Product Family Design Through Customer Perceived Utility

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Abstract
Even though functional characteristics and various forms can be measured directly and objectively, many designers and engineers still fail to clearly evaluate product criteria due to consumers’ subjective inputs, which change over time. To appropriately evaluate product criteria, an effective design decision making analysis is required. In this study, we propose a methodology to assure this harmony using a mobile phone product family design scenario. Customer perceived utility of design features are first gathered using a questionnaire (with more than 500 responses), and then modeled using multi-attribute utility theory (MAUT) to allow for clustering based on consumer demographics (e.g., race, gender, and age). Based on the clustering, several mobile phone models are tested for their fitness. The goal of the methodology is to determine the appropriate product family size in order to satisfy customer needs as well as reduce supply chain complexity.

Keywords: aggregated utility, design decision making, multi-attribute utility theory, mobile phones

1. Introduction
Every year, manufacturers invest vast sums of money in upgrading their products. However, these development practices, for the most part, remain focused heavily on increasing the number of functions regardless of consumers’ interests. These design and manufacturing decisions, which produce excessive functionality, only increase end users’ confusion and frustration. Consumers are often not able to fully enjoy their brand new products because they do not know how to use the newly added functions. Accordingly, many of their first experiences with the product reflect the slow learning curve associated with feature-dense technology. Indeed, many people only use their products for their primary application. For example, many consumers go no further than using their cell phones for making phone calls, and mp3 players for listening to music. For those people, many complicated functions are rarely or never used. Hence, consumers have difficulty making purchasing decisions based on aspects of the product that they do not intend to use. Moreover, end users might be discontented for paying more money for such unwanted functions.

To improve consumer satisfaction, manufacturers should investigate consumers’ interests and address them as the goal of their new products. It should be noted that increasing the number of functions in a product does not always improve profit in a competitive market, especially when companies are not able to satisfy customers. Therefore, manufacturers should establish evaluation methods that can screen out unimportant aesthetic features or product forms and functions. While doing this, however, diversity in the consumer body should be taken into account. Consumers’ preferences for product forms might differ by age, race, gender, and cultural backgrounds. For example, many gender studies have found that there are gender specific colors: generally, blue for male and pink for female [1]. In fact, some color assignment studies have also found that color preferences differ quite significantly for various age groups [3]. The preference for blue decreases steadily, whereas the popularity of green and red increased as age advances. In addition to changing attitudes toward color, age differences...
might also impact preferences for shapes. For example, older generations who have presbyopia may prefer bigger keypads while younger people may prefer easy-to-carry slim phones. Therefore, manufacturers need to customize products for certain populations.

Both form and functions of a product are important design factors that can motivate consumers’ desire for purchase. However, manufacturers sometimes overlook the needs of consumers, and operate under the philosophy that “newer” and “more” make a better product. But product forms and functions must first meet customers’ needs and preferences. Hence, manufacturers should develop appropriate investment strategies for developing their products and strengthen communication with consumers to save manufacturing time and cost. To this end, in this paper, we present a framework that can determine the appropriate product family size in order to satisfy customer needs as well as reduce supply chain complexity.

The next section provides a summary on the related literature. Then, a two-stage methodology is proposed to capture the preference of the customers in section 3. We demonstrate the application with a case study and discuss the results in section 4. Finally, section 5 summarizes this work.

2. Literature Review

Manufacturing companies should investigate appropriate product design elements both on product forms and functions, in order to support their vision, direction, and improve market share. Barone et al. [2] proposed the Conjoint Analysis (CA) method, which is useful for measuring how consumers’ preferences and perceptions change, and also for analyzing the relative importance that each feature plays in determining product purchasing decisions [2]. This method enables a design team to more effectively assemble the most highly valued combination of features before launching a product in the market.

The CA method is a valuable tool for Kansei engineering [8]. Kansei engineering draws close attention to the emotional responses of consumers to product forms and functions, and this type of engineering fosters understanding of consumers’ preference elements by evaluating their psychological interactions with product features and appearances [8]. Within this framework, rigorous analysis of design elements helps understand customer’s latent preferences and predict consumers consumption in yet unknown cultural environments [14]. Even when designers’ thoughts sometimes provide enough impetus in the product design process, conjoint analysis is a worthwhile approach in that it reduces statistical errors and improves innovative designs.

