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Product Value Metrics and Value-Characteristic Modeling

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Abstract

The mainstream product value-attribute models can be categorized in to two types, according to exclusion or inclusion of product price in the product attribute/characteristic vector. The characteristic price trade-off is included in popular preference/choice analysis methods, such as random utility analysis and discrete choice analysis, where price is considered as a controllable design variable. The other type of models, customer revealed value models, is focused on modeling a pure characteristic value. Product prices are used as an indicator of value, which is governed by competition and other exogenous factors.

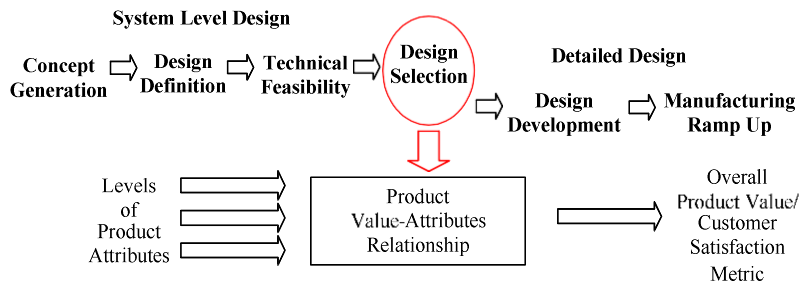
The both approaches can be used for the design decision support at the front-end product development. In the presented research study, partial least square path modeling (PLSPM) is used to get simplified meta-models of value-characteristic relationships to compare these two approaches. A data set containing US Sedan market 2008-2010 specifications, prices and sales was used to conduct the case study. The key findings of the research study are 1) using price as a value indicator is suggested in situations where customer attributes are unavailable, and 2) revealed value is a valid overall product value metric for the US Sedan market segment.

Keywords: Front-end decision support methods, product value-attribute modeling, revealed value, partial least square path modeling.

Introduction

In the front-end design phase selecting the best concept model is critical for the success of the product in the highly competitive technological product markets [1-3]. The most suitable concept design for the targeted market segment should be selected, out of many concept designs, before moving to the detailed design from the conceptual design phase (see Fig. 1). Exponentially increasing design change costs after conceptual design phase adds more weight to this screening process, in order to minimize the resources. Many approaches are used in industry to evaluate the concept designs from an experience manager's "gut feeling" to highly sophisticated mathematical models [3, 4].

Conjoint analysis [5], multi-attribute utility [6], and random utility methods [2, 7] are the mainstream statistical techniques used for the decision support in the concept screening phase by estimating the value-attribute relationship of the market segment. Revealed value analysis [1, 3, 8] is another technique, which can be used to evaluate the product concepts. Fittingly, different metrics are used in these methods to measure or predict the success of a product in a market segment such as market share, sales, prices, utility, and overall product value. Though response variables or the metrics of the customer satisfaction are varying across the methods, the product attributes are treated as the predictor or control variables in all methods except for the special case of price.



1. **Relationship Estimation** – Using observations from the market segment/ Customer surveys
2. **Concept Design Screening** – Using the predictions of estimated function generated by levels of attributes in design alternatives. The overall value or the level of satisfaction can be used to rank order the design alternatives.

Figure 1. Product design and development with front-end screening

In the popular value-attribute relationship estimation techniques, such as conjoint analysis and random utility analysis, price is included as a product attribute. The response variable of these techniques is the level of customer satisfaction obtained from survey ratings or the probability of selection. In contrast to those two popular techniques, revealed value analysis is providing a unique opportunity to work with pure characteristic value of the product by excluding price from the attribute vector [1, 8]. According to the revealed value approach, product demands and prices reflect the value generated by level of product attributes. Hence, price is considered as a value indicator instead of a product attribute, and the revealed value models are free of price endogenity related problems. There are many research studies conducted in product design and development domain using this two approaches separately. A comparative study of this two methods for a given market segment has not been done before to the best of our knowledge.

Partial least square path modeling (PLSPM) [9] is used in this paper to meta-model the random utility and revealed value approaches. It can easily outperform the structural equation modeling technique in situations where observations are limited and variables are correlated [9]. Using PLSPM, these two approaches are brought to a common platform and compared to understand the inherent merits and limitations. In addition, this opportunity is used to validate the revealed value as an indicator of product value.

