Incorporating Customer Preference in Perfume Bottle Design

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Abstract- A successful product design satisfies multiple dimensional requirements, such as offering sufficient business returns, complying with various regulatory standards, and the most important, fulfilling customers' needs and wants. It is the ultimate goal for both industrial designers and marketing managers. Industrial designers need to integrate customer preference into their design, so that their products may be competitive in the market. However, engineering, business and art are distinct academic areas, most education programs or manufacturers cannot address the design issue in a holistic manner. This study aims at analyzing customer preference with brand choice models, so that designers may employee the result of this analysis for product design to promote competitiveness. The research results provide choice probability for different bottle shapes and reveal that customers will most likely choose plastic arts and circle shaped bottles, whereas they like achromatic glass and colored glass bottle most. Moreover, male customers put more attention to perfume selection criteria than females do, and so do customers at age below 35 than those beyond 36. The result may provide industrial designers insight of market feasibility for their product design.

Index Terms- *Customer Preference, Product Design, Brand Choice Models*.

I. Introduction

Perfume, a symbol of personal style, has been worn by people for centuries. Literature in perfume has paid most attention to its ingredients and treatment composition, in spite of numerous patents of perfume bottle design in practice, only few researches have observed the influence of perfume bottle design. A fascinating bottle design may allure customers, and satisfy multiple dimensional requirements, such as offering sufficient business returns, complying with various regulatory standards, and the most important, fulfilling customers' needs and wants. It is a fusion of the ideas from industrial designers, knowledge from engineers, market insight from business managers, and customer preferences. The nature of product design involves with different fields in engineering, business, science, and aesthetics. However, engineering, business and art are distinct academic areas; most education programs cannot address the design issue in a holistic manner [16], neither can most researchers. Literature in new product design has generally focused only on objective attributes such as price or features, but industrial designers and marketing researchers have long recognized that consumers' perceptions of the subjective characteristics exert an important influence on their product evaluations, it is important to incorporate customer preferences into design [1, 7, 9].

To achieve the goal of addressing product design issue in a holistic manner, some researchers have tried different approaches to evaluate customers' perception of product attributes for product design. Qualitative methods such as hierarchical Bayesian structural equation models [9], hierarchical Naïve Bayes models [16] are employed in some papers; on the other hand, quantitative methods including brand choice models [10] used in customer behavioral research papers, or genetic algorithms [6] used in heuristics, are employed in different approaches. Among these methods, brand choice models explore preference in customers' mind and return with choice probability, which is valuable market information, so they are employed in this study.

A brand choice model represents the underlying process by which a consumer integrates information to select a brand from a set of competing brands; it estimates a customer's choice probability. The objective of this study is to provide overall consumer choice probabilities of product attribute for product design. The following section lists literature review of brand choice models; section 3 describes the process of selecting an appropriate choice model and estimating choice probabilities. Section 4 illustrates the empirical results, and section 5 states the conclusion.

II. Review of Brand Choice Models

Manrai [10] had reviewed the development of brand choice models and illustrated their definition, branches and evolution, his work is abbreviated as follows.

With varying assumptions and purposes, brand choice models differ in underlying logic structure that drives them. These models are separated into three categories, which are multi-attribute choice models, preference and choice mapping models, and conjoint analysis. The multi-attribute models are commonly used in marketing applications, including determination of market structure, customer segmentation, product positioning, demand forecasting, and prediction of consumer choice. Two fundamental principles drivethese models, the principle of utility maximization, and attribute-based sequential elimination principle. The difference is the assumptions about the way consumer processes information.

The principle of utility maximization postulates that a consumer uses all relevant information and selects the brand that maximizes his/her utility. The basic choice process assumes that all of the attributes are considered in a simultaneous compensatory structure, thus assigning a utility value to each brand. Models driven by utility maximization principle include Luce's model [8], McFadden's MultinominalLogit (MNL) model [13], Nested MultinominalLogit (NMNL) model [14], Multinomial Probit (MNP) model [3], Generalized Logit Model (GLM) [4], Multiplicative Competitive Interaction (MCI) model [2] etc.

The principle of attribute-based processing suggests that a consumer makes a selection through a simplified heuristic and may not use all the relevant information available at the time of choice. The choice is made by comparing brands on attribute-by-attribute basis. The assumption is that there is a random or hierarchical sequence in which the attributes are considered. Models driven by this principle include Elimination-By-Aspects (EBA) Model [15], Elimination-by-Cutoffs (EBC) model [11], Elimination-by-Dimensions (EBD) model [5], and other EBA-like models.

