# A NEW SHARE OF CUSTOMER PREFERENCE MODEL THAT INTEGRATES BRAND EFFECT

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## ABSTRACT

The special role that brand plays in consumer preference is analysed through customer-based brand equity. Customer-based brand equity occurs when the consumer has positive strong associations in memory, like positive emotions. Indeed, the qualifying role of the brand on product qualities leads to distortions in consumers' viewpoints [1]. Park and Srinivasan [2] conceptualized that brand associations contribute to brand equity by creating an attribute-based component of brand equity and a non attribute- based component of brand equity. The attribute-based component of brand equity is similar to the brand-specific effect in multi-attribute marketing models discussed by Srinivasan [1]. The brand effect cannot be estimated directly with a compensatory linear model such as conjoint analysis. Different solutions were proposed to estimate this brand effect [1], [2] and [3]. The approach of Park and Srinivasan [2] is the most important reference. For these authors brand effect is considered as the difference between a preference based on the subjective evaluation of the product's attributes and a preference based on the objective evaluation of the same attribute. Jourdan [3] demonstrated that the calculation of differences in utilities proposed by Park and Srinivasan included an error term that is inherent to their method. Jourdan proposed a repeated-measures experimental design to estimate brand effect that improves the results of Park and Srinivasan. A new methodological solution based on Jourdan's approach is proposed here. Unlike in Jourdan's approach, customer-based brand equity is estimated as a latent variable: it articulates conjointly rating-based conjoint analysis and structural equation modelling.

The customer's utilities can be inputed into buyer-choice simulators to predict shares of preferences. With rating-based conjoint analysis, the common probabilistic predictive models suffer from the independence of irrelevant alternative problem because they are unable to handle product similarity. This article discusses about a new probabilistic model, called RFC-BOLSE. Brand effect can be inputed into the RFC-BOLSE simulator. The major purpose of this article is the development of this new probabilistic model that takes

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into account objective utilities of products (estimated by a rating-based conjoint analysis) and brand effect (estimated as a latent variable based on repeated-measure rating-based conjoint analysis). A case study on six brands illustrates our purpose.

Finally, we will show how our approach can provide a tool to drive brand image on share of preferences. For example positive brand emotions can modify brand effect. These emotions can be introduced as latent dimensions relied to the brand-equity dimension. Their influences on brand equity would be estimated in term of share of preference by RFC-BOLSE.

***Keywords:*** *Rating-based conjoint analysis, brand effect, share of preference, Structural equation modeling, Randomized first choice*

## 1. INTRODUCTION

In marketing, Conjoint Analysis (CA) [4] is a method for measuring preferences, perhaps the most widely applied by marketing researchers [5] and [6]. According to Huber [6], 85% of current managers find CA to be the best-adapted and most widely-used method during product strategy development phases, 60% of all new product development making use of CA. 90% of managers consider CA to yield reliable results regarding consumer preferences and to constitute the best testing method for improving new product success rates. 86% of managers anticipate an increase in the number of future CA applications.

The underlying modeling principle is that a consumer perceives a product or service quite consciously as a set of attributes or characteristics to be evaluated. The consumer thereby assigns values (or utilities) to each characteristic. The total utility of a product is the sum of utilities of the individual attributes. CA presumes a rationalization in the choice of various product attributes, which are built according to a linear additive model, in referring to the set of multi-attribute approaches [7]. CA is relatively functional for product preference measurements that incorporate few parameters and whose cognitive process overrides the emotional process [7] and [8]. CA demonstrates highly accurate predictive powers in a number of studies (purchase of toothpaste, automobiles, textiles, medical therapies), which accounts for the widespread use of CA in industry [9]. CA may employ various experimental protocols. The literature generally categorizes CA into two major families: rating-based (RB-CA), and choice-based (CB-CA). Experimental results show that RB-CA yields very insightful results in several applications [10] and [11]. Furthermore, RB-CA remains heavily utilized in practice [6].

The qualifying role of the brand on product qualities leads to distortions in consumers' viewpoints. Two brands which have an identical attribute may have different utilities for this attribute, one may consider that this attribute is more credible for a brand than for another (for example, a promise of 80 000 km longevity can be evaluated in a different way between Michelin and Nokian). These effects of distortion are known as "brand-effect". This brand effect cannot be estimated directly with a compensatory linear model such as conjoint analysis [1]. Different solutions were proposed to estimate this brand effect in a multi attribute models [1], [12], [2], [3]. A new methodological solution based on repeated-measures RB-CA is proposed to estimate brand effect as a latent variable. This method articulates conjointly RB-CA and structural equation modeling.

