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CONJOINT-HOQ: A QUANTITATIVE METHODOLOGY FOR CONSUMER-DRIVEN DESIGN

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ABSTRACT

This paper presents a methodology, Conjoint-HoQ, which is meant to provide an improvement over the current House of Quality (HoQ) tool. The improvement comes in the form of *quantitative* technical information – replacing the qualitative nature of the current HoQ – through integration of conjoint analysis into the HoQ framework. The steps of the Conjoint-HoQ method are presented in detail with an accompanying hypothetical example, the design of a hair dryer. A number of research issues critical to implementation in industry are also identified and discussed. The resulting methodology is representative of design tools seen as vital to supporting the emerging paradigm of mass-customization.

KEYWORDS

quality function deployment (QFD), house of quality, conjoint analysis, Conjoint-HoQ, customer driven design, mass-customization, decision-based design

1 INTRODUCTION & MOTIVATION

The notion of consumer-driven product development has roots in Japan's Kobe shipyards as far back as the 1970s [1]. The subsequent development of the methodology adopted in the Kobe shipyards and the continued proliferation of, as it is known formally, Quality Function Deployment (QFD) ensures that consumer-driven design is a paradigm that most designers are likely to adopt and utilize throughout their careers.

There is value in adopting this paradigm and anecdotal evidence of that value can be found in numerous industry testimonials [2]. The most obvious value to adopting the QFD process is the aid it provides designers in communicating across stages in the design process; a value which Hauser eluded to nearly two decades ago [1].

Further, the QFD process, specifically its primary tool, the House of Quality (HoQ), serves as a methodology for assessing relationships between the consumer evaluated product attributes and the technical attributes that designers must work with in designing the product.

However, the value provided by the HoQ as an assessment tool is limited to a qualitative nature at best [3]. This qualitative nature limits the ability to utilize the HoQ to carry out customer-driven design in a more fundamental way. That is, the HoQ is more of a heuristic design tool than a valid model of decision-based design theory [4-6].

The heuristic nature of the HoQ limits the level of acceptance of QFD as a design tool. It is interesting to note however that much concurrent work exists in the research community that either parallels the motivation of the HoQ/QFD methodology, i.e. incorporation of customer preferences in the design process [7-9], or attempts to improve upon the methodology itself, especially its subjective nature [10-14].

Of greater importance, the heuristic nature of the HoQ is certainly a limitation to industry improving the efficacy in delivering customer-driven products. As design moves further toward the logical successor of customer-driven design, "mass-customization" [15], there will be an increasing need to model and quantify customer needs in a more mathematically rigorous manner.

Improving the validity of the HoQ as a model for decision-based design and to serve the mass-customization paradigm is

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the primary motivation for the methodology presented in this paper. Specifically, the improvements are aimed at evolving the HoQ from a qualitative assessment tool to a *quantitative* one. The work presented in this paper is offered as a *preliminary* step in that evolution with a focus on improving the primary source of the qualitative nature of the HoQ [3].

Presentation of the methodology for accomplishing that improvement is provided in Section 3 in conjunction with a case study. The case study is a hypothetical scenario for the design of a hair dryer which provides fodder for critical discussion in Section 4. First though, background critical to the methodology is presented in the next section.

2 BACKGROUND

This section provides a brief overview of both the HoQ and conjoint-analysis. In presenting the methodologies, only the fundamentals are provided, however, there is a large body of work which details particulars of each method and provides numerous examples of application.

The House of Quality

The HoQ functions as a model for understanding how attributes in one phase of the design process (e.g. "customer needs") affect attributes in the subsequent design phase (e.g. "engineering specification"). Consider Figure 1 which shows a standard HoQ as taken from [16] and provides obvious explanation for its reference as a "house". The "Customer Attributes" (CAs) represent what the customer wants in the product and are posed in customer language. The "Importance" represents the weight the customer assigns to each CA. The "Customer Ratings" section represents the customer perception of how well a current product performs on each CA. The ratings may also compare competitor products. "Technical Attributes" (TAs) represent the product characteristics necessary to meet the CAs. The TAs however, are in engineering design language. The "Relationship Matrix" is where relationships between CAs and TAs are identified and given a "weak", "medium" or "strong" relationship value. The "Technical Test Measures" and "Technical Difficulty Ratings" sections represent designer evaluations among the TAs. "Target Value Specifications" represent the target level the designers want each TA to reach. The "Technical Importance" section contains the calculated importance of each TA, which is a function of the "Importance" values and the values in the "Relationship Matrix". Finally, the "Correlation Matrix" represents a matrix of the interrelationship among TAs.

