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ABSTRACT

Usage Context-Based Design (UCBD) is an area of growing interest within the design community. Usage context is the set of scenarios in which a product (or service) is to be used, including the environments in which the product is used, the types of tasks the product performs, and the conditions under which the product is purchased and operates. It is proposed in this work that in choice modeling for usage context-based design, usage context should be a part of the primary descriptors in the definition of a customer profile, in addition to the socio-demographic attributes for modeling customers' heterogeneity. As customers become more technology-savvy and market-educated, current choice modeling methods in engineering design could greatly benefit from exploiting the rich contextual information existing in product usage. In this work, we propose a choice modeling framework for Usage Context-based Design (UCBD) to quantify the impact of usage context on customer choices. We start with defining a taxonomy for UCBD. By explicitly modeling usage context's influence on both product performances and customer preferences, a step-by-step choice modeling procedure is proposed to support UCBD. Two case studies, a jigsaw example with stated preference data and a hybrid electric vehicle example with revealed preference data, demonstrate the needs and benefits of incorporating usage context in choice modeling.

NOMENCLATURE

A	Customer-desired product attributes
β	Coefficients in customer's choice utility function
CV	Conventional vehicle
DCA	Discrete Choice Analysis
DOE	Design of experiment
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
k	Cut points in ordered logit model
M	Exogenous variables (representing sources of uncertainty in market)
MNL	Multinomial logit
P_{ni}	Choice probability for product i and customer n
PHEV	Plug-in hybrid electric vehicle
R	Subjective ratings
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
Y$_r$	Performance of service results
Y$_t$	Performance of transformation

1. INTRODUCTION

Customer choice (demand) modeling is becoming prevalent in engineering design research for designing products or product families [1-13]. Accurately capturing customer choice is essential because it allows for the prediction of future product demand as a function of engineering design across a heterogeneous customer population, characterized by multiple market segments. Capturing heterogeneous choice behavior is achieved using disaggregate demand modeling methods, with the probabilistic Discrete Choice Analysis (DCA) [14] method being the most widely used approach used in engineering design. Depending upon the degree of heterogeneity and the specific design problem, different types of DCA models, such as multinomial logit models [15], nested logit models [16], and mixed logit models [17], have been utilized in design to capture heterogeneity in customer preferences. For instance, by allowing random taste variation across the population using a Hierarchical Bayes mixed logit model, Michalek [4] modeled heterogeneity in customer preference using random model parameters (i.e. random heterogeneity) without including the customer profile into choice modeling. Sullivan et al. [7]

compared continuous representations of customer heterogeneity using Hierarchical Bayes mixed logit models with discrete representations using Latent Class mixed logit models where customers are grouped into segments based on their preferences; several limitations of the Latent Class mixed logit models for fully capturing preference behavior were identified. By introducing the customer profile attributes as explicit terms in the choice utility function, Hoyle et al. [18] introduced systematic customer heterogeneity, in addition to random heterogeneity, into a hierarchical choice modeling framework using a Hierarchical Bayes mixed logit model.

While previous works have laid the foundation for modeling the heterogeneity in consumers' choice behavior, the potential of disaggregate choice modeling in engineering design has not been fully realized due to an overreliance on marketing and demographic attributes (gender, age, income etc.) to approximate the complex drivers behind heterogeneous customer choice. Existing choice modeling methods lose their effectiveness and fail to offer insights into *why* choices were made, because of the limited scope of customer attributes included in the model. For this reason, it is necessary to investigate the reasons behind and the situations under which a product is being *used* to fully understand and model heterogeneous choice behavior. Hence, we must delve into a more proactive modeling approach to discover driving factors underlying customers' choices by taking into account the *usage context* of a product. In this work, the usage context of a product is defined as "*all aspects describing the context of product use that vary under different use conditions and affect product performance and/or consumer preferences for the product attributes*". The usage context may also have a significant impact on the product performance, which is not considered in existing methods that simply treat product performance as "constant" across all consumers and usage contexts in choice modeling.

Marketing researchers were among the first to recognize the importance of product usage context. As Belk pointed out, *use situation* has "a demonstrable and systematic effect on current behavior" [19]. Dickson [20] proposed a person-situation (*usage context* in our terminology) framework in which the market is explicitly segmented by groups of consumers within usage situations. More recently, De la fuente and Guillen [21] studied the usage suitability of household cleaning products and their influences on purchase behavior. Although existing literature illustrated the significance of usage context in the consumers' choice process, the linkage between usage context and product performance as well as product design is missing, which calls for an innovative way to explicitly model usage context's impact with analytical methods.

In this work, we propose the founding principles underlying a choice modeling approach to Usage Context-based Design (UCBD), where usage context is considered as a critical part of driving factors behind customers' choice, in addition to customer demographic attributes and product design attributes. In this paper, we first provide a review of usage context influence, based on the literature from both market research and engineering design (Section 2). A taxonomy for UCBD is proposed in Section 3 by defining the important terms and their relations. Next, we discuss how the taxonomy is integrated into a step-by-step choice modeling procedure to support UCBD which captures the impact of usage context by explicitly modeling its influence on both product performances and customer preferences (Section 4). Findings from both a jigsaw case study with stated preference data (Section 5) and a hybrid electric vehicle (HEV) case study with revealed preference data (Section 6) demonstrate the needs and benefits of incorporating usage context in choice modeling. Conclusions and future work are summarized at the end.

2. LITERATURE ON USAGE CONTEXT STUDY

2.1. Usage context literature in market research

Marketing researchers have long been interested in understanding and conceptualizing the underlying factors behind customer behavior and therefore are among the first to recognize the power of situational (usage contextual) influence on behavior [22-24]. Belk [19] laid out the definition of *use situation* as follows: "all those factors particular to a time and place of observation which do not follow from a knowledge of personal (intra-individual) and stimulus (choice alternative) attributes, and which have a demonstrable and systematic effect on current behavior." Belk later proposed a revised stimulus-organism-response (S-O-R) paradigm [25] in which the stimulus is divided into an object and a situation, or *usage context* in our terminology. Relating to Belk's S-O-R paradigm, we propose here an UCBD influence diagram as illustrated in Figure 1.
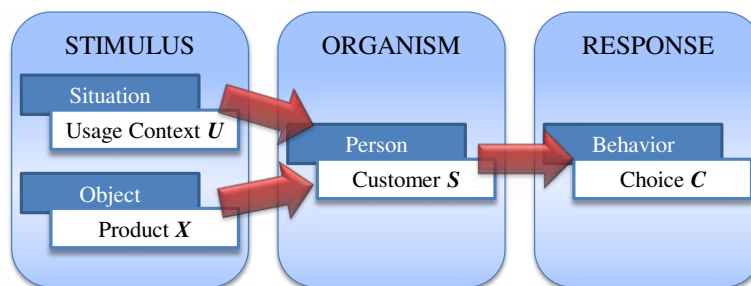

Figure 1: UCBD Influence Diagram based on Belk's S-O-R Paradigm

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*. Besides the conceptualization, Belk's categorization of five groups of situational characteristics (named *usage context attributes* **E** in this work) [25] serves as the foundation for developing and classifying the usage context attributes for choice modeling; more details on this subject will be provided in Section 3.

