

USAGE CONTEXT-BASED CHOICE MODELING FOR HYBRID ELECTRIC VEHICLES

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ABSTRACT

Usage Context-Based Design (UCBD) has become an area of growing interest in engineering design research, due to the increasingly important role that usage context plays in customers' choices. In this paper, a usage context-based choice modeling framework (UCBCM) is presented to bridge the gap between engineering product design and customers' choice of new products by using hybrid electric vehicles (HEV) as an example. Uniquely, Different from existing choice modeling works, the product performances are explicitly modeled as a function of product design variables, customer profile, and usage context to reflect the heterogeneity in customer preference and usage context. Furthermore, the multinomial logic choice model is integrated with the ordered logit model to study the impact of vehicle design on consumer's choice. The case study of HEV illustrates the usefulness of the UCBCM framework and demonstrates the importance of modeling usage context using both revealed preference data and consumer rating data.

Keywords: usage context-based design, choice modeling, customer preferences, discrete choice analysis, ordered logit model, hybrid electric vehicles

NOMENCLATURE

A	Customer-desired attributes
α	Coefficients in regression models for estimating customer-desired attributes
β	Coefficients in customer's choice utility function
CV	Conventional vehicle
DCA	Discrete Choice Analysis
E	Usage context attributes
E_w	Preference-related usage context attributes
E_y	Performance-related usage context attributes
ε_{ni}	Random disturbance of customer choice utility of product i by customer n
HEV	Hybrid electric vehicle
M	Non-engineering attributes
MNL	Multinomial logit
P_{ni}	Choice probability for product i and customer n
PHEV	Plug-in hybrid electric vehicle
S	Customer profile attributes
S_w	Preference-related customer profile attributes
S_y	Performance-related customer profile attributes
u_{ni}	Customer choice utility of product i by customer n
UCBCM	Usage context-based choice modeling
UCBD	Usage context-based design
W_{ni}	Observed (deterministic) part of the customer choice utility of product i by customer n
X	Engineering design options or variables
Y	Engineering performance

1 INTRODUCTION

Usage Context-Based Design (UCBD) has become an area of growing interest in engineering design research, due to the increasingly important role usage context plays in customers' choices. As the actual or perceived product performance depends on the usage context of a product, the impact of usage context on customers' preferences and choice behaviors needs to be studied. Take the hybrid

electric vehicles (HEVs) as an example, vehicle performances, such as mileage per gallon, are strongly influenced by the intended usages of vehicles. For instance, consumers who drives primarily on local roads are expected to prefer hybrid electric vehicle as it demonstrates superior mileage per gallon measure. As we will demonstrate in this work, usage context exhibits a critical impact on consumers' choice of HEVs and needs to be modeled explicitly in a choice model.

Alternative fuel vehicles have drawn increasing attention in the past few years, because of their promising potential of new technology in reducing the greenhouse-gas emission and utilizing renewable energy sources. The adoption of alternative fuel vehicles, such as the plug-in hybrid electric vehicles (PHEVs) in the near future is expected to grow significantly; in particular, US President Obama has called for half of all the cars purchased by the federal government to be PHEVs by 2012 and to have 1 million PHEVs on the road by 2015. Ample literature can be found in the engineering design domain that deals with battery related design issues for PHEVs (Shiau *et al.* 2009, Shahi and Wang 2010, Shiau *et al.* 2010). However, a connection between engineering design and customers' preference is lacking. While PHEVs are still under development but not in the market yet, HEVs have been in market since late 1990s and their adoption by consumers is growing. There is also the growing interest in researching hybrid electric vehicle data to gain insight of future trend in PHEV market. However, understanding consumers' choice of HEV is challenging because their preference construction process involves many aspects beyond traditional engineering considerations, which calls for a comprehensive modeling framework to incorporate usage context into the engineering product design process.

In this work, a comprehensive usage context based choice modeling framework is presented to bridge the gap between engineering product design and customers' choice of new products by using hybrid electric vehicles (HEV) as an example. The focus of our research is to illustrate the usage context based choice modeling procedure which captures the impact of usage context by explicitly modeling its influence on both product performances and customer preferences. Findings from the hybrid electric vehicle case study demonstrate the needs and benefits of incorporating usage context in choice modeling.

The rest of this paper is organized as follows: Section 2 provides a literature review on usage context influence. A systematic taxonomy of UCBD is introduced in Section 3, followed by the proposed framework for usage context based choice modeling in Section 4. In Section 5, details of the case study of hybrid electric vehicle choice modeling are provided. Conclusions and future works are summarized in Section 6.

2 USAGE CONTEXT INFLUENCE

The marketing researchers are among the first to recognize the power of situational (usage contextual) influence on behavior (Lavidge 1966, Engel *et al.* 1969, Robertson and Ward 1973). Based on Belk's stimulus-organism-response (S-O-R) paradigm (1975) in which the stimulus is divided into an object and a situation, or *usage context* in our terminology, a Usage Context-Based Design (UCBD) influence diagram was proposed in our previous work (He *et al.* 2010), as shown in Figure 1. In the context of UCBD, *object* refers to product and *situation* refers to usage context. Both *usage context* and *product* act as stimulus to a customer which leads to his/her *choice behavior*.