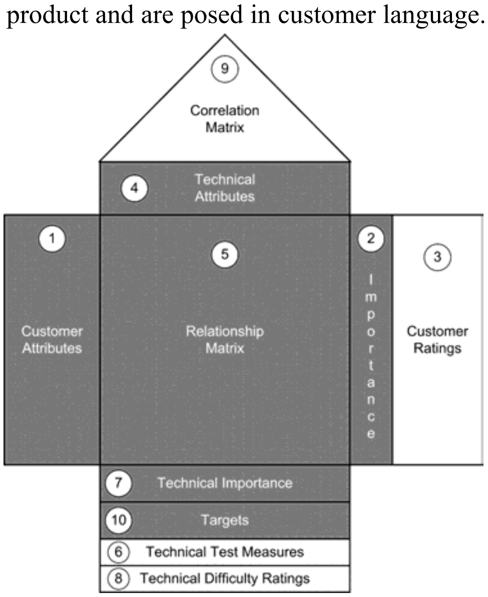

Figure 1. Standard HoQ

The goal of the HoQ is to translate the "fuzzy voice of the customer" into measurements in the company language [17]. The steps to follow in achieving this "translation" are provided by Breyfogle [16]. These steps are labeled in the HoQ of Figure 1 and are as follows:

1. *Make a list of customer attributes*. This list is usually identified through customer interviews and/or surveys.
2. *Identify the importance of each customer attribute*. This information is also determined from customer surveys.
3. *Obtain customer ratings on existing design and competitor design*.
4. *Designers compile a list of technical attributes to meet the customer attributes*. These attributes should be scientifically measurable terms that can be assigned target values [16] and designers should avoid concept specific terms [17].
5. *Relationships should be identified in the relationship matrix and assigned qualitative value (weak, medium, strong)*. These qualitative relationships are later replaced by a quantitative three number scale.
6. *Technical tests should be performed on existing design and competitor designs to gauge objective measures of difference*.
7. *Importance of each technical attribute should be calculated in either absolute values or relative weights*. This is done using Eqn. (1) or Eqn. (2) respectively, where there are m CAs and n TAs, β_{ij} represents the relationship value between the i^{th} CA and the j^{th} TA, and w_i represents the customer importance for the i^{th} CA.

$$rawscore\Big|_{j=1}^{n} = \sum_{i=1}^{m} \beta_{i,j} \times w_i \quad \textbf{(1)}$$

$$\begin{matrix} relative \\ weight \end{matrix}\Bigg|_{j=1}^{n} \frac{rawscore_j}{\sum_{j=1}^{n} rawscore_j} \quad \textbf{(2)}$$

8. *Difficulty of engineering each technical attribute should be assessed*.
9. *The correlation matrix should be filled out*.
10. *Target values for each technical attribute should be set*. This may be based on customer ratings from step 3.

11. *Select technical attributes to focus on based upon technical importance calculations of step 7 and technical difficulty assessment of step 8.*

By carrying out these steps, designers gain a *qualitative* assessment of the importance of the individual TAs relative to one another. As stated previously, this qualitative assessment is merely a heuristic to guide the designers and does not provide sound *quantitative* information [3] necessary to promote process valid design-decisions. The challenge to the validity of the HoQ [4, 5] lies in the reliance on designers to fill in the "Relationship Matrix" with scales that are seemingly arbitrary. The resulting "Technical Importance" metrics have been shown to be analogous to a random process and lacking in robustness [3].

The methodology presented in Section 3 results from a desire to advance the HoQ from qualitative to quantitative design method, improving its validity. This evolution requires replacing the arbitrary scales assigned by designers in the "Relationship Matrix" with logical scales. To determine these logical scales, it is necessary to integrate the HoQ with conjoint-analysis. Background on conjoint-analysis is provided in the next section.

Conjoint-Analysis

Conjoint analysis is a marketing method which allows for a quantitative assessment of the impact of individual product attributes on overall product demand. According to Dolan [18], conjoint analysis allows for an overall ranking of individual products and through mathematical analysis, the underlying value system of the individual can be assessed. The usefulness of conjoint analysis is that by understanding a person's preferences for an entire product (i.e. considering all product attributes at once) it is possible to make predictions on any products with the same attributes [18]. By using conjoint analysis, it is possible to estimate the aggregate utility of a consumer market for a particular class of products via statistical analysis.