The Conjoint Analysis (CA) method is used to classify consumers’ desire for market research [10], and, in the context of market research, it is useful while analyzing consumers’ preference factors in the product design decision making process [4]. However, conjoint analyses do not always provide valid results when testing new products because respondents tend to overestimate their preferences toward less important factors [2]. Accordingly, by analyzing current design elements, designers can predict the aesthetic forms and functions in the near future.

Conceptual design methods such as quality function deployment (QFD) [10], fuzzy sets [15], Analytics Hierarchy Process (AHP) [11], and Pugh’s method [9] are proposed to screen out unimportant functional concepts among multi-functional conceptual features. These methods are used to evaluate functional priorities to satisfy consumers’ requirements and desires.

With QFD, designers gather information on customers’ requirements, and use this information to fulfill the functional requirements as well as to develop more creative and efficient functional designs that save time [10]. When users are faced with vague linguistic answers such as “slightly better” and “much better”, the fuzzy set method is used to determine the best design concept. Using this approach, ambiguous linguistic terms can be represented by arithmetic operations for evaluating qualified design functions [15].

Analytic Hierarchy Process (AHP) [11] is performed by comparing the weights of relative candidate concepts in order to reach a rational decision that reflects several people’s preferences. When designers are faced with complex decision making problems, the AHP method provides one of the most suitable alternatives, and the decision makers systematically evaluate relative importance of elements by comparing various criteria [11]. However, the AHP method does not always screen out functional constraints that consumers want through decision makers’ judgments. In addition, AHP assumes all attributes to be mutually independent, which seldom happens in practical cases. Later, Wang et al. [15] proposed the evolutionary multi-objective optimization algorithm based on preference. This method is useful for determining the optimal selection for multi-objective and multi-constraint problems toward feasible domain.

When using Pugh’s method, if team members have different opinions with reference to conceptual design criteria, they tend to spend too much time to achieve a general agreement. Furthermore, if a design team member has less than adequate knowledge for the design case at hand, the probability of selecting the right concept will decrease [9]. On the other hand, Pugh’s method helps to quickly chose the best conceptual design when each designer independently selects criteria for comparison [9]. Improving the functional quality of a product is regarded as indispensable for creating a successful enterprise. Customers’ satisfaction generally increases when quality improves through suitable decisions about functional concepts.

Isiklar and Buyukozkan [5] proposed a multi-criteria decision making (MCDM) method, which is used to identify features and to control consumers' preferences. In their research, the mobile phone industry is taken as a case study. The MCDM method helps individuals or groups of people select a better potential solution by comparing multi criteria choices [5]. However, this approach may not completely take into consideration the relative importance of criteria if decision makers do not already recognize consumer preferences on product functions.
The concept selection methods summarized above either neglect the interdependence among criteria or the uncertainty in customer perceptions, or both. There is a need to address these two issues. The proposed method in this paper firstly matches the customer preferences and product characteristics using historical data mining. Then, a Multiple Attribute Utility Theory (MAUT) is applied to tackle interdependence and uncertainty issues. A product family that both satisfies the perception of customers and minimizes supply chain complexity will be generated.

3. Method

Below we describe our proposed method, which has two complementary stages. The overall flow of the methodology is provided in Figure 1.

3.1 Stage I: Initial Matching of Customer Preference & Product Characteristics

3.1.1. Historical data mining

Historical data mining [7] aims to identify the most significant variables that affect market shares of leading companies. The comprehensiveness of the market data is important for accurate results in this process. As part of the research presented in this paper, product features of 1028 mobile phones released between 2003 and 2008 were analyzed. Unimportant variables were firstly eliminated by using Variance Inflation Factor (VIF) method. For the remaining variables, several regression models were formed, and the best fitting model was determined using Mallow’s C p method. Finally, weights of important design variables were determined through partial regression coefficients. However, to accomplish the same goal other methods of data mining can also be used (e.g., visual data mining).

3.1.2 Logistic regression filtering to identify salient characteristics

Using logistic regression [7], we understand which variables should be selected for various consumer groups. The consumer grouping is done based on age, origin (e.g., Asian, American), and gender. Logistic regression filter provides odds ratios on how consumers’ preference responses are different from reference variables. We evaluate whether the results are statistically significant by comparing the probabilities in relation to each response for each question. According to logistic regression models, we estimate the relationship between one or more predictors, and then identify consumers’ preference criteria based on age, origin, and gender.