Only the real market observations are used in this study. The set of variables used in this study are limited to the product attributes, demands, and prices. Customer attributes are not considered in this study. The US Sedan market segment observations, car model specifications and sales from 2008-2010, are used to formulate the PLSPMs and to conduct this comparative study. Generally, data sets with less than 200 observations are considered insufficient for a structural equation modeling analysis [10]. Specifically, the strengths of PLSPM such as efficient handling of correlated variables and high dimensional data sets with limited observations exploited in this research study. In addition to the product attributes and the value or customer satisfaction metrics, a higher level characteristics layer is added in between the value metric and the product attributes to better understand the value structure of the market segment.

Next section covers the background of the study, giving more detailed information about value-characteristics modeling and PLSPM. Methodology is followed by Case Study with an introduction about the data set and the variables used in the study. Results of the case study are analysed in Discussion and we conclude our research study with future works.

Background

The attribute-value relationship can be viewed from two different perspectives as explained in the previous sections. A brief introduction about these two approaches is followed by two sections giving more details about the revealed value and PLSPM. Revealed value is the value metric tested in this study and PLSPM is the modeling technique used to explore the value structure of the market segment in this research study.

The most popular approach of value-attribute modeling is the approach followed in conjoint analysis and random utility analysis. In these two techniques, a product offering is considered as an attribute bundle with a given price. Also, price is considered as a predictor variable and probability of selection, market shares, or consumer survey ratings are used as the response variables for the model formulation. The second approach is the approach used in revealed value analysis. In revealed value analysis, product attributes are used as predictor variables and price is considered as an indicator of the product value as explained below.

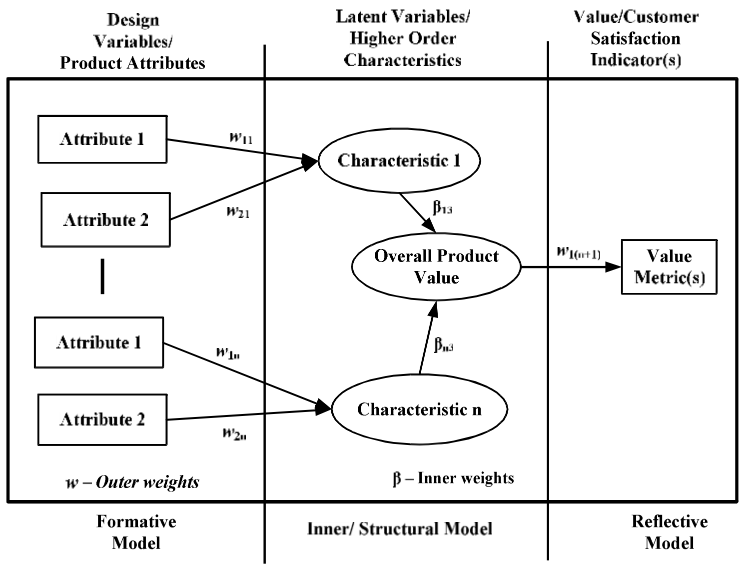


Figure 2. Proposed model structure of PLSPM

PLSPM

PLSPM, a soft modeling method introduced by Wold in mid 70s to facilitate analysis of high dimensional data in low structure environments. It is an attractive alternative to value estimation methods with “hard” assumptions used in product design and development domain. It can be effectively used to analyse the typical design and development data sets, which are suffering from low number of samples and non-normal variable distributions [9].

The structure and the essential components of PLSPM are given in Fig. 2. Mainly, there are two types of variables in PLSPM. The observable variables, such as design attributes or value indicators, are called Manifest Variables (MVs) or indicators. The hidden variables like overall product value are called Latent Variables (LVs), which cannot be measured directly. Inner or the structural model is the relationship in-between LVs and the relationships between MVs and LVs are called the outer model.

MVs, the boxed variables in Fig. 2, can be divided in to two groups by the direction of the relationship. Formative MVs are the MVs which can influence and form a LV. Reflective MVs reflect the value of a LV. Partial least square regression method [11] is used inside

PLSPM algorithm to estimate coefficients and weights robust to multi-correlated variables. Readers are encouraged to refer [9, 12] to get more information PLSPM estimation algorithm and partial least square regression.