III. METHODS

The various brand choice models are based on different assumptions and purposes, so selecting an appropriate model among them has been more difficult than before. Matsatsinis and Samaras [12] presented a process of brand choice model selection, which refers to transformation of preference table, calculation of parameters such as range type, skewness and kurtosis, selection of an appropriate brand choice model, and finally estimation of choice probability. The process involves the following steps:

1) Obtain preference tables from consumers.

2) Decide utility function $u_i(g_i)$.

$$U_i = u_i(g_i) = \sum_j \beta_j a_{ij} \quad (1)$$

where $i=1,2,\dots, 5,\ j=1, 2, 3, 4,\ 0 < U_i < 1$.

$u_i(g_i)$ transfers preference value a_{ij} into utility value U_i with coefficients β_j, in which i stands for shape style and j for material attribute.

3) Find maximum utility value Umax and minimum utility value Umin, and calculate range R (R = Umax - Umin) and range type δ, where

$$\delta = \begin{cases} 1 & if\ 0 \le R \le 0.1 \\ 2 & if\ 0.1 < R \le 0.3 \\ 3 & if\ 0.3 < R \le 0.6 \\ 4 & if\ 0.6 < R \le 1 \end{cases} \quad (2)$$

4) Calculate ε and x_i,

$$\varepsilon = \delta/(n-1) \quad (3)$$

$$x_i = U_{\min} + (2i-1)\varepsilon/2 \quad (4)$$

where $i = 1, 2, 3, 4$.

5) Calculate μ,

$$\mu = \sum_{i=1}^{4} f_i x_i \Big/ \sum_{i=1}^{4} f_i \quad (5)$$

6) Estimate r^th moment m_r,

$$m_r = \sum_{i=1}^{4} f_i (x_i - \mu)^r \Big/ \sum_{i=1}^{4} f_i \quad (6)$$

7) Estimate skewness α_3,

$$\alpha_3 = m_3 \Big/ \sqrt{m_2^3} \quad (7)$$

8) Estimate kurtosis α_4,

$$\alpha_4 = m_4 \Big/ m_2^2 - 3 \quad (8)$$

9) Search in the rule base listed in Appendix A with δ, α_3 and α_4 to find a match. If a match is found, the selected model number is returned.

10) Estimate choice probability with the corresponding choice model in Table 1.

This process extracts a consumer's intention of selecting a brand among competing brands, and quantifies the intention to choice probabilities.

Table1: Brand choice models

No.	*Name*	*Model*
1.	Luce	$P_{ij}(C) = U_{ij} \Big/ \sum_{k\in C} U_{ik}$
2.	Lesourne	$P_{ij}(C) = U_{ij}^2 \Big/ \sum_{k\in C} U_{ik}^2$
3.	Multinomial Logit Model (McFadden-1)	$P_{ij}(C) = e^{U_{ij}} \Big/ \sum_{k\in C} e^{U_{ik}}$
4.	McFadden-2	$P_{ij}(C) = e^{2U_{ij}} \Big/ \sum_{k\in C} e^{2U_{ik}}$
5.	Width of Utilities-1	$P_{ij}(C) = U_{ij}^{U_{\max}-U_{\min}} \Big/ \sum_{k\in C} U_{ik}^{U_{\max}-U_{\min}}$
6.	Width of Utilities-2	$P_{ij}(C) = e^{(U_{\max}-U_{\min})U_{ij}} \Big/ \sum_{k\in C} e^{(U_{\max}-U_{\min})U_{ik}}$
7.	Maximum of utilities	$P_{ij}(C) = \begin{cases} 1/m & \text{if } U_{\max} \ge U_j \ge U_{\max} - \varepsilon_i, \\ 0 & \text{otherwise,} \end{cases}$ where $\varepsilon_i = (U_{\max} - U_{\min})/(n-1)$
8.	Equal probabilities	$P_{ij}(C) = 1/m,$ where $U_{\max} - U_{\min} \le 0.1$

* Source: Matsatsinis and Samaras (2000)

IV. RESULTS AND DISCUSSION

A questionnaire with Cronbach's alpha value 0.829 is employed for data collection, which consists of two sections: Perfume Selection Criteria and Preference Table.

A. Data

300 copies of questionnaire are collected from male and female consumers by face-to-face interviewing in shopping malls, rail stations, night markets in Tainan and Kaohsiung; 280 out of 300 copies are effective. The demographic statistic show that service industry take 44.29% share in Profession, age group between 19 and 26 takes 53.57% share in Age, southern area takes 61.43% in Area, and female takes 87.14% share in Gender variable.