3.2 Stage II: Utility Function Based Confirmation

In this stage, we develop multi-attribute utility (MAUT) models to rank order the consumer preferences on mobile phone models using the pre-selected mobile phone models at the end of stage I. Through MAUT, taking into account uncertainty, we evaluate the appropriateness of the mobile phone models for various consumer groups.

4. Case Study

In order to demonstrate the methodology, we used data our research team has collected relevant to the mobile phone market [6, 7]. As stated earlier, the data set included 1028 different mobile phones. In addition to the examination of product features and determination of important form and function features through historical data mining, a survey was administered to understand the customer preferences. A total of 527 people (274 U.S citizens, 253 non-U.S citizens of Asian origin) participated in the survey [7]. Subjects’ ages ranged between 14 to 39. 274 U.S citizens consisted of 142 males and 132 females. Of the 253 non-U.S citizens, 125 were males and 128 were females), and were primarily Asian who live in the U.S. Asians who responded to the survey were predominantly Korean. The survey respondents varied by age, gender, education level, and ethnicity. We developed 11 questions to investigate user preferences for various mobile phone factors, design characteristics, and function usage frequency. Based on survey results, we analyzed consumer preferences using logistic regression as explained in section 3.1.2.

As a result of stage I activities (in 3.1.1 and 3.1.2), we understand what kinds of criteria are important for consumers. Based on the data, we determine consumers’ preference variables, and matching mobile phone models for each 16 different group. These groups are formed as a result of four age categories, two gender categories, and two origin categories. Accordingly, nine variables were incorporated as consumers’ important consideration factors for mobile phone choices. After a lengthy examination of the market offerings in summer 2009, we suggest past and present mobile phone models for each different group. Matching mobile phone models for the American sample are provided in Figure 2, and the same for the Asian sample are provided in Figure 3.

4.1 Utility Theory Based Preference Assessment

4.1.1 Single Attribute Utility Modeling

As the evaluation criteria set for mobile phones in fulfilling customer preferences, a total of nine attributes are determined in the earlier stages. In this stage, single attribute utility (SAU) functions to reflect decision maker’s priorities using the certainty equivalent concept are formulated. While the boundaries for attribute utility functions are ultimately defined by the decision maker, a utility scale of 0-1 is mostly used. For those cases, the most preferred attribute level will return the best utility value of 1 (U_{best}=1), while the least preferred level will yield the worst, 0 (U_{worst}=0).
Figure 1. Flow of the Methodology

Figure 2. Consumer’s Preference Models for USA
Exponential SAU formulation is shown in Eq. (1). For the nine attributes, utility functions are scaled between 0 and 1. The risk tolerance (RT) values for the attributes are assessed by determining the best and worst values in the data and using the concept of the certainty equivalent (CE). The CE is the value of the attribute, for which the decision-maker is indifferent between the CE and a lottery between the best and worst consequences.

Risk attitude of the decision maker can be modeled in utility functions. For monotonic increasing functions, the risk prone utility will have an expected consequence that is greater than the certainty equivalent, while the risk averse utility indicates that the expected consequence is less than the certainty equivalent. Accordingly, the risk prone attitude reflects that the decision maker has confidence in achieving good consequence values, while risk averse attitude might show a lack of it. A higher CE indicates a lesser risk averse attitude. Likewise, a lower CE indicates a more risk averse attitude.

\[
U_i(x_i) = A - B \cdot e^\frac{-\text{Min}(x_i)}{RT} \quad (1)
\]

\[
A = \frac{e^{\text{Min}(x_i)}}{e^{\frac{-\text{Min}(x_i)}{RT}} - e^{\frac{-\text{Max}(x_i)}{RT}}} \quad (2)
\]

\[
B = \frac{1}{e^{\frac{-\text{Min}(x_i)}{RT}} - e^{\frac{-\text{Max}(x_i)}{RT}}} \quad (3)
\]

Where,
RT = Risk tolerance for the attribute \( x_i \)
Min \( (x_i) \) = Minimum value of the attribute across all alternatives
Max \( (x_i) \) = Maximum value of the attribute across all alternatives