Cronabach's Alpha or Eigen Values can be used to check the quality of reflective type of MV blocks. Bootstrapping and cross validation, the widely used data simulation techniques, are the only available ways to validate prediction based formative type of models [9, 13]. Similar to other regression model validation, t-statistic is used as the decision variable for variable selection. Cross-validation is done by leaving some observations behind and estimating them through existing data. This is done for each data point at distance *d* from the initial data point (usually *d* is a prime number 5-10). The goodness of prediction value Q^2 is obtained using the sum of squares of prediction E^2 and the sum of squares of error O^2.

$$Q^2 = 1 - \left(\sum_d E^2 \Big/ \sum_d O^2 \right) \tag{2}$$

Revealed value analysis

The roots of revealed value analysis could be traced back to the price-demand analysis of product market segments [14, 15]. According to the microeconomic theory, demand is considered as a function of consumers' value, product prices and income constraints [16]. Following this definition, Cook introduced a model of demand in terms of values and prices of the competing products in a market segment [8, 15].

This demand function is the basis of Simple market model (S-model) [14] and eventually it shaped the method of revealed value analysis. Revealed value analysis has been employed before in automobile industry and airplane manufacturing. Revealed value (RV) of a product *i* in the units of currency is expressed using the total demand of the market segment D_T, demand of the product D_i, price of the product P_i and partial derivative of demand with price K for a market segment of N competing products.

$$RV_i = \frac{N}{(N+1)K}(D_i + D_T) + P_i \tag{1}$$

The perceived overall value of a product is represented by the revealed value and it provides a metric to evaluate a product or a product concept. According to Donndelinger and Cook [8] revealed value obtained from demand price analysis is equivalent to the value generated by the level of attributes of a product. We use their theory to equalize the predictor variables or product attributes against the revealed value to estimate the "black box" value- attribute relationship of the market segment. PLSPM, introduced in next section, is used to extend this study from a value-attribute analysis to a value-characteristics analysis by introducing a latent "higher level" characteristics layer.

Methodology

The methodology proposed to compare the different approaches in value-characteristic modeling is given from the initial product market segment/data selection to validation and final analysis in this section. The methodology is broken down to five major steps and the tasks done inside each step are given below.

Market Segment Selection – Step 1

Most importantly, the product selected for this analysis should represent a leading technological product with a well established product platform, where customer driven design is the key to success. The product market segment for the analysis should be selected carefully to avoid any extreme outliers, which can significantly affect the structure of PLSPM and the results. This is a bit difficult task due to the reason there is no clear defined market segments in the product markets. A selection strategy can be developed according to the type of the product selected for the analysis.

Observation Selection – Step 2

The observations or the training set selection is also important to get a meaningful model. The training set should reflect the market segment behaviour and the most popular product models in the market. After selecting the sub set of products using a strategy to define a market segment, it should be further screened and inspect to check the representation of the actual market size.

Variable Selection – Step 3

The variable selection should be done in order to accurately reflect the consumer behaviour in the market segment. Gathering all available variable information at the forefront and screening them subsequently to get the most important variables is the strategy used by many statisticians. Including as much as possible variables permits by model requirements, will ensure the minimum presence of endogeneity errors in the formulated model.

Model Formulation – Step 4

Two PLSPMs to represent the different approaches taken for the value modeling and an additional PLSPM to validate the use of revealed value as a value indicator are proposed to formulate in this step. Partial least square regression is used to avoid any unrealistic assumptions, since the design variables are highly correlated with each other.

Validation and analysis – Step 5

Eventually, the model validation and analysis of the value structure carried out for the selected market segment. Here, the goodness of fit of the models can be used to measure the efficiency of the approach and Eigen values of LVs can be used to measure the importance of them to the value structure of the market segment.