The need for considering situational (usage contextual) variables in market segmentation was first recognized in the 1980s. Dickson [20] 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. [26] recommends ending the common practice of segmenting customers based on their demographics and replacing it with ways that reflect how customers actually live their lives. The "substitution in use" (SIU) approach by Stefflre [27] was developed based on the premise that consumers think about product category instances within their functional roles in various possible usage contexts. As a further validation of this premise, in a more recent case study of snack foods, Ratneshwar and Shocker [28] showed that products which do not belong to the same category could be considered as comparable in certain usage contexts, highlighting the need for constructing different choice set alternatives based on customer profile and usage context. More recently, De la fuente and Guillen [21] analyzed consumer perceptions with regard to the suitability of household cleaning products to anticipated usage contexts, as well as their influences on purchase behavior. In the case of multiple usage context scenarios, Berkowitz, Ginter and Talarzyk [29] suggested aggregating an individual's given usage situation demand weighted by the situation's frequency of occurrence or importance. While their approach

demonstrated the influence of usage suitability on consumer choice, the linkage between usage context and product performance, as well as product design is absent.

2.2. Usage context literature in engineering design

Even though the study of usage context in consumer behavior has been prevalent for years, it had not been applied to engineering design until 1990s. In Ulrich and Eppinger's product design and development book [30], the need for designers to envision a product's "use environment" in identifying customer needs is emphasized. Methods have been suggested to observe a product in use as a way of gathering raw data from customers. More recently, Green et al. published three successive papers [31-33] on a frontier design method for product usage context, which is defined as a combination of application and environment in which a product will be used. A broader concept of *product design context* is constructed, consisting of three contexts that influence customer preferences: *usage context*, *customer context* and *market context*. 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. Most recently, study on usage context attributes of Hybrid Electric Vehicles [34] suggested that usage context should be treated as an additional dimension of the customer characterization process to reflect their preference heterogeneity.

While previous work introduced usage context-based design, their findings on usage context are mainly focused on qualitative analysis to support concept generation. However, the benefits of understanding usage context have great potential in an analytical design process as well. Through a choice model, we can understand the impact that usage context has on product performance and customer preferences, and therefore optimize product design to maximize the customer demand, or profit contributed by the product. In this work, we propose a comprehensive choice modeling framework for Usage Context-Based Design (UCBD) to quantitatively incorporate usage context into the product design process. In the following sections, a taxonomy for UCBD is first provided and is followed by a presentation of the four-phase choice modeling procedure, illustrated with two case studies.

3. TAXONOMOY IN USAGE CONTEXT-BASED DESIGN

As shown in Section 2, previous works in marketing research and product design have employed different definitions and terminologies for usage context related variables. For instance, *usage context* is also called *use situation*; a *usage context attribute* is also referred to as a *situational variable*. To establish a common foundation for choice modeling in UCBD, we devote this section to defining a taxonomy by following the established classification in the market research domain and the specific needs associated with product design. To illustrate the taxonomy, the design of a jigsaw for cutting wood is used as an example throughout this section.

Usage context attributes – **E**

Usage context attributes **E** refer to the characteristics or attributes used to describe the usage context. Associated with this taxonomy is the definition of "usage context". Belk [19] stated that use situation includes all factors that influence the customer behavior at a given time and place, except for the customer profile and product attributes. Unlike Belk, Green et al. [33] narrows down the scope of "usage context" to two major aspects, the application context and the environment context, and limits the influence of usage context to customer preferences only. Usage context in real life varies significantly across product categories. In our view, its influence on customer behavior includes the impact on product performance, choice set, and customer

preference. Hence, we define the usage context in our work as "*all aspects describing the context of product use that vary under different use conditions and affect product performance and/or consumer preferences for the product attributes*". This definition emphasizes two concepts key to our approach. First, usage context covers all aspects related to the use of a product, but excludes customer profile (demographic attributes) and product attributes, which will be defined later on in this section. Second, usage context influences customer behavior through product performance, the choice set, as well as customer preference.

One consideration to note is that, under many circumstances, it is difficult to draw a clear distinction between the customer profile and usage context as separate sources of influence on customers' choice. In some cases, customer profile attributes may also seem like a usage context attribute, or vice versa. For example a customers' purchase history can be regarded either as a customer attribute or as a usage context. As a guideline, we refer to customer profile attributes as those stable characteristics of a customer that do not vary over a set of usage contexts, while those temporal, transitory characteristics of a customer that do vary over usage contexts belong to the area of usage context. In other words, these usage context attributes change from application to application or from environment to environment over time. For example, the skill of the customer to successfully accomplish a cutting task using a power tool, brand loyalty, and positive or negative experiences with a particular brand [35], are considered as *customer profile attributes*, since they are more stable over time than the *usage context attributes*.

Specific to the choice modeling process, we can divide usage context attributes $\mathbf{E}$ into *performance*-related and *preference*-related, according to the way in which they impact customer behavior. These usage context attributes $\mathbf{E}$ can be either continuous or discrete. While performance-related attributes $\mathbf{E_Y}$ influence product performance $\mathbf{Y}$, preference-related attributes $\mathbf{E_W}$ have an impact on the choice set and customer preference. In some cases, performance-related and preference-related usage context attributes are not mutually exclusive. For example in using a jigsaw, if the saw is to be used for cutting outdoors, the density of saw dust experienced by the user may be different than if the saw were used indoors (performance impact), whereas the user may prefer a bright saw color for outdoor use so that the saw will be easily identified if placed on the ground (preference impact). Whether a usage context attribute is related to performance or preference can be determined by prior knowledge of experienced users or by the observations of products being used. Prior knowledge of a usage context attribute's influence on preference can be used to reduce the complexity of estimating a choice model, and hypothesis testing of a usage context attribute in the choice model estimation process can be used to confirm this knowledge.

Customer profile attributes – $\mathbf{S}$

The customer profile $\mathbf{S}$ includes all stable or permanent aspects of customer profile attributes impacting customer choice behavior, for example, *gender*, *age*, *income* bracket, etc. In the choice modeling of UCBD, customer profile attributes $\mathbf{S}$ may have a direct impact on customers' preference and therefore may influence their choices. Similar to usage context attributes, customer profile attributes $\mathbf{S}$ can be categorized into performance-related $\mathbf{S_Y}$ and preference-related $\mathbf{S_W}$ to differentiate their impact. For example, household income belongs to $\mathbf{S_W}$, 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, skill level of the customer operating jigsaw is considered as a performance-related $\mathbf{S_Y}$, because jigsaw performances vary when operated by a beginner, intermediate, or experienced user.