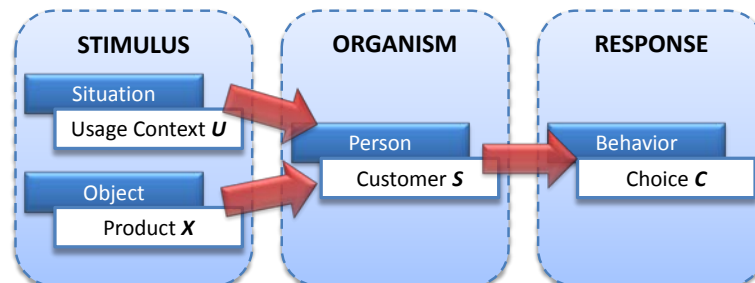


Figure 1: Usage Context-Based Design Influence Diagram (He *et al.* 2010)

The need for considering situational (usage contextual) attributes in market segmentation was recognized in the 1980s. Dickson (1982) pointed out that usage situation is overlooked in market segmentation and presented a person-situation segmentation framework in which the market is explicitly segmented by groups of consumers within usage situations. The work by Christensen *et al.* (2005) recommended stopping the common practice of segmenting customers based on their

demographics and replacing it with ways that reflect how customers actually live their lives. More recently, De la Fuente and Guillén (2005) analyzed consumer perceptions with regard to the suitability of household cleaning products to anticipated usage contexts, as well as their influences on purchase behavior.

While the study of usage context in consumer behavior has been prevalent for years, it had not been applied to engineering design until 2000s. In Ulrich and Eppinger's product design and development book (2003), the need for designers to envision a product's "use environment" in identifying customer needs is emphasized. Green et al published three successive papers (2004, 2005, 2006) on designing for product usage context, which is defined as a combination of application and environment in which a product will be used. Their work supports the idea that context can be differentiated based upon functional attributes, indicating a link between engineering parameters and perceived usefulness, which occurs under the influence of different usage contexts.

The existing literature demonstrated the influence of usage suitability on consumer choice. However, the linkage between usage context and product performance as well as product design is absent. Understanding usage context has a great potential in analytical design process as well (Yannou *et al.* 2009). Through a choice model, we can understand the impact that usage context has on customer preferences, and therefore optimize product design to maximize the customer demand, or the profit contributed by the product. In this work, the usage context-based choice modeling framework is presented with a case study of hybrid electric vehicle to demonstrate the impact of usage context on customers' choice.

3 USAGE CONTEXT TAXONOMY

The taxonomy of Usage Context-based Design (UCBD) is laid out in this section. To illustrate the concepts, the hybrid electric vehicle example is used throughout this section.

Usage Context Attributes E refer to the characteristics or attributes used to describe the usage context. Usage context in real life varies significantly across product categories. In our view, its influence on customer behavior includes the impact on product performance, the choice set, and on customer preference. Hence, we define the usage context in our work as "*all aspects related to use of a product that have influence on customer choice behavior.*" Here we emphasize two things: first, usage context covers all aspects related to the use of a product, but excludes customer profile and product attributes, which will be defined later on in this section; second, usage context influences customer behavior through product performance and customer preference.

Relating to the interest in choice modeling, we divide usage context attributes E into performance-related and preference-related, according to the way in which they impact customer behavior. While performance-related attributes E_Y influence product performance Y , preference-related attributes E_W have an impact on choice set and customer preference. For instance, miles driven daily, an example of E_Y , determines the working mode, engine or battery powered, of a plug-in hybrid electric vehicle, and therefore greatly influences vehicle performance. Similarly, a customer will have different preference when purchasing a new vehicle for commuting to work than someone who uses the car for leisure. The vehicle usage purpose is an example of preference-related attributes E_W . In some cases, E_Y and E_W are not mutually exclusive. Whether a usage context attribute is related to performance or not can be determined by prior knowledge of experienced users or by the observations of products being used; whether a usage context attribute belongs to the preferences-related type is identified through the choice model estimation process. Prior knowledge of usage context attribute's influence on preference can be used to reduce the complexity of estimating a choice model.

Customer Profile Attributes S includes all stable or permanent aspects of customer attributes impacting customer choice behavior, for example, gender, age, income bracket, etc. Similar to usage context attributes, customer profile attributes S can be categorized into performance related S_Y and preference-related S_W to differentiate their impact on performance and preference, respectively. For example, household income belongs to S_W , as it is expected to have a large impact on customers' sensitivity on price: the more they earn, the less they care about the price. On the other hand, the number of children living in the household is a performance related S_Y that impacts how consumers evaluate vehicle's storage and space usage.

One thing to note here is that a clear distinction sometimes is hard to find between customer profile and usage context as separate sources of influence on customers' choice. In some cases, customer attributes may also seem like a usage context attribute, or vice versa. For example a

customer' purchase history can be regarded either as a customer attribute or as a usage context. As a guideline, we refer to customer attributes as those stable or permanent characteristics of a customer, while those temporal, transitory characteristics of a customer belong to the area of usage context. Therefore, purchase history is treated as a usage context attributes in this framework.