With a CA, the customer's utilities at different profiles can be inputed into buyer-choice simulators to predict share of preferences. With RB-CA, the common probabilistic predictive models suffer from the independence of irrelevant alternative problem because they are unable to handle product similarity [13]. This article discusses about a new probabilistic model, called RFC-BOLSE. Brand effect, estimated with a Path-PLS approach, can be inputed into this new simulator.

The major purpose of this article is the development of this new model to predict share of preferences that takes into account objective utilities of products (estimated by a RB-CA) and brand effect (estimated as latent variable based). In section 2 we will start by discussing about the brand effect and its estimation with a RB-CA. Section 3 is dedicated to the new model, RFC-BOLSE, and the integration of the specific brand effect in the previsions of share of preference. Section 4 discusses about a case study on six brands. Conclusions and perspectives on follow-up work will be set forth in Section 5.

## 2. BRAND EFFECT ESTIMATION WITH RB-CA

The special role that brand plays in consumer preference is analysed in marketing research through customer-based brand equity. Customer-based brand equity occurs when the consumer has positive strong associations in memory, like positive emotions. The concept of brand equity appeared in the 1980s. Keller's definition is certainly the most useful :*"the differential effect of brand knowledge on consumer response to the marketing of the brand"*[14]. Studies on brand equity have followed two main directions: the consequences of brand equity, which are revealed by the preferences [2] or choices [12] of the consumer and the antecedents of brand equity, which are defined as a set of strong, positive and unique associations with the brand [14], [15], [17], [18]. This study will focus on the first approach, which estimates directly brand effect revealed by preference. The approach of Park and Srinivasan [2] is the most important reference in the direct estimation of brand effect. Park and Srinivasan [2] conceptualized that brand associations contribute to brand equity by creating an attribute-based component of brand equity and a nonattribute- based component of brand equity. We will discuss here only about the attribute-based component of brand equity, which is similar to the brand-specific effect in multi-attribute marketing models discussed by Srinivasan [1].

### 2.1. A review of the estimation of brand effect with CA.

Indeed, the qualifying role of the brand on product qualities leads to distortions in consumers' viewpoints. These distortions can bias results from a RB-CA because brand effect generates interactions between brand and the other attributes. These interactions cannot be estimated correctly by a standard statistical procedure [3]. Moreover, the experimental design with brand leads to unrealistic product profiles. To compensate for such a potential distorsion factor, Srinivasan [1] recommends not to introduce the brand as a variable in the experimental design. Srinivasan demonstrates that taking into account this brand effect improves significantly the predictive validity of the CA.

The approach of Park and Srinivasan [2] is the most important reference in the estimation of brand effect. Park and Srinivasan proposed to estimate the brand effect (i.e. attribute-based component of the brand equity) as the difference between a preference based on the subjective evaluation of the product's attributes and a preference based on the objective evaluation of the same attribute. Jourdan [3] demonstrated that the calculation of differences in utilities proposed by Park and Srinivasan includes an error term that is inherent to their method. Jourdan suggested methodological improvements. Jourdan proposed an equation of the utility of product with the brand i for individual j: $u_{ij} = v_{ij} + a_{ij} + \delta + \varepsilon_j$ where $a_{ij}$ is the brand effect on brand i for the individual j, $v_{ij}$ is the utility based on objective measured attribute levels (when brand is hidden), $\delta$ is an error systematic of the multi-attribute model (proposed by Jourdan) and $\varepsilon_j$ is a random error particular to each subject (independent of the brand, like in the Park and Srinivasan model). Jourdan proposed to use a repeated-measures experimental design to estimate brand effect: each subject evaluates two times the same product whose brand name is first hidden ($v_{ij}$) then revealed ($a_{ij}$ ). Because a product without brand name is non-realistic, Jourdan used a store Brand ("Carrefour") for the utility of objective measured attribute levels (when the brand is hidden). Using a store brand such as Carrefour is more relevant than proposing a product without a brand. Carrefour has a poor brand effect in comparison with premium brands. Moreover, by a RB-CA approach, utilities are estimated as relative utilities [4]. The brand effect measure is also a relative measure (like differences between premium brand effect and store brand effect) [2].