Customer desired product attributes – **A**

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

Engineering performance **Y** refers to all performance-related engineering attributes. Since **Y** plays a critical role in the engineering design process, engineering performance **Y** is our focus in this work. In the jigsaw example and other similar cases, engineering performance **Y** is further divided into *performance of service results* and *performance of service delivery* or transformations. The performance of service results Y_r represents the measures of the end performances of the resulting service, such as cutting precision, planarity, etc. On the other hand, the performance of service delivery or transformations Y_t represents the measures of the performances related to the delivery of the service, such as linear speed, noise, vibration, safety conditions, etc. The performances of the service delivery are no longer visible in the results once it has been delivered.

Non-engineering attributes **M** include all non-engineering aspects of customer desires attributes, for example, price, brand, aesthetics and other common marketing measures. 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.

Product choice set – J_n

The product choice set J_n is defined as a group of product alternatives customers consider during their choice procedure. Simonson [36] showed that choices are made in the context of a consideration set, i.e. a choice set. Since only differences in utility matter due to the nature of choice models, the selection of a product choice set exhibits great impact on customer choice. Methods for determining the appropriate choice set considering usage context are described in Section 4.

Product design variables – **X**

Product design variables describe the engineering decisions involved in product design. In the jigsaw case, blade tooth height, stroke frequency, step distance between two teeth, etc., all belong to the product design variables **X**.

4. CHOICE MODELING FRAMEWORK IN USAGE CONTEXT-BASED DESIGN

In order to capture the impact of usage context and utilize usage context information in a design process, a framework for choice modeling in UCBD is proposed. Our discussion follows the sequence of four major phases for implementing the choice modeling framework.

Phase I   Collect usage context information and identify usage context attributes **E**. (**usage context identification**)

Phase II   Collect customer choice data together with choice set information J_n, customer profile **S** and their usage context attributes **E**. In a stated preference survey, a choice experiment representing different combinations of customer profile and usage context is designed where each respondent makes the selection among a

choice set for given usage scenarios. For revealed preference data collection, all data from real customer purchases are recorded. (**data collection**)

Phase III Create a physics-based model or a human-appraisal-based ordered logit model for predicting engineering performance **Y** as a function of usage context attributes **E**, customer profile $\mathbf{S_Y}$, and design variables **X**. (**linking performance with usage context and customer profile**)

Phase IV Create a choice model for market share and demand estimation (**choice model estimation**)

In the rest of this section, details for each phase are provided.

Phase I: Usage Context Identification

A successful product design requires an understanding of customers' needs so that the products produced will match customers' interest. Similarly, in the proposed choice modeling framework for UCBD (Figure 2), we start with a survey through which important usage context attributes and common usage context scenarios among target customers are identified. Widely used survey methodologies include focus groups, one-on-one interviews of experienced users, and observations of the product being used [30].
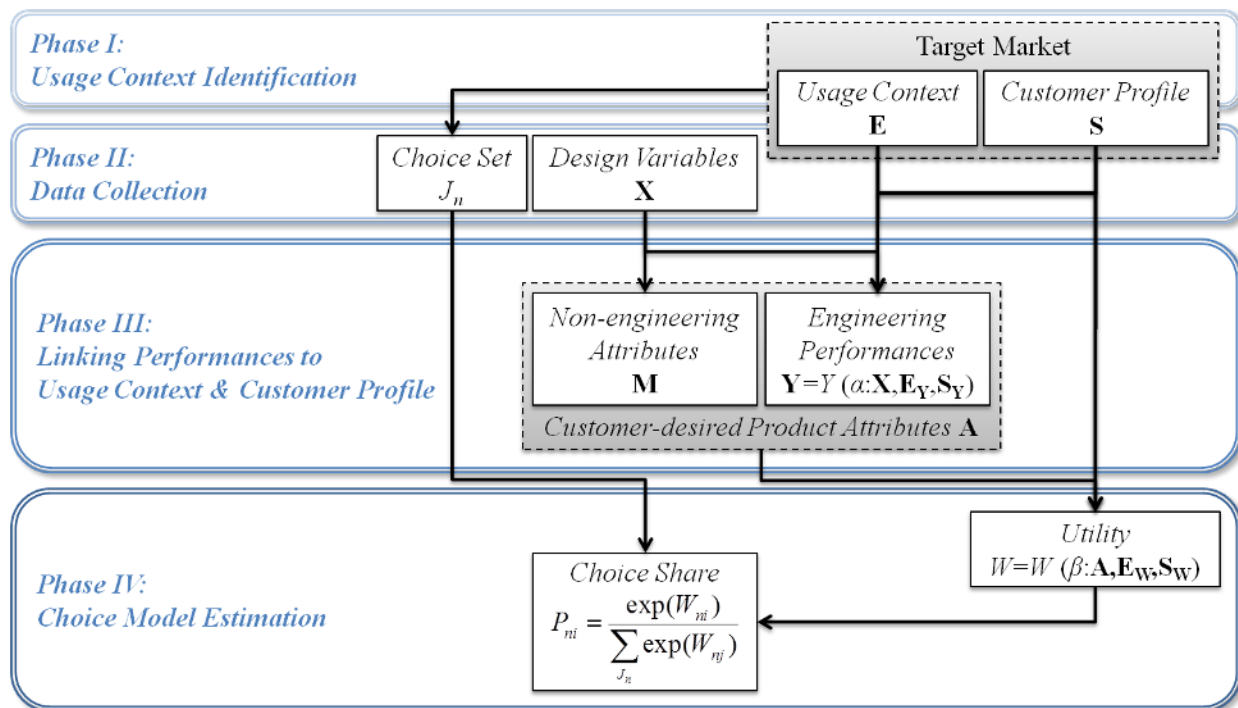
Figure 2: Choice Modeling for Usage Context-based Design

Following Belk's classification [25], usage context can be categorized into five types: *physical surroundings*, *social surroundings*, *temporal perspective*, *task definition*, and *antecedent states*. In Table 1, we use the jigsaw example to illustrate how the usage context attributes can be defined by following these five basic categories. It should be noted that based on Belk's classification, the scope of the usage context attributes is beyond the act of using the product, but also includes the context of purchase.

Table 1: Five Categories of Usage Context

Usage Context Type	Jigsaw Example
Physical surroundings	Location of cutting, Accessibility of an outlet, Availability of workbench, Distance to do-it-yourself (DIY) stores.
Social surroundings	Presence of children, neighbors.
Temporal perspective	Expected process duration, Lifetime of similar cutting tools in possession, Estimated time needed to purchase the tools in a nearby DIY store.
Task Definition	Material properties, Board thickness, Minimal linear speed, Maximal vibration level, Noise and safety conditions, Accuracy requirements.
Antecedent states	Set of saw tools already in possession, New life conditions or projects, Cash at disposal.

Physical surroundings are the most apparent characteristics of a usage. These characteristics include geographical location, weather condition, lighting, and other physical characteristics of a usage, as well as the distance to do-it-yourself (DIY) stores when the new tool is needed. In the case of using a jigsaw for cutting a board, the location where the operation must take place (indoor/outdoor), the accessibility of a power outlet, the availability of a workbench are typical examples of physical surroundings.