The fundamental idea in conjoint analysis is that a product can be represented as a group of attributes and the component utility of each attribute can be assessed through conjoint analysis. The research and application of conjoint analysis is a rich field of work [19-21].

The purpose of this paper is to introduce a methodology which integrates the strengths of conjoint analysis into an engineering design tool (the HoQ) which is intuitive and widely used by designers. For that reason, a simplified explanation of conjoint analysis is provided and the development of the methodology in the next section utilizes a simplistic conjoint approach. There are five stages to conjoint analysis [18]:

1. <u>Determination of relevant attributes</u> – Before interviewing consumers, there should be confidence that the important attributes are accounted for. Dolan suggests that consideration should be given to three attribute types, namely, physical attributes, performance benefits and psychological benefits.
2. <u>Stimulus representation</u> – This refers to the way in which the customer is presented the product profile. They could be presented a full profile or partial profile. The choice is highly dependent on the number of attributes and levels. For example, if a product type has two attributes each with three levels, then there are only nine (i.e., 3^2) possible product profiles, so a full profile would be reasonable. However, consider a product type with four attributes, each with five levels, here there are 625 (i.e., 5^4) possible product profiles. Obviously, a full profile would be unreasonable here. By using a properly selected partial profile, however, the preferences for all 625 possible products could be estimated [18].
3. <u>Response type</u> – The consumers interviewed can respond to the product profiles in two ways. They can either rank or rate the products. In ranking, the respondents can either choose between paired comparisons or put a list of product profiles in order from most desirable to least desirable. In the rating approach, the respondents are asked to assign a value from a scale on likelihood of purchase or desirability. The major difference between the two approaches is that ranking allows for comparison of product profiles, while rating is done without a comparison.

   Ranking and rating have been found to generally produce similar final results [22] although, ranking methods are traditionally preferred because it better mimics the way consumers purchase products, i.e., comparison [22]. However, comparisons (rankings), and specifically pair-wise comparisons, can be dangerous when individual responses are aggregated to represent a group preference. The danger results from the fact that individuals who display transitive behavior may and probably will display intransitive behavior as a group [23].
4. <u>Criterion</u> – Whatever the decision in response type, there is still the related issue of which standard to be used in judgment, namely, preference or likelihood of purchase. Obviously, the product a customer prefers is not always that which they are likely to purchase. Dolan uses the example of a BMW versus a Ford Taurus. Though the customer may prefer the BMW, due to budget constraints they may be more likely to purchase the Ford Taurus [18]. The choice of criterion is largely dependent on whether interest is in estimating market share or market size. If the latter is the case, likelihood of purchase is a more appropriate criterion.
5. <u>Method of data analysis</u> – The method of data analysis is dependent on choices made in previous stages. If ratings are collected, simple regression can be used; for probability of purchase, Logit models can be used; finally, if rankings are used, MONANOVA is recommended since "how much" one alternative is preferred to another is not indicated [18]. Once the data is collected and analyzed, it can be used in three ways; to judge the relative importance

of attributes, to identify market segments within the target market or to assess market share for different products.

Conjoint analysis has seen use in engineering design research in both general approaches to integrate preferences into design [7, 24-26] (though not utilizing an existing approach like the HoQ), and to improve the QFD process directly [27]. This research goes toward extending this integration and improvement by specifically determining quantitative values for the Relationship Matrix in the HoQ which eliminates the source of the qualitative nature of the HoQ [3] and renders a more rigorous quantitative design-decision aid. Further, the methodology is developed as an integration of existing methods (conjoint analysis and HoQ) rather than a completely new method because in the view of the authors, maintaining a tool intuitive to designers (HoQ approach) while improving the quantitative nature of the tool is an important contribution of this research. Identification of utility functions is not the goal, rather finding the importance of each TA that makes up a product from a technical standpoint through component utility measures is the objective. The methodology is detailed in the next section.

3 CONJOINT-HOQ METHODOLOGY

To support the development of the quantitative improvement methodology in this section, it is beneficial to refer to a generic Conjoint-HoQ template, as shown in Figure 2. Note that the Conjoint-HoQ template includes the grey sections of the standard HoQ from Figure 1 and an additional section, "L/U Limit". The steps followed in applying this template are similar to those of the HoQ method described in Section 2, and the overall primary objective of the Conjoint-HoQ tool is still the same, i.e., determination of the importance of each TA. However, there are some important differences which allow for the integration of conjoint analysis, resulting in a more rigorous design tool.