### 2.2. A new measure of brand effect with RB-CA.

Jourdan improved the brand effect estimation by a repeated measure experimental design. A shortcoming of Jourdan's approach is the systematic error and the random error particular to each subject, which are very difficult to articulate in fact (Jourdan found very important values of individual errors). Moreover Jourdan explained that Brand effect is a "latent variable" but estimated as a simple variable. We propose to use the same repeated measure experimental design as Jourdan, but we propose to estimate brand effect as a latent variable. To do so, we use these equations: for a profile "k", $U_{ij}^k$ is the utility of the profile k for the brand i and the individual j: $U_{ij}^k = v_j^k + a_{ij} + \delta + \varepsilon_j$. $U_{Oj}^k$ is the utility of the profile k for the store brand and the individual j: $U_{Oj}^k = v_j^k + \delta + \varepsilon_j$. The difference is $U_{ij}^k - U_{Oj}^k = a_{ij}$. Because errors terms are eliminated, this approach is easier to articulate than Jourdan's approach.

In the repeated-measure RB-CA, we introduce K different profiles. For each of these, we have $U_{ij}^k$ and $U_{Oj}^k$. We can consider that we have K measures of a latent variable $a_{ij}$. According to Jarvis et al. [16] we can estimate $a_{ij}$ with a structural equation modeling as a reflexive latent variable.

With this approach, we eliminate the error problem discussed by Jourdan. Moreover, using latent variable to estimate brand effect is actually the usual way in marketing research [17], [18]. We cannot consider that we estimate here the global brand equity because brand equity integrates a non-product brand equity which is not estimated here. But we can consider that our approach gives a reliable estimation of the attribute-based component of brand equity (i.e. brand effect).

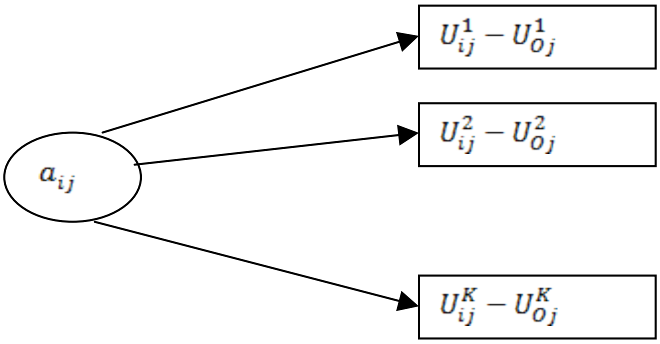


**Figure 1:** Brand effect estimates by a latent variable

## 3. A NEW SHARE OF PREFERENCE MODEL

Following model estimation, share of preference predictions subsequent to a conjoint analysis are generated by artificially placing different products (profiles) in competition with one another. For each respondent, the results from previously conducted conjoint analysis are used to estimate the global utility of these competing profiles. The academic literature most frequently proposes the multinomial logit model (MNL) or Bradley, Terry, Luce model (BTL) [5], [19]. These probabilistic models suffer from the IIA hypothesis [13]). A new probabilistic model, RFC-BOLSE, avoids IIA problem.

### 3.1. A new predictive model for rating-based conjoint: RFC-BOLSE

RFC-BOLSE uses the Randomized First Choice algorithm [20] based on an adaptation of RB-CA. RFC is an iterative algorithm for CB-CA that determines the probability a respondent prefers one profile over another. This behavior is simulated by adding random noise or "variability" to the product or attributes utilities. For each individual and each profile, RFC generates noisy global utilities with two sorts of noises: those associated with utility estimates specific to each attribute level ("estimate noise"); and the "error noises" specific to each profile. Each iteration entails applying the first choice model with these noisy utilities. In the end, the probability for each profile equals the average iteration results. To avoid bias due to similarity problems among the various profiles, Orme and Baker introduced correlations between profiles. During an algorithm's iteration, a given level will keep the same numerical value of "estimate noise" for the entire set of profiles.