Social surroundings provide additional information about the social situation of a usage. Whether another person is present, his/her influence on the user, and other social characteristics belong to this category. For instance in cutting a board, one may prefer a jigsaw to a circular saw often used under these conditions, for reasons of safety and noise because of the presence of children nearby.

Temporal perspective refers to those aspects of the purchasing situation or to those of a given usage which are specific for a given range of time. For instance, the expected process (cutting task) duration may be a reason for preferring a circular saw to a jigsaw or a powerful jigsaw to a more basic one (faster linear speed). The age and expected lifetime of the cutting tools in possession are also deciding factors to determine how to upgrade the set of cutting tools in order to complete a set of cutting tasks. In terms of purchase situation, the time and emergency aspect for buying a new tool in a surrounding DIY store may also be determining under certain circumstances.

Task definition covers all features that explain the purpose of the purchase. For instance, one must consider the type of material to cut (wood, steel, etc.), the specification of the cut (blind or not, straight or wiggly, orthogonal or inclined), the properties of material (cutting hardness which is physically proportional to the material density), the thickness of the board to cut (beyond a certain thickness, the cut is impossible), the minimal linear speed that is acceptable when the

user delivers the maximal amount of pushing arm forces and wrist torques, the maximal vibration level that is tolerable, or the admissible noise and minimal safety conditions.

Antecedent states define a dimension of usage which is antecedent to the purchase. The factors for a new jigsaw acquisition may be the set of saw tools one already possesses (circular, chain, panel, bow, miter, etc.) and their respective age and expected remaining lifetimes, a new life condition or project (moving from an apartment to a house, or a house remodeling), and the cash at one's disposal.

The above-mentioned five categories of usage context attributes can be used as a checklist in the process of determining the potential usage context attributes. For stated preference surveys, as will be demonstrated in the jigsaw case study (Section 5), a user survey is used to collect the set of primary usage context attributes **E**. For problems with a large number of usage context attributes **E**, a cluster analysis becomes essential to reduce the possible combinations of usage context attributes **E** to a manageable size, and focus the study on a set of common usage context scenarios, i.e. the most common combinations of usage context attributes **E**.

Phase II: Data Collection
Due to the nature of data collection, surveys can be divided into Stated Preference (SP) [37] and Revealed Preference (RP) [38]. SP refers to choice experiments where respondents are presented with a set of simulated product options from which they make a choice. This approach is attractive for model building because a high level of control can be exercised over the collected data, resulting in a data set optimized for choice modeling. However, SP data does not represent real purchase behavior and such surveys require significant time and additional cost to administer, thus resulting in a limited size and quality [39] dataset. For these reasons, it is sometimes desirable to utilize actual purchase data and customer satisfaction surveys collected.

In a stated preference survey, a choice experiment is conducted in which customers are asked to make a choice among several available alternatives under given usage context scenarios. Since the number of products available is usually much larger than the number of products a customer can use and compare in a choice experiment within a reasonable amount of time, an optimal experimental design can be applied to reduce the number of products in the choice set to a feasible level. For example, a nested design of experiments (DOE) on $(J_n \mid S, E)$ can be applied to find the optimal set of choice alternatives for respondents based on their customer profile *S* and usage context *E*. The D-optimal experiment design algorithm for human appraisal surveys [40] can be used to select the products to include in the choice set for best model estimation.

A try-it-out survey is highly recommended for collecting SP data, in which customers are asked to use the products under given usage scenarios, rate the performances, and make a choice of one of the products. There are many advantages to conducting a try-it-out survey: first, hands-on experience is very important as it often simulates a real purchase process better for products that are typically tested prior to purchase; second, customers experience the product under certain usage contexts, which ensures the relevance; and third, assessments of the product performance reflect customers' perceived product performance. On the other hand, the try-it-out survey often requires more resources than a paper survey, where photos (or images) and data specification sheets are commonly used to present the products.

As for the revealed preference survey, all interesting product attributes, the customer profile, the usage context, and the choice set considered by each customer are recorded, together with the purchase decisions. RP data has the advantage in that it reflects consumers' real choice behavior;

however, RP data may present issues with collinearity, endogeneity, and lack of randomization. An examination of the information matrix from choice model estimation could identify the possible orthogonality issues in RP data. In some cases, customers' ratings of product performances are also collected in RP surveys to capture customers' perceived product performances. Such level of detail is required to model the impact of usage context on product performance and customer preference as introduced next.

Phase III: Linking Performance with Usage Context and Customer Profile
    This is a unique phase for UCBD applications in which product performances $\mathbf{Y}$ are formulated as a function of performance-related usage context attributes $\mathbf{E_Y}$, performance-related customer profile attributes $\mathbf{S_Y}$, and product design variables $\mathbf{X}$, as shown in Equation (1):
$$\mathbf{Y}_{ni} = Y(\alpha : \mathbf{E}_{\mathbf{Y}n}, \mathbf{S}_{\mathbf{Y}n}, \mathbf{X}_i) . \tag{1}$$

where the coefficients α can either be established by a physics-based model or determined through a human-appraisal-survey-based regression model. The physics-based model is constructed based on the physical relations. Taking the jigsaw design as an example, a system of equations can be derived to calculate the translational force and the torque on the user's wrist to assess the user's comfort level during the cutting process as a function of wood type and thickness as well as of admissible force and torque depending on the user experience [41]. The second approach utilizes rating data given by customers in a human appraisal survey and builds a regression model to predict the ratings of performances $\mathbf{Y}$. While the physics-based model saves the time and cost of a survey, a human appraisal survey can be used to assess either quantitative or qualitative performance perceived by the consumers. Such surveys can be integrated into the try-it-out survey for choice modeling, as described in Phase II. The ordered logit model [42] is used for modeling the discrete rating data in the hybrid electric vehicle case study in this work.

Phase IV: Choice Model Estimation
    As shown in Figure 2, in Phase IV a predictive model of demand Q is established using Discrete Choice Analysis (DCA), a statistical technique of building probabilistic choice models [14, 43]. 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):
$$u_{ni} = W_{ni} + \varepsilon_{ni} . \tag{2}$$

    As shown in Equation (3), the observed or deterministic part of utility W_{ni} is expressed as a function of customer desired product attributes $\mathbf{A}$, usage context attributes $\mathbf{E}$, customer profile attributes $\mathbf{S}$.
$$W_{ni} = W(\beta : \mathbf{A}_{ni}, \mathbf{E}_{\mathbf{W}n}, \mathbf{S}_{\mathbf{W}n}) . \tag{3}$$

where $\mathbf{A}_{ni}$ denotes the customer-desired product attributes of respondent n, alternative i, $\mathbf{E}_{\mathbf{W}n}$ and $\mathbf{S}_{\mathbf{W}n}$ denotes the preference-related customer profile attributes and usage context attributes of respondent n. The coefficients β are estimated based on the data collected in Phase III. From the

observed utility, W_{ni}, the probability P_{ni} of an individual i choosing a given alternative n can be estimated. By following the information flow in the four-phase diagram (Figure 2), we can see clearly how product design variables **X,** together with the definitions of usage context **E** and consumer profile **S**, are first mapped to product performance **Y** (Eqn. (1)), then to deterministic utility W (Eqn.(2)), and finally to the probability of choice P_{ni} , which can be aggregated to the total market share based on predictions for a population. This flow creates a mathematical link between product design decisions, represented by **X**, to consumer demand, represented by P_{ni}.