A decision maker’s preference over each attribute range is represented by the mathematical expression of the single attribute utility function. All attributes in this case study are monotonic. The single attribute utility functions for the nine

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attributes, namely, number of contacts \(k_1\), weight \(k_2\), screen size \(k_3\), camera \(k_4\), battery life \(k_5\), memory \(k_6\), transfer speed \(k_7\), keypad \(k_8\), and form \(k_9\) are given below, respectively.

\[
U_1(x_1) = 1.007 + 12.265 \times e^{-\left(\frac{x_1}{400}\right)}
\]

\[
U_2(x_2) = -0.685 - 354.900 \times e^{-\left(\frac{x_2}{20}\right)}
\]

\[
U_3(x_3) = 1.157 + 651.154 \times e^{-\left(\frac{x_3}{0.3}\right)}
\]

\[
U_4(x_4) = 1.093 + 2.600 \times e^{-\left(\frac{x_4}{1.5}\right)}
\]

\[
U_5(x_5) = 1.089 + 161.685 \times e^{-\left(\frac{x_5}{60}\right)}
\]

\[
U_6(x_6) = 1.163 + 1.374 \times e^{-\left(\frac{x_6}{120}\right)}
\]

\[
U_7(x_7) = 1.134 + 3.766 \times e^{-\left(\frac{x_7}{3}\right)}
\]

\[
U_8(x_8) = 1.019 + 2.769 \times e^{-\left(\frac{x_8}{1}\right)}
\]

\[
U_9(x_9) = 1.157 + 466.573 \times e^{-\left(\frac{x_9}{0.5}\right)}
\]

The single utility function of the attribute “weight” \(k_2\) implies a monotonically decreasing exponential function. With increasing values of weight \(k_2\), its utility will decrease. This monotonically decreasing condition indicates that if value of the attribute \(k_2\) is minimized, the utility gets better. In this case, our decision maker is risk prone for the weight attribute \(k_2\). Its certainty equivalent \((CE_2)\) is 116g, and the corresponding \(RT_2\) value is 20.

On the other hand, the rest of the attributes can be modeled using monotonic increasing functions. When their consequence values increase, the utility values will also increase. Our decision maker is risk averse for screen size \(k_3\), camera \(k_4\), battery life \(k_5\), memory \(k_6\), and transfer speed \(k_7\). \(CE_3\) of screen size is 2.2 inch, and \(RT_3\) value is 0.3. \(RT_4\) of camera is calculated as 1.5, and its \(CE_4\) is 3.5 megapixels. With \(CE_5\) = 375 minute, battery life is determined as \(RT_5\)=60. The risk tolerance of memory, \(RT_6\), is calculated as 120, and \(CE_6\) indicates 140 mb. \(CE_7\) of transfer speed is 6.5 mbs, and the corresponding \(RT_7\) is 3.0. In the same manner, \(CE_8\)=2.5, \(RT_8\)=1, \(CE_9\)=1.5, and \(RT_9\)=0.3.

### 4.2. Aggregated Utility Function

Every subset of attributes is preferentially independent. Accordingly, we proceed with modeling the aggregation of the single attribute utility functions to reflect the overall view of the decision maker while taking into account risk and uncertainty. In order to find mobile phone alternatives for each group with an overall utility approach, the multiplicative form is used. Using the following relationship (Eq.14), the multiplicative form helps to solve decision problems by ranking alternatives based on the utility scores.

\[
U(x) = \frac{1}{K} \left[ \prod_{i=1}^{n} (Kk_i U_i(x_i)) + 1 \right] - 1 \tag{13}
\]

\[
1 + K = 1 + K = \prod_{i=1}^{n} (1 + Kk_i) \tag{14}
\]

Where,

- \(U(x)\): The total utility
- \(x_i\): The value of attribute \(i\)
- \(U_i(x_i)\): The single attribute utility for attribute \(i\)
- \(k_i\): Attribute-trade-off parameter for attribute \(i\)
- \(K\): Normalizing constant

For measuring relative influence of each attribute, attribute-trade-off parameter \(k_i\) values are determined. Trade-off parameters reflect the decision maker’s desirable tradeoffs under uncertainty. With respect to a decision maker, the importance of each attribute is classified. For example, for the group including America female, who are 30-39 of age, the lottery assessment is conducted. Importance order of all attributes is established as: keypad \((k_8)\) = Form \((k_9)\) = Battery life \((k_9)\) > Screen Size \((k_3)\) > Weight \((k_5)\) > Contact \((k_1)\) = Transfer speed \((k_7)\) > Camera \((k_4)\) > Memory \((k_6)\). Based upon consumer preferences as compiled by the survey data, the most significant attributes are ranked as keypad, form, and battery life.