Product Design Variables X describe the design options and other engineering decisions which influence product performance. In designing a complex system such as vehicles, numerous engineering design variables are to be determined before the product enters the market. Usually those design decisions follow a hierarchical structure with different levels of complexity. For example in the vehicle design case, there are system level, subsystem level, component level, and part level (Kumar *et al.* 2009) design variables throughout the product hierarchy. Which level to select for choice modeling depends on the desired level of details. When multiple lower-level design variables are included in the choice modeling, potential confounding and correlating issues may occur. Hence in our case study, we focus on the system level vehicle design variables, such as exterior and interior dimensions, horsepower, torque, and mileage per gallon target, as they are among the most critical high-level design variables.

Customer-desired Attributes A are defined as key product characteristics that influence customers' choice in selecting a product. In a market survey, consumers are usually asked to rate these customer-desired product attributes. They include not only product performance **Y**, but also non-engineering attributes **M**, etc.

Product performance **Y** measures customers' perception of all performance-related product attributes. Different from product design variables **X**, product performance **Y** not only is a function of product design variables **X**, but also depends on customer profile **S** and usage context **E**. One typical form of product performance **Y** is the rating data collected in the market survey where respondents use discrete rating scores to measure their satisfaction of the product. For instance, customers are asked to provide estimate of mileage per gallon of their newly purchased vehicle. This formulation of product performance captures the individuality of a customer and the usage context, as detailed in Section 4. Once the choice model is built, targets can be set for the product performance **Y** through optimization to guide the engineering design process.

Non-engineering attributes **M** include all non-engineering aspects of customer-desired attributes, for example, price, brand, aesthetics and other common marketing traits. Price is one of the most influential non-engineering attributes **M** in customers' choice. In practice, price can enter the utility function as a single term, or can be scaled by income or log income to reflect the connection between income and price sensitivity, as shown in the case study of this paper.

4 USAGE CONTEXT-BASED CHOICE MODELING

In order to capture the impact of usage context attributes and utilize usage context information in a design process, the framework for usage context based choice modeling (UCBCM) proposed in our earlier work (He *et al.* 2010) is employed in this work and its benefits for choice modeling are demonstrated using hybrid electric vehicles as a new example.

The usage context based choice modeling methodology utilizes a decision-theoretic methodology (Wassenaar and Chen 2003, Hoyle and Chen 2009) to select the *preferred* product design alternative for the enterprise undertaking the design activity, as well as to set *target levels of performance* for the product. This is accomplished through a hierarchical model in which design concepts and variables (*product design variables X*) are linked to demand, Q , through engineering analysis and attribute mapping between *product design variables X* and *customer-desired attributes A*.

As shown in Figure 2, the linkage between product design variables X and market share P_{ni} is established using Discrete Choice Analysis (DCA), a statistical technique of building probabilistic choice models (Ben-Akiva and Lerman 1985, Koppelman and Bhat 2006). DCA originates in mathematical psychology (Luce 1959, Thurstone 1994) and has found wide applications in transportation (Wen and Koppelman 2001), marketing research (Ben-Akiva and Boccara 1995) and econometrics (Greene 2003). It is used to model product demand by capturing *individual* customers' choice behavior, in which performance of a given product is considered versus that of competitive products. DCA is based upon the assumption that individuals seek to maximize their personal *customer choice utility*, u , when selecting a product from a choice set. The concept of choice utility is derived by assuming that the individual's (n) true choice utility, u , for a design alternative, i , consists of an observed part W , and an unobserved random disturbance ε (unobserved utility):