5. JIGSAW EXAMPLE

In this section, the design of a jigsaw is used to demonstrate the implementation of the proposed usage context-based choice modeling approach with stated preference data. The jigsaw is a common power tool for cutting wood. Under different usage contexts, the jigsaw performances, as well as the customers' preferences for the saw, change. The choice set considered in the user survey is formed by a few representative jigsaw products in the market. The four phases of choice modeling for UCBD are illustrated with the hypothetical saw design and a few representative attributes for demonstration. A choice model is built and estimated on synthetic survey data generated using a few key assumptions about customer preferences. Results are discussed which demonstrate the proposed framework.

- *Phase I: Usage context identification*

Phase I is completed with three tasks: *collect usage information*, *identify common usage contexts through cluster analysis*, and *identify usages context attributes*. We start with a user survey in which questions about primary usages are asked. It should be noted that the primary usage context is not limited to the most frequent usage context, and can be defined by the user. In some cases, for instance, a saw is expected to accommodate the most-demanding usage context. As described in Section 4, five categories of usage context can be used as a guideline for determining the usage context attributes. Figure 3 shows a small portion of the sample user survey questionnaire as an example. A few typical usage context questions for a jigsaw user would include wood type, working environment, etc.

Please answer the following question by choosing the best description of your primary saw usage context.

1. The woods you are cutting are:
   soft   medium   hard
2. The working environment of your cutting is:
   indoor   outdoor

Figure 3: Sample User Survey Questionnaire for Phase I

In this case study, we select *wood type* and *working environment* as two usage context attributes **E** for demonstration purpose; wood type (it amounts to wood density in fact) is considered as a performance-related attribute $\mathbf{E_Y}$ that influences product performance **Y**, while both wood type and working environment are treated as preference-related attributes $\mathbf{E_W}$ with an impact on customer preference. The *wood type* attribute is coded as 1 for soft, 2 for medium, and 3 for hard, while the *working environment* attribute is coded as 0 for indoor and 1 for outdoor. Based on the survey data of common usages, cluster analysis is performed. For our case study, indoor cutting for soft wood, outdoor cutting for medium wood, indoor cutting for medium wood,

and outdoor cutting for hard wood are identified to be the most common usages (Table 2) based upon the results from a k-means clustering analysis [44] on the hypothetical survey data with two usage context attributes, *working environment* and *wood type*, and k (number of clusters) = 3.

Table 2: Common Usage Contexts Identified from Cluster Analysis

No.	Working environment E_1	Wood type E_2	Usage context description
1	0	1	indoor cutting for soft wood
2	1	2	outdoor cutting for medium wood
3	0	2	indoor cutting for medium wood
4	1	3	outdoor cutting for hard wood

- *Phase II: Data collection*

Various human-appraisal experiments can be utilized to collect consumers' preferences under different usage contexts as described in Section 4. The question lies in how to minimize the amount of surveys to cover the various attributes included in choice modeling. Here we assume that each respondent is surveyed for more than one usage context (but only one primary usage context at a time in the choice experiment). We also assume that all respondents have some level of experience with the product and are able to differentiate between the different usage contexts described in the survey questionnaire. Eight jigsaw products available in the market are considered, but only four products that are most relevant for a given usage context form the choice set J_n in each choice experiment. Three customer profile attributes are included: *gender* (0 for male and 1 for female), *income* (annual income in $1,000s), and *skill level* (1 for elementary user, 2 for experienced user, and 3 for professional user).

The synthetic data are simulated with 500 respondents, 4 choices alternatives, and 4 usage contexts (8,000 observations in total) based on a few key assumptions about customer preferences. Table 3 presents three categories of attributes considered for choice modeling, including three customer-desired product attributes **A** (*price*, *advance speed*, and *comfort*), two usage context attributes **E** (*working environment*, and cutting board *wood type*), three customer profile attributes **S** (*income*, *gender*, and *skill level*), together with four design variables **X** (*blade tooth height*, *stroke frequency*, *blade translation*, and *step distance between teeth*).

Table 3: List of Attributes and Design Variables included in Jigsaw Case Study

Customer Desired Product Attributes **A**		
M	Price	
Y_{t1}	Advance speed S_a	
Y_{t2}	Comfort level $P_{comfort}$	%
Usage Context Attributes **E**		
E_1	Working environment	indoor, outdoor
E_2	Cutting board wood type	soft, medium, hard
Customer Profile **S**		
S_1	Income	uniform dist. , [50k, 150k]
S_2	Gender	male, female
S_3	Skill level	1, 2, 3
Product Design Variables **X**		
H_d	Blade tooth height	

F	Stroke frequency
A	Blade translation
s	Step distance between teeth

It should be pointed out that the experimental design is not unique, and can be designed based on the number of respondents who are available [40, 45]. For example, when there are a large number of respondents, fewer choice experiments can be used for each respondent, than in experiments with fewer respondents. Pairing the usage contexts to customers' primary usages is recommended, as it yields a better understanding of the influence of usage context attributes. If a two-stage (consumer) decision making process is considered (i.e., first the choice set is selected followed by the specific product), the survey will be designed for predicting the choice set for each customer first.

- *Phase III: Linking performances with usage context and customer profile*

In this study, the link between product variables **X**, performance-related usage context attributes $\mathbf{E_Y}$, performance-related customer profile attributes $\mathbf{S_Y}$, and engineering performance **Y** (Eqn. (1)), is established using a series of physics-based equations based on the functional principles of the jigsaw [41, 46]. Both engineering performances **Y** considered in this study, the advance speed S_a and comfort level $P_{comfort}$, belong to Y_t (performance of transformation). The advance speed S_a is calculated as follows:

$$S_a = \frac{2H_d f \cdot A}{s} \tag{4}$$

where H_d is the blade tooth height, f is the stroke frequency, A is the blade translation, and s is the step distance between two teeth. All variables in the equation (H_d, f, A and s) are product design variables **X**; usage context doesn't influence this particular performance. The comfort level $P_{comfort}$ is associated with the required wrist torque with respect to user' maximum wrist capability, as shown in the following equation:

$$P_{comfort} = 1 - \left| \frac{M_w}{M_{w-max}} \right| \tag{5}$$

where M_w is the wrist torque and M_{w-max} is the maximal wrist torque that can be delivered by the user. In [41, 46], M_w is modeled as a function of both product design variables **X** and usage context attributes $\mathbf{E_Y}$ (i.e., wood type), while M_{w-max} is modeled as a function that depends on customer profile attributes $\mathbf{S_Y}$. Details of the above physics-based equations can be found in references [41, 46].

