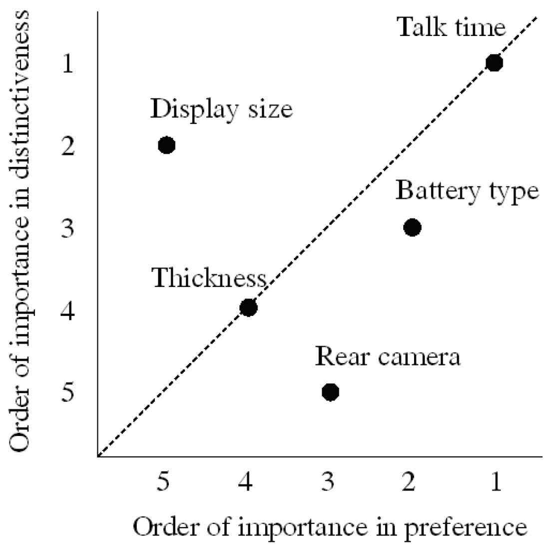


FIGURE 2. Comparison of order of attribute importance in fixed effect

distinctiveness. Actually, we see that many newly launched smart phones equipped with superior technical specifications, are considered as just ‘me-too’ products.

6. **Conclusions and Future Work.** In this study, we confirmed a common belief that consumers may judge preference and distinctiveness of a product in different ways. However, some of this disparity comes from diversity of consumers especially in preference judgment. A manufacturer needs to carefully consider both average and variable perception in order to achieve both higher preference and distinctiveness.

This study has limitation in attribute types. Technical attributes are mainly considered in this paper. Other distinguishing attributes could make different results of judging distinctiveness and preference. For example, it would be interesting and practically useful to examine what aesthetic attributes make products look different since emotional perception becomes more and more important. In addition, judgment by consumers can be different across product types. While smart-phone buyers care about technical specifications, brand image is more important to car buyers. Thus, we will study how judgement on preference and distinctiveness is interacted with diverse product and attributes types in the future.

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