$$u_{ni} = W_{ni} + \varepsilon_{ni} \quad (1)$$

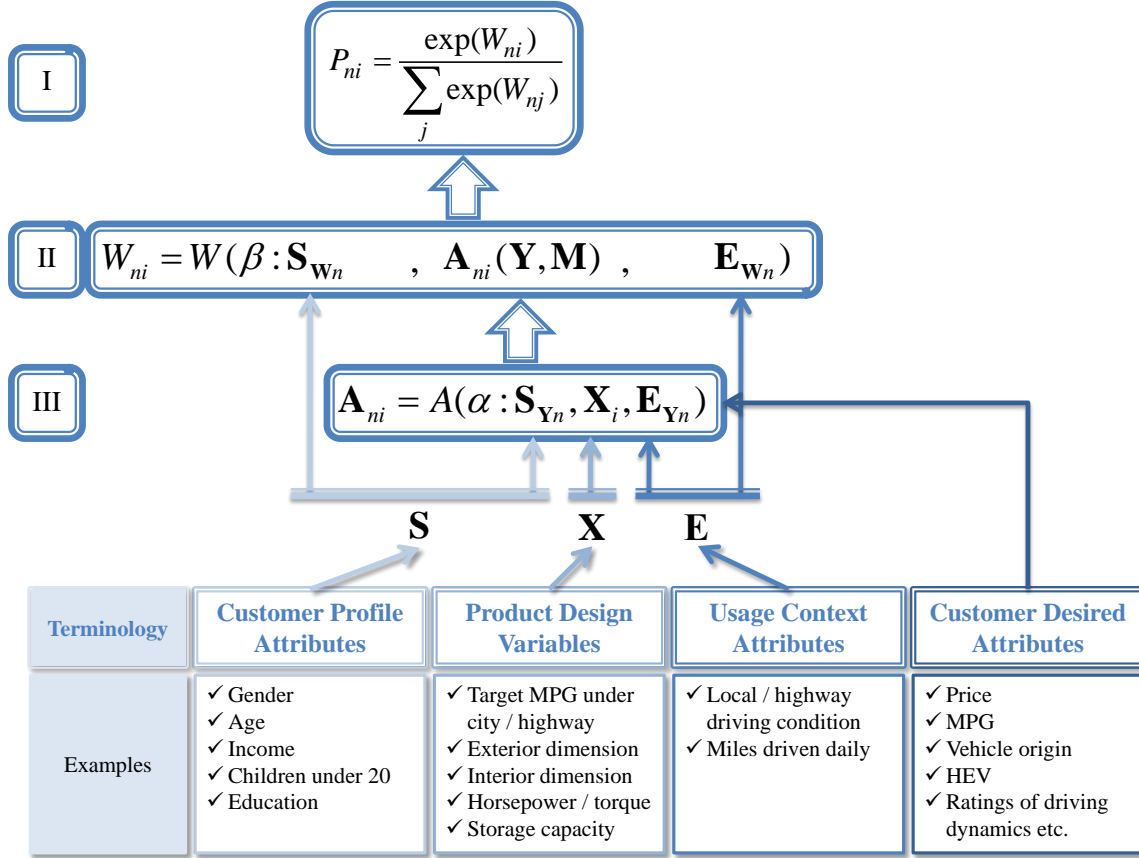


Figure 2: Usage Context Based Choice Modeling for Hybrid Electric Vehicle

The key component in UCBCM is the inclusion of customer profile attributes \mathbf{S} and usage context attributes \mathbf{E} , in addition to customer-desired attributes \mathbf{A} , in the estimation of demand, to capture the heterogeneity of consumer preference and their usage context. As shown in Equation (2), the observed or deterministic part of utility W_{ni} is expressed as a function of customer profile attributes \mathbf{S} , customer desired attributes \mathbf{A} , and usage context attributes \mathbf{E} .

$$W_{ni} = W(\beta : \mathbf{S}_{Wn}, \mathbf{A}_{ni}, \mathbf{E}_{Wn}) \quad (2)$$

where \mathbf{A}_{ni} denotes the customer-desired attributes of respondent n , alternative i , and \mathbf{S}_{Wn} and \mathbf{E}_{Wn} denotes the preference-related customer profile attributes and usage context attributes of respondent n . In this formulation, W indicates that W_{ni} is a function of \mathbf{S} , \mathbf{A} and \mathbf{E} as well as the β coefficients, which are estimated by observing choices respondents make. Note that W_{ni} can take any prespecified function form.

Depending on the expected level of details and the assumptions made, various choice modeling techniques, such as multinomial logit, nested logit, and mixed logit (Train 2003) can be used to identify the model coefficients in the choice utility function W . By far, the most basic and most widely used discrete choice model is the multinomial logit (MNL) model, in which each ε_{ni} is assumed to be independently, identically distributed extreme value, also called Gumbel or Type I Extreme Value. In multinomial logit, the choice probability for product i and person n can be calculated in the following closed form expression:

$$P_{ni} = \frac{\exp(W_{ni})}{\sum_j \exp(W_{nj})} \quad (3)$$

With multinomial logit modeling, the heterogeneity of consumer preferences is captured by including both \mathbf{E}_W and \mathbf{S}_W in the choice utility (also called systematic heterogeneity). Inclusion of \mathbf{E}_W and \mathbf{S}_W explicitly in the choice model enables a better estimate of individual-level choice probability and allows for choice predictions to be made for a new target market with a different demographic and

usage context distributions than the survey market used for model estimation. Other types of consumer heterogeneity, e.g., random heterogeneity, can be captured by treating the model coefficients as random parameters (Hoyle *et al.* 2009, Hoyle *et al.* 2010).

Figure 2 illustrates the relation between Equations (2) and (3) in the context of HEV. From the top down, level I shows the choice probability (market share) expression, while level II represents the choice utility function with respect to \mathbf{S} , \mathbf{A} , and \mathbf{E} . Level III at the bottom is the unique step for UCBD applications in which a prediction model needs to be established to link customer desired attributes \mathbf{A} with product design variables \mathbf{X} , customer profile attribute \mathbf{S} , and usage context attributes \mathbf{E} . In the set of \mathbf{A} , product performance \mathbf{Y} depends on customer profile attributes \mathbf{S}_Y and usage context \mathbf{E}_Y . For example, in designing hybrid electric vehicle, mileage per gallon (MPG) has a direct impact on customers' choices. Vehicle manufacturers provide target mileage per gallon measures under city and highway driving condition for each of their car models. However, the mileage per gallon varies significantly from customer to customer because of the heterogeneous usage scenarios and customer driving habits. Therefore, the customer desired attributes \mathbf{A} are formulated as a function of performance-related customer profile attributes \mathbf{S}_Y , product design variables \mathbf{X} , and performance-related usage context attributes \mathbf{E}_Y , as shown in Equation (4):

$$\mathbf{A}_{ni} = A(\alpha : \mathbf{S}_{Yn}, \mathbf{X}_i, \mathbf{E}_{Yn}) \quad (4)$$

where the coefficients α can either be identified through physical relations or determined through regression model estimations. While physical relations are often used for assessing quantitative attributes, regression analysis is often applied to establish the mapping from customer profile \mathbf{S} and usage context \mathbf{E} to qualitative attributes. When ratings are used to measure qualitative attributes, an ordered logit model (McCullagh 1980) can be used due to its capability of handling discrete data. The use of ordered logit model will be illustrated in Section 5 for the case study.