The noisy utility $\widetilde{U}$ given by RFC can be written as: $\widetilde{U} = X_q \widetilde{\beta} + \xi$ with $X_q$: matrix of the "q" profiles in competition ; $\widetilde{\beta} = \hat{\beta} + \gamma$ : the noisy estimates, with $\gamma$ as the "estimate noise" ; $\xi$ : the "error noise".

Adapted to CB-CA, Orme and Baker proposed using Gumbell's Laws in order to parameterize the noises. The option of using Gumbell's Laws is hardly satisfactory for RB-CA since it rejects regression hypotheses (Gaussian errors). Moreover, Gumbell's Laws that Orme and Baker proposed are independent of prior RB-RB estimation results, which could constitute a limitation. Our proposal is to use RFC with RB-CA, by means of introducing Gaussian errors based on the linear regression estimates.

RFC-BOLSE introduces an "estimate noise" $\gamma$ , which is Gaussian: $\gamma \approx N(0, \hat{\sigma}'_{\hat{\beta}} I_{K+1})$ , where $\hat{\sigma}'_{\hat{\beta}}$ is the vector of dimension K+1 used for estimating the variances of regression-estimated coefficients. K+1 denotes the number of variables in the regression. RFC-BOLSE introduces an "error noise" $\xi$ , which is also Gaussian: $\xi \approx N(0, \hat{\sigma} I_q)$ , where $\hat{\sigma}$ is the variance estimate from the regression error estimate and "q" the number of profiles in competition. The role of such error laws is to integrate into the predictive model variations in the utilities, with respect to their reliability, for each interview and for each level. Error noise is further added to each profile and directly related with global regression reliability. Like with conventional RFC, RFC-BOLSE circumvents the IIA problem.

### 3.2. Brand effect in RFC-BOLSE

Because we use a repeated-measure RB-CA, brand effect and utilities of attributes are in the same scale. So, it is possible to estimate global utility for each profile, which is the sum of profile utilities without a brand and the utility of brand effect. These global utilities can be inputed in RFC-BOSLE.

To use RFC-BOLSE we must have the standard deviation of the brand effect estimation. We will now show how to get it. In the equations, we eliminate the "j" term because the equations are for one individual. We consider we have "p" profiles with the design $X_p$. We consider that the estimations are based on hidden brand product (i.e. with a store brand). The estimation of the utilities is : $\hat{U} = X_p \hat{\beta}$ . We showed that RFC-BOLSE gives noisy utilities. With a brand hidden profile, we have $\widetilde{U} = X_p(\hat{\beta} + \gamma) + \xi$ . The law of $\gamma$ is $\gamma \approx N(0, \hat{\sigma}'_{\hat{\beta}} I_K)$ where $\hat{\sigma}'_{\hat{\beta}}$ is a vector of dimension K of the estimations of the variances of the estimated levels of attributes and $\xi \approx N(0, \hat{\sigma}' I_P)$ .

We introduce brand effect in the RFC-BOLSE like an attribute with a noise built in the same way as the other attributes. RFC-BOLSE with brand effect becomes: $\widetilde{U} = X_p(\hat{\beta} + \gamma) + \hat{a}_i + \varphi + \xi$ and $\varphi \approx N(0, \hat{V}(\hat{a}_i))$ .

We have to get $\hat{V}(\hat{a}_i)$ . Consider $U = X_p \beta + \varepsilon$ , the utility for the hidden brand product and $U^j = X_p \beta^j + \zeta^j$ , the utility of the brand product, where $\beta^j$ is the utilities of attributes biased by the brand with the same design $X_p$ . $\zeta_j$ is the error of the utility with the brand product and ε the error of the utility of the hidden brand product (errors which are independent), $u_j$ the vector of the rates for the brand profile, $u_0$ the vector of the rates for the hidden brand, "n" the number of profiles, "p" the number of variables when the brand is hidden, X the design when brand is hidden, $\hat{\lambda}_k$ the loading estimation for the profile "k" estimated by a path-PLS model.

$$
\begin{aligned}
V(a_j) &= V(\sum_k \lambda_k a_j^k) = V(\sum_k \lambda_k (u_j^k - u^k)\\
&= \sum \lambda_k^2 V(u_j^k - u^k) = \sum \lambda_k^2 V(x^k \beta^j + \zeta_j - x^k \beta - \varepsilon)\\
&= \sum_k \lambda_k^2 (V(\zeta_j) + V(\varepsilon))
\end{aligned}
$$