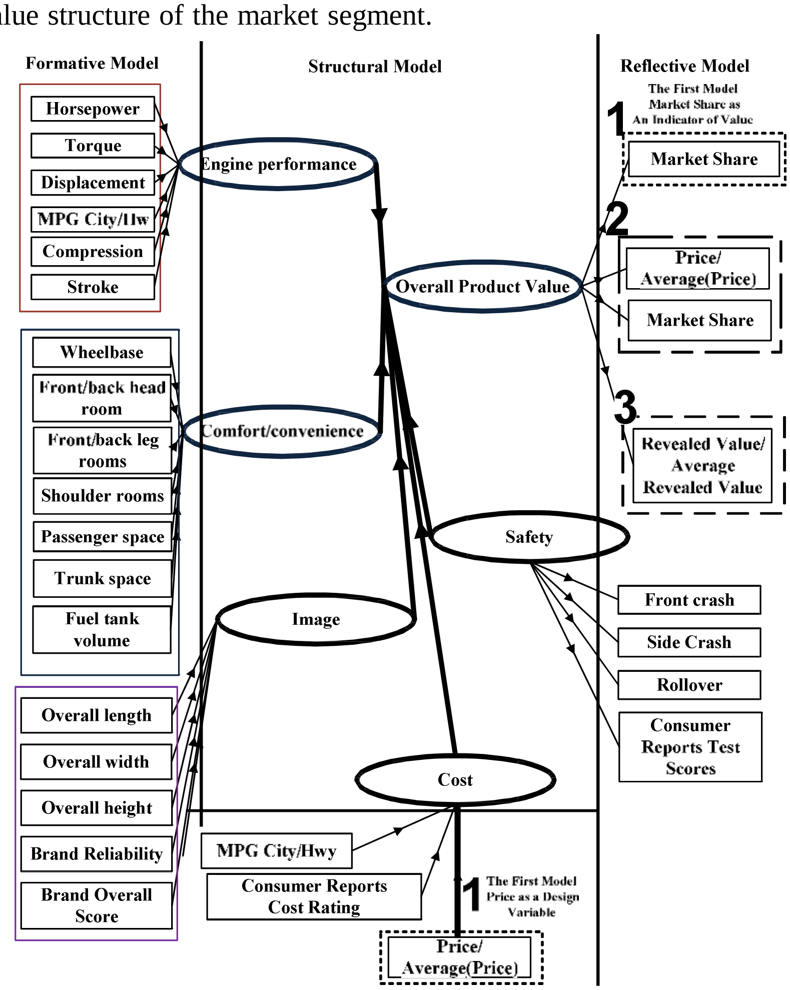


Figure 3. Case study PLSPM structures

Case Study

Using the five step approach given above a case study was conducted using the US automobile market data. Mid and compact size Sedan car models from 2008-2010 were selected to represent the family car market segment. The main reasons behind this market segment selection were the well established technological product platform and the survey results showing the customers in this market segment are more sensitive to the levels of product attributes [17]. The luxury and sports car markets are more biased towards the brand power and customer attributes, but the family car market segment better reflects the rational selections of customers.

The observations are selected to represent more than 80% of the market segment using most popular Sedan models. Price upper bound and the sales lower bound are used to screen the observations and select the popular family Sedan cars, which can represent the market segment accurately. All the available variables were used for the model formulation, since PLSPM can handle high dimensional data with a low number of observations.

Three PLSPMs were formulated as shown in Fig. 3 to compare the two approaches of modeling value and to validate the use of revealed value as an indicator. The difference of first two approaches is the placement of price in formative/design variable model or in reflective/value indicator model. In the third PLSPM price and market share was replaced by revealed value, which was used as the sole indicator of overall product value. The units of the variables were not important due to the fact all observations are auto-scaled (normalized) before the analysis [11, 18].

The three PLSPM models were validated using standard and data simulation methods. The goodness of fit values of PLSPMs were compared to check the accuracy of each approach. In addition, the outputs of the third and second PLSPMs were compared against each other to check the validity of the revealed value as an indicator.

Results

The goodness of fit (GoF) values of the three PLSPMs are given in Table 1. The first model has got the minimum GoF value, and second and third shares GoF values in same levels. Also, it can be seen that the inner model fit is higher than the outer model.