- *Phase IV: Choice model estimation*

A multinomial logit model is estimated using STATA [47]. The goodness of fit, measured by the rho square is 0.82 with a log likelihood of -500.76. The coefficients the estimators, standard errors, and the significance of their *p* values are provided in Table 4. The price *M* is divided by the income S_1, as customers with higher income are expected to be less sensitive to the price. The sign of the M/S_1 coefficient shows that price has a negative impact on the utility function. The coefficients of Y_{t1} and Y_{t2}, are both significant, showing that both performances are important in

users' choice. Therefore, in-service and service performance results must be considered in the jigsaw design. The coefficient for S_2*Y_{t2} is significantly positive, which indicates that the female users tend to care more about the comfort than male users do. This is important to consider in the design process if the intended market for the saw has a sizable female population. Similarly, the coefficient for S_3*Y_{t1} is significantly positive, meaning that skilled users care more about the advance speed during cutting, compared with amateur users. As for the interactions between performance Y_{t1} and usage context variable E_1 (indoor / outdoor) and performance Y_{t2} and usage context variable E_2 (wood type), both coefficients are statistically significant, which indicates that both E_1 and E_2 belong to the category of preference-related usage context variable E_W. Moreover, the negative sign suggests that Y_{t2} (comfort) is less important when users are cutting outdoors (E_1=1), while the positive sign indicates that advance speed is more critical when users are cutting hard wood (E_2=3). This again provides direction in the design process: for example, if the intended market for the saw is users cutting soft to medium woods (e.g. framing materials), then advance speed is not as important in the design than if the intended market is for those cutting hard woods (e.g. hardwood flooring). The results from this case study are consistent with the general trend in customer preferences assumed in data generation.

Table 4: Multinomial Logit Model Estimation Results in Jigsaw Case Study

Variables	Coef.	Std.Err.	P>|z|
Y_{t1}	5.39	1.42	0.00
Y_{t2}	27.30	1.98	0.00
M/S_1	-35.86	1.76	0.00
S_2*Y_{t2}	4.13	1.51	0.01
S_3*Y_{t1}	7.42	0.49	0.00
E_1*Y_{t2}	-4.94	1.62	0.00
E_2*Y_{t1}	4.06	0.49	0.00

6. HYBRID ELECTRIC VEHICLE EXAMPLE

Alternative fuel vehicles have drawn increasing attention in the past few years, because of their potential to reduce greenhouse-gas emissions and utilize renewable energy sources [48-50]. However, understanding consumer choices of alternative fuel vehicles 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 engineering design. Taking hybrid electric vehicles (HEVs) as an example, vehicle performances, such as mileage per gallon, often depend highly on their usage contexts, while consumers' attitudes towards new technology, especially "green" products, are strongly influenced by their intended usage. In this section, a hybrid electric vehicle case study is used to illustrate the proposed usage context based choice modeling framework. Different from the jigsaw problem, the revealed preference data collected by JD Power and Associates for both HEVs and conventional vehicles (CVs) is utilized for model estimation. It should be noted that in our current study, the impact of HEV policies and other purchase incentives is not considered.

- *Phase I: Usage context identification*
    Two usage context attributes are considered for HEV choice modeling: a *local/highway indicator* and *average miles driven daily*. While both attributes are treated as preference-related

attributes E_W, the local/highway indicator is also considered as a performance-related attribute E_Y in mileage per gallon (MPG) calculation, as detailed later. The local/highway indicator is assessed based on the combined MPG published by US Environmental Protection Agency [51] and the estimated MPG given by survey respondents. The indicator is a continuous parameter, ranging from 0 for pure local driving to 1 for pure highway driving. It is assumed that the local/highway indicator reflects the general driving condition a respondent faces, 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 for hybrid vehicles. The other usage context attribute considered is *average miles driven daily*, a commonly used descriptor of customers' travel pattern. The data is derived from the recorded miles driven in the first three months in the J.D. Power and Associates data. This is an important usage context attribute in designing new HEV and future plug-in hybrid electric vehicles (PHEV), as average miles driven daily strongly influence the target performance of the batteries.

- *Phase II: Data collection*

The Vehicle Quality Survey (VQS) conducted by J.D. Power and Associates belongs to the revealed preference data because the customer satisfaction survey is strictly about the new vehicles respondents purchased instead of hypothetical design alternatives. In the 2007 VQS, vehicle purchase data from 90,000 nation-wide respondents on over 300 vehicles 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, data collected from 8025 respondents, who reported their vehicle choice sets, are selected. The attributes and design variables included in the choice model are summarized in Table 5.

Table 5: List of Attributes and Design Variables included in HEV Case Study

Customer-desired product 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 rating	
$A_{interior}$	Interior attractiveness rating	
$A_{storage}$	Storage and space usage rating	
A_{audio}	Audio rating	
A_{seats}	Seats rating	Discrete rating on a scale from 1 to 10
A_{hvac}	HVAC rating	
$A_{dynamics}$	Driving dynamics rating	
A_{engine}	Engine and transmission rating	
A_{safety}	Visibility and safety rating	
Usage context attributes **E**		
E_1	Local / highway indicator	0 – local, 1 – highway
E_2	Average miles driven daily	Unit: miles
Customer profile attributes **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
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

There are 288 car models covered in the data set, each of them is chosen by at least one respondent. Fifteen customer-desired product attributes **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 attribute "price" is the money respondents paid excluding tax, license, trade-in and etc. Since VQS only provides price for the purchased vehicles, the price data for other vehicles considered are estimated from a linear regression model based on vehicle make and model, and customers' geographic locations. As shown in the third column in Table 5, vehicle origins are categorized as domestic, European, Japanese, and Korean; vehicle sizes are grouped into compact, midsize, large, and premium; vehicle type includes mini, car, sport utility vehicles (SUV), minivan, van, multi-activity vehicles (MAV), and pickup. 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 a vehicle, including exterior attractiveness, interior attractiveness (as stated by the average purchaser), 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' perceived vehicle performance (quality).

Meanwhile, *gender*, *age*, *household income*, *number of children under age 20 living together* and *education level*, are included as five customer profile attributes **S**. Among the set of **S**, critical preference-related attributes S_W will be identified through choice modeling in Phase IV. All five **S** attributes are considered in the ordered logit regression for predicting the performance rating scores, as will be shown in Phase III.

- *Phase III: Linking performances with usage contexts and consumer profile*

Different from the jigsaw example in which physics-based modeling can be used to establish the relationship between performance and usage context attributes, in the HEV example, respondent survey data is used to create the relationship as shown in Equation (1) by using the ordered logit modeling method [18] for nine customer desired product attributes (**A**) in the form of ratings. Here the ratings are used to represent product performances **Y**. Seven high level engineering design variables **X** are used in this case study, including *exterior dimension*, *interior dimension*, *performance*, *MPG targets*, etc. The obtained ordered logit models are also used to predict the

ratings of other vehicle designs in the choice set as customers only rate the vehicles they purchase. This limitation of the rating data in VQS may cause ownership bias in model estimation and potentially lead to inaccurate estimates of some coefficients due to the missing heterogeneity in owners' ratings. Further details for implementing the ordered logit model based on the VQS data by JD Power and Associates can be found in [52]. In addition to the design variables $\mathbf{X}$, customer profile $\mathbf{S_Y}$ such as *gender*, *age*, etc., are included to capture customers' heterogeneity in rating. The coefficients estimators are later used for what-if-scenario analysis to forecast potential market share for targeting customer and usage attributes.