Examples of each category of attributes in the context of hybrid electric vehicle case study are provided at the bottom of Figure 2. Typical customer profile attributes \mathbf{S} are *gender, age, household income, number of children under 20* and *education level*, while *target MPG, exterior* and *interior dimensions, horsepower, torque, and storage capacity* are examples of high-level vehicle design variables \mathbf{X} . *Local/highway driving condition* and *miles driven daily* are two of the most critical usage context attributes \mathbf{E} for vehicle design. In our case study, the local/highway driving condition is considered as \mathbf{E}_Y to estimate the ratings of qualitative performance attributes as shown in Equation (4). Last but not least, customer desired attributes include non-engineering attributes \mathbf{M} such as *price, vehicle origins*, as well as performance measures \mathbf{Y} such as *MPG, HEV* and customers' *rating of driving dynamics* etc.

5 HYBRID ELECTRIC VEHICLE CASE STUDY

In this section, a hybrid electric vehicle (HEV) case study based on the revealed preference data from JD Power and Associates is presented to demonstrate the proposed Usage Context-Based Choice Modeling (UCBCM) framework. The results show the influence of usage context through revealed preference data collected for both hybrid electric vehicles (HEVs) and conventional vehicles (CVs). Once the choice model is created, for the given target population and usages, the optimal MPG target for HEVs can be identified together with the settings of other HEV design variables. Moreover, customers' preferences toward HEVs identified in this case study can be used as a basis for the choice modeling of PHEVs as HEVs and PHEVs share many common consumer desired product attributes associated with the new vehicle technology. It should be noted that in our current study, the impact of HEV policies and other purchase incentives is not modeled.

In the 2007 Vehicle Quality Survey (VQS) done by J.D. Power and Associates, vehicle purchase data from 90,000 nation-wide respondents on over 300 vehicles available in the market are collected, including data for 11 HEV models. Further, respondents' demographic attributes and their usage patterns are recorded in the questionnaire. For model estimation in this study, data collected from 8025 respondents, who listed the three other vehicles considered in their choice set in addition to the vehicle they purchased, are studied. The attributes included in the choice model are listed in Table 1.

There are 288 car models covered in the data set, each of them is chosen by at least one respondent. Fifteen customer-desired attributes \mathbf{A} are selected including price, vehicle origin, vehicle size, vehicle type, mileage per gallon (MPG), hybrid electric vehicle indicator, and nine rating scores given by the respondents. The hybrid electric vehicle indicator, coded as 1 for hybrid vehicles, and 0

for conventional vehicles, reflects customers' attitude toward new hybrid technology. Nine aspects of the vehicle, including exterior attractiveness, interior attractiveness, storage and space usage, audio/entertainment/navigation system, seats, heating ventilation and air conditioning, driving dynamics, engine and transmission, and visibility and driving safety, are rated on a scale of 1 to 10, 10 being the most satisfactory. These discrete ratings are included in the choice modeling procedure, as they are considered to be a good measure of customers' perception of qualitative as well as quantitative vehicle attributes.

Table 1: List of Attributes in Usage Context-Based Choice Modeling for HEVs

Customer-desired attributes A		
A_1	Price	Price paid, excluding tax, license, trade-in, etc.
A_2	MPG	Mileage Per Gallon under usage
A_3	Vehicle origin	Domestic / European / Japanese / Korean
A_4	Vehicle size	Compact / Midsize / Large / Premium
A_5	Vehicle type	Mini / Car / SUV / Minivan / VAN / MAV / Pickup
A_6	Hybrid electric vehicle	1 for hybrid, 0 for conventional
$A_{exterior}$	Exterior attractiveness	Discrete rating on a scale from 1 to 10
$A_{interior}$	Interior attractiveness	
$A_{storage}$	Storage and space usage	
A_{audio}	Audio	
A_{seats}	Seats	
A_{hvac}	HVAC	
$A_{dynamics}$	Driving dynamics	
A_{engine}	Engine and transmission	
A_{safety}	Visibility and safety	
Product design variables X		
X_1	Exterior dimensions	Vehicle length / width / height (unit: in.)
X_2	Vehicle weight	Unit: lbs
X_3	Interior dimensions	Front head / shoulder / hip / leg room (unit: in.) Rear head / shoulder / hip / leg room (unit: in.)
X_4	Storage capacity	Luggage capacity Cargo capacity
X_5	Engine specifications	Engine size Number of cylinders
X_6	Performance	Horsepower Torque
X_7	MPG targets	Target Mileage Per Gallon level under city / highway condition
Usage context attributes E		
E_1	Local / highway indicator	0 – local, 1 – highway
E_2	Miles driven daily	Unit: miles
Customer demographics S		
S_1	Gender	1 for male, 2 for female
S_2	Age	Age
S_3	Income	Household income last year
S_4	Children	Number of children under 20 living in the household
S_5	Education	Level of education completed

As described earlier in the UCBCM flow diagram (Figure 2), the product design variables **X** at the bottom level need to be linked to customer desired attributes **A** through Equation (4). Seven high level engineering design variables are used in this case study, including exterior dimension, interior dimension, performance, MPG targets, etc. The random effect ordered logit modeling method (Hoyle *et al.* 2010) is used to bridge the gap between engineering product design variables and nine qualitative customer desired attributes in the form of ratings. Due to limited space, the results are not reported in this paper but are available from the authors upon request.