Table 1. Goodness of fit (GoF) values of PLSPMs

	1St PLSPM		2nd PLSPM		3rd PLSPM	
	GoF	GoF (Bootstrap)	GoF	GoF (Bootstrap)	GoF	GoF (Bootstrap)
Absolute	0.354	0.390	0.666	0.673	0.645	0.650
Relative	0.575	0.603	0.915	0.908	0.893	0.885
Outer model	0.671	0.719	0.933	0.933	0.912	0.909
Inner model	0.857	0.840	0.981	0.974	0.980	0.973

The path coefficients and the upper and lower bounds of the path coefficients are given in Table 2. Clearly, the results of the first PLSPM cannot be considered significant looking at the upper and lower bounds. The second and third PLSPM are giving some significant results without including zero within upper and lower bounds. A detailed description about the results and their implications is given in the next section.

Discussion

The set of results given in Table 1 shows that PLSPMs are fitted more accurately, when price is positioned as an indicator of value. Anyway, it can be seen that inner model fit is better than the outer model for all PLSPMs. This is due to the formative nature of the MVs where the outer model fit is sacrificed for to get a better inner model, and accurate predictions [9].

Table 2. Path coefficients and upper and lower bounds

	LV	Path coeff.	Path coeff. (Bootstrap)	Standard error (Bootstrap)	Lower bound (95%)	Upper bound (95%)
1st PLSPM	Comfort/convenience	-0.312	-0.364	0.111	-0.634	-0.103
	Cost	0.346	0.264	0.197	-0.224	0.608
	Image	-0.206	-0.256	0.145	-0.539	0.031
	Engine performance	0.139	0.226	0.124	-0.016	0.458
	Safety	-0.070	0.018	0.150	-0.425	0.285
2nd PLSPM	Comfort/convenience	0.561	0.462	0.132	0.206	0.705
	Cost	0.088	0.034	0.097	-0.217	0.241
	Image	-0.170	-0.064	0.092	-0.270	0.118
	Engine performance	0.462	0.380	0.090	0.156	0.556
	Safety	0.230	0.263	0.077	0.116	0.425
3rd PLSPM	Comfort/convenience	0.394	0.378	0.055	0.275	0.531
	Cost	0.129	0.097	0.045	-0.004	0.192
	Image	0.276	0.262	0.041	0.156	0.342
	Engine performance	0.093	0.104	0.046	-0.014	0.200
	Safety	0.347	0.341	0.038	0.267	0.425

The reason for poor performance of the first approach of modeling, where the price is included as an attribute, might be due to the nature of data. The variables are playing a huge part in deciding the validity of a model and exclusion of customer attributes can be the reason for the poor fit. Especially, in discrete choice analysis customer attributes are considered as the most important set of attributes, because they make the model heterogeneous [2].

Comfort and convenience is the only attribute significant across the models by looking at the upper and lower bounds of path coefficients. The bounds containing zero show the insignificance of the variables and modeling uncertainties. The second and third PLSPM have got comfort and convenience and safety as common significant variables; while engine performance is a significant variable in the second model and image in the third. High GoF values and the closeness to the second PLSPM model support the use of revealed value as an indicator of overall product value.

Conclusions

A case study was conducted using PLSPM to compare three approaches in value-attribute relationship modeling. In the first approach price was used as a product attribute and in the second approach price was used as an indicator of product value. The second approach provided a PLSPM with a better GoF value and significant path coefficients. Exclusion of customer attribute might be the reason behind the poor model fit of the first PLSPM. The third PLSPM was used to validate the use of revealed value as an indicator of overall product value. Significant path coefficients and higher GoF values back the use of revealed values.

Two conclusions can be drawn from the case study results. The second approach, use of price as an indicator, is more suitable for data sets similar to the one used in the study. Aggregated, high dimensional, revealed choice data sets can suffer from absence of customer attributes looking at the results. The second conclusion is the validity of use of revealed value as a value metric for the product concept evaluation. Revealed values of existing products and product attribute levels can be used to estimate the value-attribute relationships. The estimated relationship can be used to predict the revealed values of product concepts, using the levels of attributes as predictor variable inputs. The revealed value estimations can be used to rank order the concepts and select the best design or designs according to the need. A more detailed analysis, including customer and product attributes, is proposed as future works of this research study.

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