Furthermore, the impact of usage context (local/highway indicator E_1) on the vehicle performance (A_2, *mileage per gallon*) is represented in the following equation:

$$A_2 = \frac{1}{\frac{1-E_1}{MPG_{city}} + \frac{E_1}{MPG_{highway}}}. \qquad (6)$$

where MPG_{city} and $MPG_{highway}$ belong to the product design variables $\mathbf{X}$ listed in Table 5.

- *Phase IV: Choice model estimation*

In Phase IV, as a result of choice modeling, interactions between customer-desired product attributes $\mathbf{A}$, usage context attributes $\mathbf{E}$, and customer demographics $\mathbf{S}$ are explicitly modeled in the utility function. The coefficients for all attributes and their interactions based on a multinomial logit model estimation (MNL with $\mathbf{E}$) are listed in Table 6, together with the estimation results from a multinomial logit model without usage context attributes (MNL without $\mathbf{E}$) as a comparison.

Table 6: Selected 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	-0.0003	0.0000	***	-0.0004	0.0000	***
A_2	/	/		-3.1080	0.0846	***
A_2_city	0.0456	0.0139	***	/	/	
$A_2\_highway$	-0.0791	0.0141	***	/	/	
E_1*A_2	/	/		5.9454	0.1697	***
E_2*A_2	/	/		0.0002	0.0003	
$A_3\_European$	1.9353	0.0900	***	2.1886	0.1045	***
$A_3\_Japanese$	0.2314	0.0505	***	0.5161	0.0576	***
A_3_Korean	1.2617	0.0904	***	1.3313	0.1065	***
A_4_Large	-0.5636	0.0907	***	-0.9111	0.1024	***
A_4_Medium	0.0907	0.0534	**	-0.1376	0.0601	*
$A_4\_Premium$	-0.2496	0.0780	***	-0.3136	0.0888	***
A_5_MAV	-0.9746	0.0782	***	-1.3558	0.0847	***
A_5_Mini	0.6717	0.1312	***	1.3347	0.1568	***
$A_5\_Minivan$	-0.6733	0.1393	***	-0.9826	0.1607	***
A_5_Pickup	1.6354	0.1973	***	1.4446	0.2227	***
A_5_SUV	-0.0632	0.0971		-0.2733	0.1115	*
A_5_Van	1.2458	1.2891		0.8806	1.3755	

$A_6\_d\_hybrid$	2.8933	0.5878	*	57.0667	2.4840	***
$E_1*A_6\_d\_hybrid$	/	/		-105.8431	4.8316	***
$S_5*A_6\_d\_hybrid$	0.2875	0.1213	***	0.1686	0.0846	*
$A_{exterior}$	0.0593	0.0340	***	0.0407	0.0385	
$A_{interior}$	0.4835	0.0174	***	0.4585	0.0190	***
$A_{storage}$	0.5804	0.0146	***	0.6253	0.0175	***
A_{audio}	0.1741	0.0312	***	0.1421	0.0355	***
A_{seats}	0.1636	0.0373	***	0.1046	0.0424	*
A_{HVAC}	0.1242	0.0340	***	0.1285	0.0391	***
$A_{dynamics}$	0.2362	0.0380	***	0.1640	0.0433	***
A_{engine}	0.2565	0.0301	***	0.3061	0.0343	***
A_{safety}	0.0999	0.0384	**	0.0455	0.0437	

*** Significant with p value <=0.001.
** Significant with p value <=0.01.
* Significant with p value <=0.05.

From the results of the MNL including **E** attributes in modeling, we note that the coefficient for price/income is negative as expected. Only two customer profile attributes, *household income* and *education level*, are statistically significant as preference-related attributes S_W. 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, in addition to the utility increase experienced by the change in MPG. 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). This finding presents an opportunity to design a HEV which performs well in highway driving to help overcome this issue. On the other hand, most coefficients from the MNL without modeling **E** have the same sign as the ones in MNL with **E**, but they are very different in magnitude, as the usage heterogeneity is not explicitly modeled. Inclusion of usage context will help designers more specifically target the vehicle design to the usage contexts of the intended market for the vehicle. It should be noted that the results shown in Table 6 are attained through sequential estimation of a hierarchical model and do not account for error propagation. Moreover, the negative coefficient of $A_2\_highway$ is due to high correlation between A_2_city and $A_2\_highway$. Multicolinearity between explanatory variables should be cautioned in model estimation.

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 7, 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. This is important for designers so that they may best understand the preferences and usage contexts of the intended users.

Table 7: 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	0.4203	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, as listed in Table 8.

Table 8: 5-fold Cross-Validation Results for UCBCM of HEVs

Test	MNL without E		MNL with E	
Measure	ρ^2	hit rate	ρ^2	hit rate
1	58.72%	67.41%	68.10%	75.76%
2	57.10%	66.60%	66.87%	76.20%
3	56.10%	66.42%	65.61%	74.02%
4	56.35%	65.67%	65.84%	74.14%
5	55.77%	66.79%	65.98%	75.20%
Average	56.81%	66.58%	66.48%	75.07%

    On average, the likelihood ratio index ρ^2 shows an over 17% improvement from 56.81% in the MNL without **E** to 66.48% in the MNL with **E**. The hit rate, though not theoretically consistent with random utility theory, is another commonly used 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. Similar to ρ^2, the hit rate increases from 66.85% in the MNL without **E** to 75.07%, which shows that usage context greatly influences customers' choice and should be modeled explicitly. As the choice model estimation and cross-validation are performed with choice set information from the VQS, future work is needed to address the challenges in predicting choice set construction for new market.

What-If-Scenario Analysis

    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 is simulated with customer profile distribution drawn from the hybrid owner pool in VQS 2007 data set. Assuming that they are choosing a new vehicle to purchase from a choice set of 4 car models selected from 10 car models available 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 choice set of customers who considered at least one HEV. The choice set of each customer can also be predicted using statistical learning or data mining methods with existing market data. Since not all customers would consider a hybrid electric vehicle when they shop for a new car, we assume that 40% of customer would include hybrid electric vehicles in their choice set, while the rest of them don't. Additionally, we consider a series of nine different usage contexts: a uniformly distributed *local/highway indicator* with 0.2 range and mean value

from 0.1 to 0.9 (with 0.1 interval), while average *miles driven daily* matches with the original dataset. Aggregated choice probability in target population calculated using our proposed framework is summarized in Figure 4.