B. Perfume Selection Criteria

The importance of each criterion Brand, Fragrance, Price, Reputation and Bottle Design was granted by survey responsers. The results of t-test and ANOVA show that the perfume selection criteria of responsers do not make significant difference in different residential areas, and types of profession. But it makes

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significant difference between male and female, as shown in Table 2.

Table 2 Difference between male and female for perfume selection criteria

	Male	*Female*
Male	0	0.261**
Female		0

* *p< 0.05 ** p < 0.01*

Table 3 reveals responsers who are below 35 years old pay more attention to perfume selection criteria than those beyond 36 significantly.

Table 3 Difference between age groups for perfume selection criteria

	Below 35	*Beyond 36*
Below 35	0	0.202*
Beyond 36		0

* *p< 0.05 ** p < 0.01*

C. Preference Table

Part II refers to a preference table which contains a_{ij}, *i=1, 2, …., 5, j=1, 2, 3, 4. i*represents shapes of Circle, Rectangle, Triangle or Rhombus, Cylinder, and Plastic Arts; *j* stands for different material, like transparent glass, colored glass, metal material, plastic material. a_{ij} is transferred into utility value U_i via a utility function. Table 4 is a real example of preference table. In this table, a survey responser fills in his/her grade from 1 to 5, 5 means "Like best".

Table 4 A real example of preference table

Material / Shapes	Achromatic Glass	Colored Glass	Metal	Plastic
Circle	3	5	3	4
Rectangle	1	2	2	1
Triangle/Rhombus	2	1	5	2
Cylinder	4	3	4	3
Plastic Arts	5	4	1	5

Table 5 shows the evaluation result of the above example, and the overall probability.

Table 5 Final results of choice probability evaluation

Result / COM	Utility	Example Probability	Overall Probability
Circle	0.859	0.248	0.210
Rectangle	0.501	0.121	0.193
Triangle/Rhombus	0.653	0.164	0.185
Cylinder	0.834	0.236	0.190
Plastic Arts	0.819	0.229	0.221

Figure 1 depicts the curves of an individual probability and overall probability.

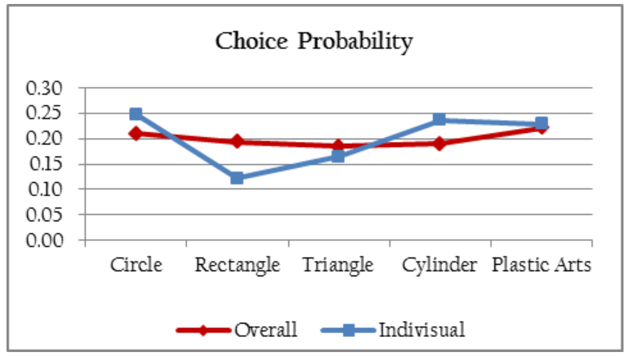

Figure 1: Comparison between individual and overall probability

Figure 2 shows each material share takes in overall result. Apparently achromatic glass and colored glass are the most popular material for perfume bottle design as usual.

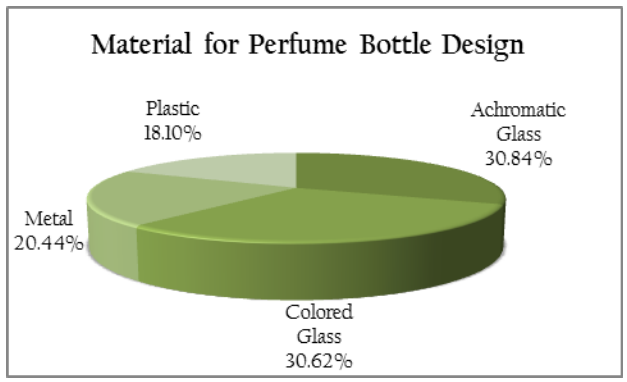

Figure2 Material shares for perfume bottle design

The parameters of the example are as follows: U_{max} is 0.859, U_{min} is 0.501, R is 0.358, δ is 3, εis 0.09, α_3 is -0.707, and α_4 is -1.707. Searching in rule base in Appendix Awithδ, α_3 and α_4 will get a returned model number 4, which corresponds to the 4th choice model in Table 1. Other parameters referring to the example are listed in Appendix B.

This process works on each preference table and estimates an individual probability table, then all the probability tables are averaged to obtain the overall probability table. In Figure 1, the individual probability draws a sharper curve than the overall curve, which means the overall probability mitigates the difference between all responsers' choice, and provides an objective aspect of customer preference. Industrial designers may integrate the overall probability with their design and make a competitive product.

V. CONCLUSION

A successful product design is a fusion of knowledge, creativity, and regulatory standards from different fields; it may offer sufficient profits if it fulfills customers' needs and wants.