Beyond a rank order of importance, \(k_i\) values are determined through standard lotteries. An example of such a lottery is presented in Figure 4. Let us assume the lottery giving \(P_0\) chance represents the maximum values \(x^*\) in potential consequences, and 1- \(P_0\) chance shows the corresponding minimum values, \(x^0\). The preference of expected utility function is assessed through the lottery question between a probability \(P_0\) and 1- \(P_0\) values. For example, when \(P_0\) value is 0.5, the design decision maker might find both the lottery and the certain situation (presented on the right in Figure 4) to be equal. Keypad’s alternative consequences are quantified as follows: Full QWERTY keyboard & Touch screen = 1, Full QWERTY Keyboard = 2, Touch screen = 3, QWERTY keypad & Touch screen = 4, QWERTY keypad = 5. This would indicate that keypad \((k_8)\) trade-off parameter is 0.5.
4.3. Results and discussion

By evaluating the most effective attributes of mobile phone forms and functions, we can determine appropriate mobile phone alternatives for each age, origin, and gender group. The use of multi-attribute utility theory (MAUT) enables alternative ranking across the mobile phone data set. In Stage I, historical data mining, logistic regression filtering, and survey results provide important criteria in the decision making progress. In stage II, the aggregated utility values demonstrate that proposed alternatives for each group show similar utilities. Among determined alternatives of mobile phones, consumers’ preference rankings can be established. Based on the highest utility rankings, mobile phone models of each age, origin, and gender groups are generated.

According to consumers’ preference rankings shown in Table 1, American males and females of 14-22 years old, are more likely to be influenced by “Block or Flip” style as form and “Full QWERTY keyboard” as keypad. On the other hand, American males and females of the 23-29 age group are more likely to be motivated by “Block” style as form and “Touch screen” as keypad, moreover large screen size and long battery life are also considered as important factors in consumers’ decision making.
Asian males and females between the ages of 14 and 22 choose “Slider” style as form and “Full QWERTY keyboard and touch screen” as keypad, and colorful design also influences their preferences. While on the other hand, Asian males and females of 23-29 years old regard “Qwerty keyboard and touch screen” as keypad, and “Slider” as the form. High resolution camera and easy user interface are also among the significant factors with high impact on consumers’ psychological response.

To assess the aggregated utility can help provide the best tradeoffs under uncertainty, and rank ordering of mobile phone alternatives. For the 14 -17 age group, optimal models such as rumor II, VU cu920, impression SGH A877, and chocolate vx8550 are recommended. The proposed models for the 18-22 age groups are alias II U750, behold t919, propel pro, and N9. For the 23-29 age group, b410 new chocolate, gm750, sgfh-a777, and LG gd900 models should become popular preferences. For the 30-39 age group, HTC touch HD, w510, s8300 ultratouch, and s8003 jet are considered. Multi-attribute utility analysis can help determine important design criteria and improve consumers’ desirable tradeoffs by avoiding irrationality.

5. Conclusion
In this paper, we demonstrate that the best model alternatives of mobile phones can be recommended by matching consumer preferences and criteria using historical data mining, logistic regression filtering, and consumer surveys, and then...
confirming aggregated utility values of product preferences through multi-attribute utility theory. This proposed method provides better fitting alternatives by satisfying consumer requirements from design decision making perspective, and helps predict future mobile phones that have a high likelihood of success in the marketplace.

Although the sole application of multi-attribute utility analysis might have some limitations in determining feasible tradeoffs, our proposed method avoids biases and inconsistencies in consumer preference attributes and their ranges. Furthermore, it determines the set of desirable tradeoffs, and provides the optimal alternatives by assessing available information and prioritization. Future work on the proposed method will focus on: (1) confirming the results by comparisons to real market data, and (2) applications of the methodology to different product and consumer groups so that the general applicability of the method can be tested.

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