As for the usage context attributes **E**, two most commonly considered usage context attributes for HEV are included in the choice model: *local/highway indicator* and *miles driven daily*. While both usage context attributes are included in the choice modeling as preference-related attributes **E_w**, only *local/highway indicator* is introduced in mileage per gallon calculation as a performance-related attribute **E_y**, as detailed later. As the original data set does not include any information related to local

vs. highway driving, the *local/highway indicator* is introduced and calculated based on the combined MPG published by US Environmental Protection Agency (EPA 2008) and the real MPG given by survey respondents. The indicator is a continuous parameter, ranging from 0 for local driving to 1 for highway driving. It is a reasonable assumption that the local/highway indicator reflects the general driving condition the respondents face, therefore the vehicle usage context. The local/highway driving condition not only greatly impacts vehicles' performances, e.g. MPG, but is also expected to influence customers' choice preference, especially with hybrid vehicles. The other usage context attribute considered is the *miles driven daily*, a popular descriptor of customers' travel pattern. The data is derived from the recorded miles driven in the first three months from the market survey. This is an important usage context attribute in designing new HEV and PHEV, as miles driven daily strongly influence the target range of batteries.

Meanwhile, *gender, age, household income, number of children under age 20* living together and *education level*, are included as five customer profile attributes S . From the choice model estimation, only two customer profile attributes, *household income* and *education level*, are statistically significant as preference-related attributes S_w . As for the performance-related attributes S_y , all five customer profile attributes are included in the ordered logit regression for predicting the performance rating scores, as will be shown later.

The coefficients for the all attributes and their interactions based on multinomial logit model estimation (MNL with E) are listed in Table 2, together with the estimation results from a multinomial logit model without usage context attributes (MNL without E) as a comparison. From the results of MNL including E attributes in modeling shown in Table 2, we note that the coefficient for price/income is negative as expected. A positive estimator for E_1*A_2 indicates that the usage context attribute E_1 (local/highway indicator) has a positive impact on customers' preference on MPG measure. In other words, people primarily driving on highways tend to care more about the MPG value. Moreover, the attitude toward HEV itself has a fairly large coefficient estimator of 57.0667, which shows that people driving locally tend to favor HEV. Similarly as we expected, highway drivers do not prefer HEVs, as shown in the negative coefficient estimator of the E_1 and HEV indicator interaction (E_1*A_6). On the other hand, coefficients from MNL without modeling E all have the same sign as the ones in MNL with E, but they are very different in magnitude, as the usage heterogeneity is missing without explicitly modeling usage context attributes in the choice model.

Table 2: Coefficients of MNL with E and MNL without E for HEV

Attributes	MNL without E			MNL with E		
	Coefficients.	Std.Err.	Sig.	Coefficients	Std.Err.	Sig.
A_1/S_3	-0.0004	0.0000	*	-0.0004	0.0000	*
A_2	-0.1581	0.0069	*	-3.1080	0.0846	*
E_1*A_2	/	/		5.9454	0.1697	*
E_2*A_2	/	/		0.0002	0.0003	
$A_6_d_hybrid$	4.9808	0.7023	*	57.0667	2.4840	*
$E_1*A_6_d_hybrid$	/	/		-105.8431	4.8316	*
$S_5*A_6_d_hybrid$	-0.2183	0.1036	*	-0.2875	0.1213	*
$A_{exterior}$	0.0463	0.0343		0.0407	0.0385	
$A_{interior}$	0.4870	0.0176	*	0.4585	0.0190	*
$A_{storage}$	0.5706	0.0149	*	0.6253	0.0175	*
A_{audio}	0.1476	0.0318	*	0.1421	0.0355	*
A_{seats}	0.1246	0.0379	*	0.1046	0.0424	*
A_{HVAC}	0.1379	0.0347	*	0.1285	0.0391	*
$A_{dynamics}$	0.1932	0.0388	*	0.1640	0.0433	*
A_{engine}	0.3145	0.0309	*	0.3061	0.0343	*
A_{safety}	0.0778	0.0389	*	0.0455	0.0437	*

* Significant with p value ≤ 0.05 .

Goodness-of-fit Measures

Goodness-of-fit measures based upon the log-likelihood of the converged model, such as the likelihood ratio index ρ^2 (also known as pseudo R-square), reflect how well the estimated model predicts actual individual choices in the data set. Higher values of ρ^2 indicate better predictions of the choices. As shown in Table 3, a significantly higher log-likelihood of -4825.26 and subsequently ρ^2 value of 0.5663 are achieved using the MNL model with usage context attributes E versus the MNL

model without **E**. This implies that introducing the usage context attributes in choice modeling has captured the systematic taste heterogeneity of customers under different usage contexts.