$\hat{\sigma}_j^2$ and $\hat{\sigma}^2$ are the standard deviations (estimated by OLS) of $V(\zeta)$ and $V(\varepsilon)$. We have, with the design $X$:

$$
\hat{V}(\hat{a}_j) = \sum_k \hat{\lambda}_k^2 (\hat{\sigma}_j^2 + \hat{\sigma}^2) = \sum_k \hat{\lambda}_k^2 \left(\frac{u_j' u_j - u_j' X(X'X)^{-1} X' u_j}{n - p - 2} + \frac{u_0' u_0 - u_0' X(X'X)^{-1} X' u_0}{n - p - 2}\right)
$$

RFC-BOLSE, with brand effect, is: $\widetilde{U} = X_p(\hat{\beta} + \gamma) + \hat{a}_j + \varphi + \xi$, with $\varphi \approx N(0, \sum_k \hat{\lambda}_k^2 (\hat{\sigma}_j^2 + \hat{\sigma}^2))$

We can simulate this RFC-BOLSE very easily and get reliable estimations of share of preference with brand effect.

## 4. A CASE STUDY

An experience, with a sample of three hundred students, three categories of products and two brands for each product, illustrates our approach. To select products, we used the classification of products proposed by Park et al. [21]: a functional product (in our study, DVD burners by Sony and Philips), an experiential product (in our study, Ice creams by Miko and Haagendaz) and a symbolic product (in our study, perfumes by Chanel and Hermès). A hypothesis was that brand effect (i.e. non-product brand equity) would exist for functional and experiential products, but would not exist for a symbolic product. For that one, only non-attribute-based component of brand equity would exist.

In order to avoid the potential bias introduced by a non-involvement effect, we kept only students who have a real involvement: a sample of 150 for the DVD burner; a sample of 255 for the ice cream and a sample of 235 students for the perfume. The objective is only to illustrate the reliability of the new approach, so the design was very simple (2x2x2) to get four measures for each brand effect (four times the differences between the rate on a product with the premium brand and the rate with the same product with the store brand Carrefour).

### 4.1. Estimation of brand effect

All variables seem to be Gaussian (checked by statistical tests). We used LISREL approach to test the reliability of each brand effect scale. For functional products and experiential products, all brands have reliable brand effect scale (rhô of Jöreskog > 0.70; GFI > 0.90; RMSEA < 0.08; CFI > 0.95; communities > 0.50; variance explained > 70%). The two perfume brands have not reliable brand effect scale (GFI<0.85; RMSEA >0.40; CFI <0.85). As supposed in the hypothesis, functional and experiential products seem to have a brand effect; symbolic products seem not to have a brand effect.

As we used a path-PLS approach, we can estimate the brand effect and compare these with other utilities of the different attributes.

**Table 1:** Brand effect estimations

| | Sony | Philips | Haagendaz | Miko | Hermès | Chanel |
|---|---|---|---|---|---|---|
| Estimation of brand effect | 4.21 | 3.03 | 3.98 | 2.45 | NS | NS |
| Estimation of the standard deviation of brand effect | 2.41 | 2.07 | 3.04 | 1.93 | NS | NS |

We tested the difference between brand effects by a paired-Student test. Sony has a significantly more important brand effect than Philips (p-value less than 0.0001) and Haagendaz a more important brand effect than Miko (p-value less than 0.0001).

**Table 2:** Estimations of the attributes utilities

| | DVD burner | | Ice Cream | | Perfume | |
|---|---|---|---|---|---|---|
| Attributes | Internal recording | DVD+rw | Black chocolate coating (vs milk chocolate coating) | chocolate flavour (vs vanilla flavour) | Rectangular Bottle (vs circle bottle) | Blue bottle (vs red bottle) |
| Utilities estimated | -1.12 | -1.96 | 0.81 | 1.22 | 0.15 | 0.09 |
| Standard deviation | 3.70 | 2.44 | 2.79 | 3.79 | 2.63 | 1.90 |

These results show that brand effects are important for each brand except perfume. Brand effects of perfume brands seem not to exist and physical attributes have very poor utilities too. These results correspond to our hypothesis.