To achieve market competitiveness, industrial designers have to know what customers want, and integrate customer preference with the design. This study employs a brand choice process to estimate customer preference, and provides customers' choice probability for perfume bottle attributes. The results show that male customers pay more attention to perfume selection criteria than female ones do. So do customers at age below 35 than those beyond 36.

The research results show that achromatic glass and colored glass are the most popular bottle material in customers' mind, and plastic arts and circle shapes are the most likely they will choose. The overall choice probability may provide industrial designers insight of market feasibility for their product design.

The research limitation is that bottle design is the only attribute employed for choice probability evaluation in this study; more attributes such as price may be used to explore choice probability evaluation in future research.

VI. Appendix

VII.

A. *Selection Rule for Brand Choice Models*

Rule 1	If δ= 1 then Model = 8
Rule 2	if δ= 2 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 < -0.5$ then Model = 1
Rule 3	if δ= 2 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 2
Rule 4	if δ= 2 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 > 0.5$ then Model = 3
Rule 5	if δ= 2 and $\alpha_3 > 0.25$ and $\alpha_4 < -0.5$ then Model = 2
Rule 6	if δ= 2 and $\alpha_3 > 0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 3
Rule 7	if δ= 2 and $\alpha_3 > 0.25$ and $\alpha_4 > 0.5$ then Model = 4
Rule 8	if δ= 2 and $\alpha_3 < -0.25$ and $\alpha_4 < -0.5$ then Model = 3
Rule 9	if δ= 2 and $\alpha_3 < -0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 4
Rule 10	if δ= 2 and $\alpha_3 < -0.25$ and $\alpha_4 > 0.5$ then Model = 5
Rule 11	if δ= 3 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 < -0.5$ then Model = 3
Rule 12	if δ= 3 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 4
Rule 13	if δ= 3 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 > 0.5$ then Model = 5
Rule 14	if δ= 3 and $\alpha_3 > 0.25$ and $\alpha_4 < -0.5$ then Model = 2
Rule 15	if δ= 3 and $\alpha_3 > 0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 3
Rule 16	if δ= 3 and $\alpha_3 > 0.25$ and $\alpha_4 > 0.5$ then Model = 4
Rule 17	if δ= 3 and $\alpha_3 < -0.25$ and $\alpha_4 < -0.5$ then Model = 4
Rule 18	if δ= 3 and $\alpha_3 < -0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 5
Rule 19	if δ= 3 and $\alpha_3 < -0.25$ and $\alpha_4 > 0.5$ then Model = 6
Rule 20	if δ= 4 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 < -0.5$ then Model = 3
Rule 21	if δ= 4 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 5
Rule 22	if δ= 4 and ($\alpha_3 \geqq -0.25$ and $\alpha_3 \leqq 0.25$) and $\alpha_4 > 0.5$ then Model = 4
Rule 23	if δ= 4 and $\alpha_3 > 0.25$ and $\alpha_4 < -0.5$ then Model = 5
Rule 24	if δ= 4 and $\alpha_3 > 0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 6
Rule 25	if δ= 4 and $\alpha_3 > 0.25$ and $\alpha_4 > 0.5$ then Model = 7
Rule 26	if δ= 4 and $\alpha_3 < -0.25$ and $\alpha_4 < -0.5$ then Model = 6
Rule 27	if δ= 4 and $\alpha_3 < -0.25$ and ($\alpha_4 \geqq -0.5$ and $\alpha_4 \leqq 0.5$) then Model = 7
Rule 28	if δ= 4 and $\alpha_3 < -0.25$ and $\alpha_4 > 0.5$ then Model = 7

Source: Revised from Matsatsinis& Samaras (2000)

B. *Example of Estimating Choice Probability*

i	x_i	f_i	$x_i f_i$	$x-\mu$
1	0.5457	1	0.5457	-0.2507
2	0.63522	0	0	-0.1611
3	0.72475	1	0.72475	-0.0716
4	0.81428	0	0	0.01791
5	0.90381	3	2.71142	0.10743
Total	3.62376	5	3.98187	-0.3581

i	$f(x-\mu)^2$	$f(x-\mu)^3$	$f(x-\mu)^4$
1	0.06284	-	0.00215
2	0	-	0.00043
3	0.00513	-	1.9E-05
4	0	4.67E-	8.37E-
5	0.03463	0.00112	0.00012
Total	0.10259	-	0.00272

	U_{max}	U_{min}	*R*	δ	ε	μ
	0.8590	0.5009	0.3581	3	0.0895	0.7964

	m_2	m_3	m_4	α_3	α_4	*Model*
	0.0205	-0.0021	0.0005	-0.7073	-	4

Source: the author

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