Table 3: Model Statistics of MNL without E and with E

Multinomial Logit Model	without E	with E
Log likelihood at zero	-11125.01	-11125.01
Log likelihood at convergence	-6178.62	-4825.26
ρ^2	0.4446	0.5663

Cross-validation

For cross-validation of a choice model, the original data are divided into 5 subsets of samples. For each of the five cross-validation tests, a choice model is trained on 4 subset samples and later validated using the remaining hold-out sample. The likelihood ratio index ρ^2 values and hit rates (percentage of correctly predicted choices) are calculated and averaged out. On average, the likelihood ratio index ρ^2 shows an over 17% improvement from 56.81% in MNL without E to 66.48% in MNL with E. The hit rate is another measure of the prediction accuracy of an estimated model at the individual level. It is calculated by dividing the number of correctly predicted choices by the total number of respondents. Similarly to ρ^2 , the hit rate increases from 66.55% in MNL without E to 75.07%, which shows that usage context greatly influences customers' choice and should be modeled explicitly.

Market Segment Prediction Tests

The two models, MNL with E and MNL without E, are compared based upon the error in choice share prediction for conventional vehicles (CVs) and hybrid electric vehicles (HEVs). The market segment prediction test is conducted for three segments of driving conditions (local, combined, highway). Figure 3 illustrates the comparison of the predicted choice share using MNL without E and MNL with E. The real choice share is shown in middle columns, while the predicted choice share by MNL without E and with E are shown in left and right columns, respectively. The comparison confirms that predictions by MNL with E are more accurate than those from MNL without E for local and highway driving condition segments, while both market segments have significantly different choice shares for HEVs, compared to the average in total.

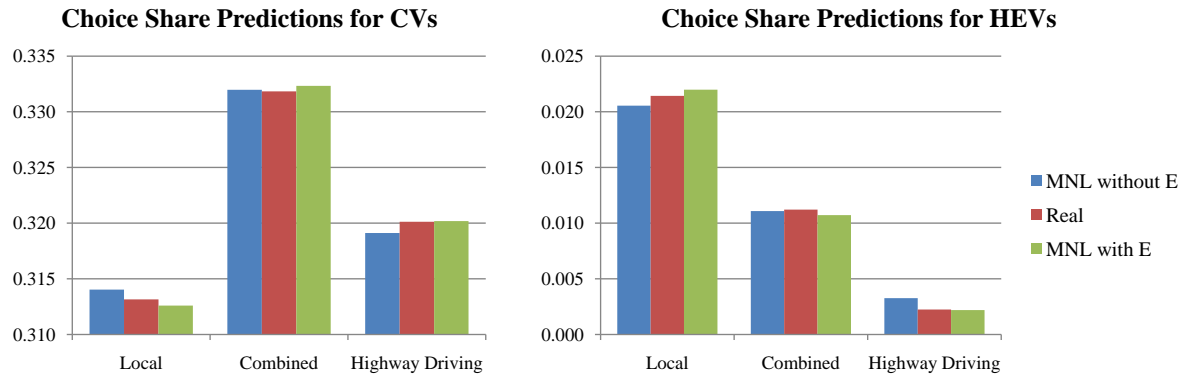


Figure 3: Comparison of Choice Share Predictions using MNLwoE and MNLwE

What-If-Scenario Analysis

As mentioned earlier, the ordered logit regression analysis is performed on the nine performance ratings of customer desired attributes to demonstrate how to build the linkage from customer desired attributes **A** to product design variables **X**, customer profile **S**, and usage context **E** in Equation (4). In the model estimation, in addition to the design variables, customer profile **S_Y** such as *gender*, *age*, etc., are included to capture customers' heterogeneity. The coefficients estimators are later used for what-if-scenario analysis to forecast potential market share for targeting customer and usage attributes.

On the other hand, customer desired attribute A_2 , *mileage per gallon*, is calculated based on our previous knowledge. As no detailed information about customers' driving habits is available, we only consider the impact of usage context on the MPG measure here. Assuming that local/highway indicator E_1 represents the percentage of miles driven under local condition, the mileage per gallon A_2 can be expressed in Equation (5).

$$A_2 = \frac{1}{\frac{E_1}{MPG_{city}} + \frac{1-E_1}{MPG_{highway}}} . \quad (5)$$

where MPG_{city} and $MPG_{highway}$ belong to the product design variable \mathbf{X} listed in Table 1.

With the formulations described above and choice model results from MNL with E, a prediction model can be built to forecast the customers' choice. For example, a target population of 260 customers are simulated with customer profile distribution drawn from the hybrid owners pool in VQS 2007 data set. Assuming that they are selecting a new vehicle to purchase from a given choice consideration set of 10 car models in the market. The ten car models, among which two (vehicle 4 and vehicle 8) are HEVs, are selected based on their popularity in the consideration set of customers who considered at least one HEV. Here we consider a series of nine different usage contexts: uniformly distributed *local/highway indicator* within 0.2 range with mean value from 0.1 to 0.9 (with 0.1 interval), while average *miles driven daily* matches with original dataset. Aggregated choice probability in target population calculated using our proposed framework is summarized in Figure 4.