In Figure 4, the grey lines (conventional vehicles) and green lines (hybrid electric vehicles) 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**. For instance, when the target population, on average, drives 40% under local conditions, the hybrid electric vehicle 4 and vehicle 8 have the predicted choice probabilities of 10.72% and 12.64%, respectively in MNL with **E**, as opposed to the constant 7.32% and 8.11% in MNL without **E**. According to the prediction from the MNL with **E**, their predicted market shares gradually decrease, as E1 increases. When E_1 is less than or equal to 0.3, conventional vehicle 1 have the largest market share, closely followed by conventional vehicle 5.When E_1 increases to 0.5, 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 preferences for a specific car model, which is consistent with our experience. In comparison, the predicted dominant vehicle choice by the MNL without **E** turns out to be conventional vehicle 2 with a choice probability of 16.51%, which is significantly different from the one predicted by the MNL with **E**. Since the missing usage information plays a key role in customer choice and it is natural to expect that customers make distinctive decisions when usage context changes, the MNL with **E** is able to reveal relationships between usage context and consumer preference for product attributes that would not be revealed without E. Accurately predicting the choice probabilities (i.e. market share) for a given vehicle design, consumer population and set of usages is an important tool for vehicle designers to tailor the vehicle design to the target market as closely as possible. Further research is needed to assess implications of model specification assumptions and to test external validity on predictions of choice shares for different usage contexts.
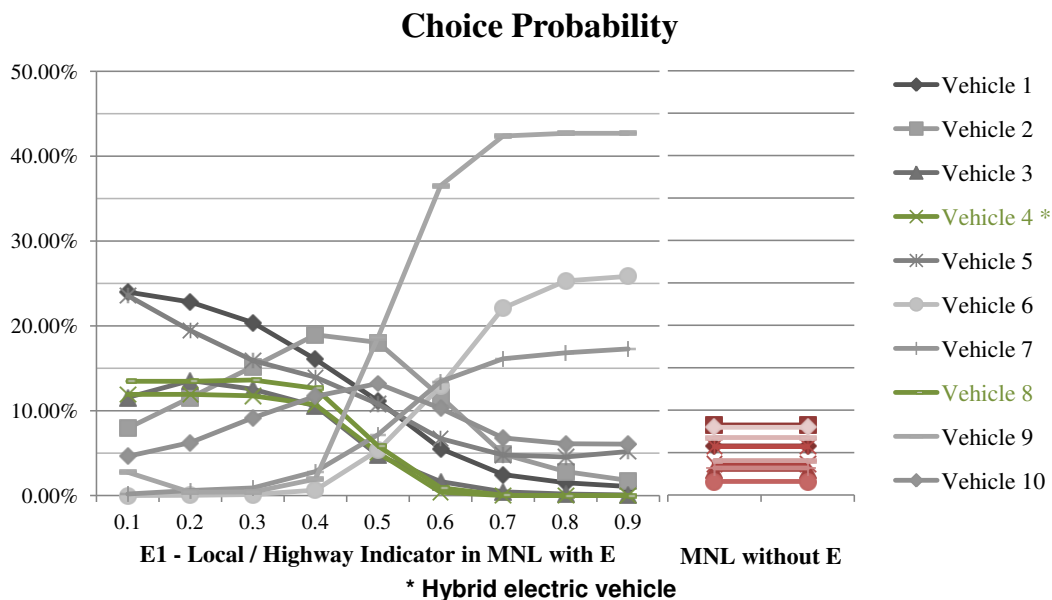

Figure 4: Choice Probability of Target Population under Different Usage Contexts

7. CONCLUSION

In this work, we propose a choice modeling framework for Usage Context-based Design (UCBD) to quantify the impact of usage context on customer choices. Previous works have illustrated the importance of considering usage context in design, but did not present a systematic and quantitative approach to choice modeling. The primary focus of this work is the development of a systematic UCBD taxonomy and a step-by-step procedure to quantitatively assess the impact of usage context on product performance and consumer preferences.

A taxonomy for UCBD is first defined by following the established classification in the market research domain and the needs associated with choice modeling. The step-by-step procedure for creating choice models in UCBD is then presented. To facilitate the identification of usage contexts in Phase I, it is recommended to elicit the usage context attributes from five categories of product usages including *physical surroundings*, *social surroundings*, *temporal perspective*, *task definition*, and *antecedent states*. In Phase II data collection, both the methods of Stated Preference and Revealed Preference surveys are presented to account for the choices respondents make conditional on the given usage context, which allows us to examine simultaneously the influence of product design, customer profile, usage context, and their interactions, on consumer choices. Furthermore, Phase III is a unique step in a quantitative usage context-based design process in which the influence of usage context and consumer profile on product performance is analytically modeled. Additionally, in Phase IV, usage context enters into an individual's choice utility function directly to capture its influence on product preferences. In Phases III and IV of modeling, both customer profile attributes $\mathbf{S}$ and usage context attributes $\mathbf{E}$ are further classified into performance-related $\mathbf{S_Y}$, $\mathbf{E_Y}$ and preference-related $\mathbf{S_W}$ and $\mathbf{E_Y}$ to differentiate their impact on product performance and customer preferences, respectively. The usage context choice modeling approach in this work represents a significant expansion of traditional choice modeling approaches in the design literature.

Two case studies, a jigsaw design example with synthetic stated preference data and a hybrid electric vehicle example with real revealed preference data, illustrate the proposed modeling framework. Both case studies follow the four-phase modeling procedure. The jigsaw case study emphasizes usage context identification, data collection with stated preference surveys, and the use of physics-based modeling to capture the impact of usage context on performance. On the other hand, more details of the modeling steps (Phases III and IV) are reported in the hybrid electric vehicle case study based on its revealed preference survey data that reflects customers' real choices and the use of ordered-logit modeling for predicting customer ratings for system attributes. Results from both examples demonstrate the impact of usage context upon customer preference as well as product performance. A set of validation tests are included for the HEV case study which demonstrate the necessity of expanding a traditional choice modeling framework to include usage context for improved model predictive capability. What-if-scenario analysis in the hybrid electric vehicle example showed that predicted choice share in the target market changes in response to the change of performance ratings in distinctive usage contexts for given vehicle designs, which illustrates the potential of the proposed choice modeling framework in supporting engineering product design. 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 both city and highway MPG as well as vehicle horsepower and torque. This work is limited to single primary usage of a product which may not be true of many market offerings. Therefore, the expansion of the current framework to model multiple-usage contexts for product family design is one of the interesting

directions for future work. Also, the proposed framework creates performance models and preference models in two separate steps (Phase III and Phase IV, respectively), in which error from lower level model may cause issues in upper level model estimation. Hence, the all-in-one Hierarchical Bayesian choice modelling approach [18] can be used to improve the stability of model estimation in the proposed framework. Furthermore, the potential influence of usage context upon the choice set construction in a two-stage decision making process [53] would be another interesting research topic. Lastly, the introduction of the social impact into the hybrid electric vehicle example would bring new light to understanding customers' choice behaviour and attitude towards new technology.

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