### 4.2. Estimation of shares of preferences

We simulated artificial markets. The shares of preference were estimated with and without brands.

**Table 3:** Share of preferences without brands for DVD burner

| | DVD burner with DVD+rw | DVD burner with DVD-rw |
|---|---|---|
| Means of global utilities | 8.47 | 9.31 |
| Share of preferences estimated by RFC-BOLSE | 45.33% | 54.67% |

These shares of preferences do not have a significant difference (p-value=0.204).

**Table 4:** Share of preferences without brands for ice creams

| | Vanilla flavour with milk chocolate coating | Chocolate flavour with black chocolate coating |
|---|---|---|
| Means of global utilities | 7.68 | 9.54 |
| Share of preferences estimated by RFC-BOLSE | 34.70% | 65.30% |

These shares of preference have a significant difference (p-value<0.001).

Now we introduce brands to estimate shares of preference with RFC-BOLSE.

**Table 5:** Share of preferences with brands for DVD burner

| | DVD burner Sony with DVD+rw | DVD burner Philips with DVD-rw |
|---|---|---|
| Means of global utilities | 12.67 | 12.34 |
| Share of preferences estimated by RFC-BOLSE | 54.14% | 45.86% |

These shares of preferences do not have a significant difference (p-value=0.238). Sony's most important brand effect is not significant enough here to have a more attractive product in comparison with the Philips product.

**Table 6:** Share of preferences with brands for ice creams

| | Haagendaz vanilla flavour ice cream with milk chocolate coating | Miko chocolate flavour ice cream with black chocolate coating |
|---|---|---|
| Means of global utilities | 11.66 | 11.93 |
| Share of preferences estimated by RFC-BOLSE | 49.36% | 50.64% |

These shares of preference do not have a significant difference (p-value=0.819). A chocolate flavour ice cream with black chocolate coating has a better utility than a vanilla flavour ice cream with milk chocolate coating. This is not true when the first is a Haagendaz product and the second a Miko product.

The design and products used in this experience are too simple when seeking to estimate true market shares. All of these estimations are only here to illustrate the interest of RFC-BOLSE and its capacity to integrate brand effect.

## 5. CONCLUSION

The contribution of our research is in the improved reliability of the measurement of the attribute-based component of brand equity. brand effect. in relation to that proposed by Park and Srinivasan [2] and Jourdan [3]. Based on a repeated measure RB-CA and structural equation modeling. our approach proposes to estimate brand effect as a latent variable. A second improvement lies in the probabilistic model to predict shares of preference. The major purpose of this article is the development of this new probabilistic model that takes into account objective utilities of products (estimated by a rating-based conjoint analysis) and brand effect (estimated as a latent variable based on repeated-measure rating-based conjoint analysis). Our experimental results attest that our approach gave reliable scale of brand effect for functional or experiential products. Our results checked that brand effect is very poor for a symbolic product. Our experimental method is not exempt from criticism because it was built with a simple design and a more important experience is certainly necessary to confirm these results.

A potential extension is in the introducing of brand image. as antecedents to the brand effect. As Keller explained [14]. strong. unique and positive brand association are related to the brand equity.

For Srinivasan et al. [22] three sources have a direct effect on brand equity i.e. (i) increased brand awareness. (ii) incremental preference due to enhanced attribute perceptions. and (iii) incremental non attribute preference. Our approach allows to introduce a latent variable of brand effect in a structural equation modeling. Yoo et al. [17] or Netemeyer et al. [18] for example proposed models to explore the relationship between brand image and the brand equity. A new objective with our approach could be to find which brand associations dimensions are related to the attribute-based component of brand equity. A first research would be to validate Park and Srinivasan's hypothesis: the attribute-based component of brand equity is created by brand associations related to product attributes resulting in favorably biased attribute perceptions; the non-attribute-based component of brand equity is created by brand associations unrelated to product attributes [2]. Another hypothesis would be how brand emotions can modify brand effect. These emotions can be introduced as latent dimensions related to the brand-equity dimension. Their influences on brand equity would be estimated in terms of share of preference by RFC-BOLSE.We will be able to estimate these influences on the attribute-based component of brand equity in terms of market share preference with RFC-BOLSE. By introducing these exogenous latent variables that are related to the brand effect. we will provide a tool to estimate their impact on the brand effect in terms of share of preferences.

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