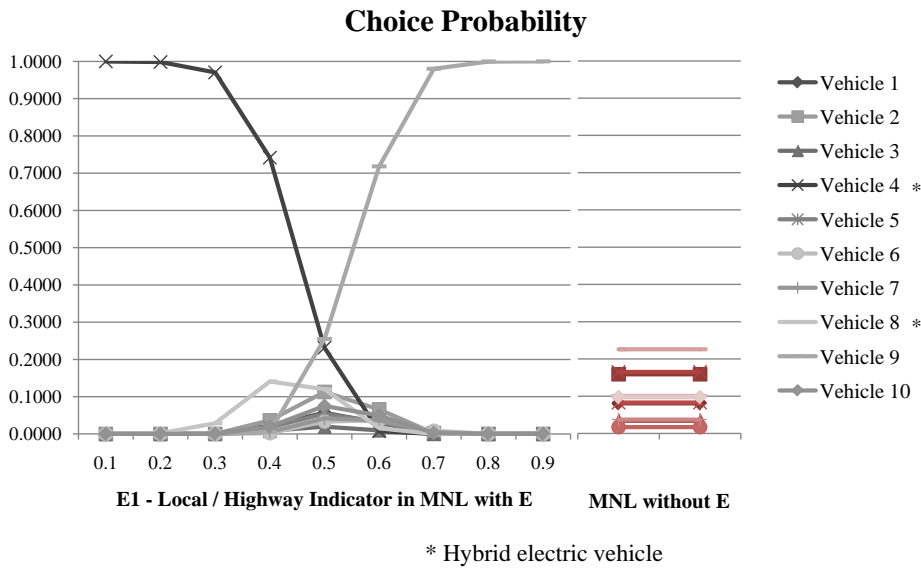


Figure 4: Choice Probability of Customer A under Different Usage Scenarios

In Figure 4, the grey lines on the left hand side show the predicted choice probability by MNL with E, while the red lines on the right hand side represent the constant choice probability predicted by MNL without E. Based on the utility maximization theory in DCA, alternative with the highest probability is the customer's final choice. For instance, when the target population, on average, drives 40% under local conditions, the hybrid electric vehicle 4 has the highest predicted choice probability, i.e. biggest predicted market share in this case, of 0.74 (in MNL with E). According to the prediction from MNL with E, when E_1 is less than or equal to 0.4, hybrid electric vehicle 4 dominates the target market. However, when E_1 increases to 0.5 level, the predicted choice probabilities change significantly, as shown in the middle of the figure. Each car model has its niche in the market. Similarly, when E_1 is larger than or equal to 0.6, conventional vehicle 9 becomes the dominant car model, as it has the highest choice probability. This suggests that customers with extreme driving conditions (E_1 close to 0 or 1) have stronger, or clearer preference to a specific car model, which is consistent with our experience. In comparison, the predicted dominant vehicle choice by MNL without E turns out to be hybrid electric vehicle 8 with a choice probability of 0.2258, which is significantly different from the one predicted by MNL with E. Since the missing usage information plays a key role in customers' choice, as demonstrated earlier in this section, and it is natural to expect customers make distinctive decisions when usage context changes, the results of MNL with E are more trustworthy.

6 CONCLUSION

Forecasting future demand for alternative fuel vehicles, such as hybrid electric vehicles and plug-in hybrid electric vehicles, is a challenging yet promising task. It is not only of interest for consumers and vehicle manufacturers, but also critical for policy makers in support of their energy saving strategies. Many aspects are involved in consumers' decision making process when they are shopping

for a new vehicle, which calls for a comprehensive modeling framework to incorporate the heterogeneous usage context and customer preference into the traditional engineering product design process.

In this paper, a systematic taxonomy is laid out based on established literature in marketing domain to provide foundation for usage context based design. Further, a comprehensive framework of usage context based choice modeling is presented to capture the usage context's impact on product performance and customer preference. Uniquely, product performances, one type of customer desired attributes, are explicitly modelled as a function of product design variables, customer profile, and usage context, which reflects heterogeneity in customer preference and their usage context.

The case study of hybrid electric vehicle illustrates the usefulness of the modeling framework and demonstrates the importance of modeling usage context using revealed preference data. The results show that both product performance and customer preference are influenced by usage context. Further, the choice model is integrated with the ordered logit model to study the impact of vehicle design on consumer's choice of HEVs. Several interesting implications are reported. For instance, customers who drive primarily under local condition prefer hybrid electric vehicles while the highway drivers don't. In the what-if-scenario analysis, it is shown that customers change their choice in response to the change of performance ratings in distinctive usage context.

The key contribution of this work is to bridge the gap between engineering product design and customers' choice of new products through the usage context based choice modeling framework. The presented framework can greatly benefit the traditional engineering design by linking the product design to customers' choice. Moreover, an optimization problem can be formulated using the proposed framework to determine the optimal performance targets for engineering design. For example, in the case of HEV battery design, performance targets include MPG city and highway measured as well as vehicle horsepower and torque. Future work is to demonstrate the use of HEV choice model for usage context based vehicle design and to extend the choice model of HEV to that of PHEV by incorporating stated preference data.

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