Customer Attributes	Technical Attributes					Customer Importance
	TA_1	TA_2	…	…	TA_n	
CA_1	*	*			*	α_1
CA_2	*				*	α_2
:		*	*	*		:
:			*	*		:
CA_m	*	*			*	α_2
Technical Importance						raw score
						relative weight
	0	0	0	0	0	Target
	-1 / +1	-1 / +1	-1 / +1	-1 / +1	-1 / +1	L/U Limit

Figure 2. Conjoint-HoQ template

The similarities between the HoQ and the Conjoint-HoQ methods lie in the identification of the CAs and TAs by designers, as well as the identification of relationships between those CAs and TAs. These relationship locations are represented by the asterisks in Figure 2. The difference between the methodologies takes two forms, which leads to a two step process for the Conjoint-HoQ.

The first difference is that the Customer Importance section in the Conjoint-HoQ is no longer a set of ratings (1-5) as in the traditional HoQ method. Rather, the Customer Importance becomes component-values, α, of each CA based upon hypothetical product evaluation of customers.

The second difference lies in the quantification of the relationships between CAs and TAs. In the traditional HoQ method, the relationships are quantified by designers using arbitrary, three number scales (e.g. 1-3-9) to represent the "weak", "medium", and "strong" relationships. An example of this is shown in Figure 3, which shows the HoQ for a hair dryer, a simplified example taken from [28]. Using these 1-3-9 relationships, the designers calculate the importance of each TA (i.e., relative weight) using Eqns. (1) and (2).

Rather than applying an arbitrary scale, like 1-3-9, the Conjoint-HoQ method provides a means to determine the relationship values in a more rigorous manner. The recovered component values (α) are utilized to determine the relationship scales analytically.

Customer Attributes	Technical Attributes					Customer Importance
	air flow	air temperature	weight	volume	energy consumption	
dries quickly	9	9			9	5
quiet	9				9	4
comfortable to hold		1	9	9		5
portable			3	9		2
energy efficient	9	9			9	3
	108	77	51	63	108	raw score
	26.5%	18.9%	12.5%	15.5%	26.5%	relative weight

Figure 3. Hair dryer example in original HoQ

The creation and presentation of hypothetical products is accommodated by the "Target" and "L/U" sections of the Conjoint-HoQ. Each TA has a "Target" level of specification which represents a nominal value the designers intend to design for (represented by a zero in Figure 2). The "L/U Limit" for each TA represents a lower and upper target specification level that the design could feasibly achieve for each TA (represented by -1/+1 in Figure 2). Specifying a target value along with upper and lower limits for TAs is analogous to development of potential level settings for factors in a design of experiments.

Conjoint analysis is the approach that allows the designers to leverage the "Target" and "L/U Limit" information to generate hypothetical products and query customers. The resulting analysis will yield relationship information which designers can utilize to calculate the importance of each TA. The steps necessary to apply the Conjoint-HoQ methodology are explained here using the five stages of conjoint analysis described in the previous section. In order to aid in the presentation of the Conjoint-HoQ methodology, a hypothetical design scenario is presented. The example scenario to be explored in this section is the design of a hair dryer, which was introduced in Figure 3, now shown in Figure 4 in the Conjoint-HoQ template style.

Customer Attributes	Technical Attributes: air flow	air temperature	weight	volume	energy consumption	Customer Importance
dries quickly	*	*			*	α_1
quiet	*				*	α_2
comfortable to hold		*	*	*		α_3
portable			*	*		α_4
energy efficient	*	*			*	α_5
Technical Importance						raw score
						relative weight
	1.7 ft^3/s	115° F	1 lb	430 in^2	1800 W	TARGET
	1.5/1.9	105/125	0.75/1.25	380/480	1600/2000	L/U LIMIT

Figure 4. Hair dryer Conjoint-HoQ

Determination of relevant (customer) attributes

The simplified Conjoint-HoQ was determined based upon *the CAs which are most critical to prospective consumers*, hypothetically speaking. It is important to identify these critical CAs from an implementation perspective, since the Conjoint-HoQ methodology does not lend itself to products with many CAs due to the potentially overwhelming number of hypothetical products that must then be represented. However, it is important to realize that these attributes are also deemed "critical" in the sense that they represent the attributes which most affect consumer perception/purchase of a product. That is, although a product might be thought of as a collection of multiple customer attributes, it is likely that only a subset of those attributes has a true impact on perception/purchasing. For example, the original HoQ for the hair dryer example used in the case study has eight CAs (ignoring the environmental customer group) [28] which leads to nine TAs for consideration. However, it is likely that only a subset of the eight CAs are truly considered by a given customer when they stand in the store and select from a set of hair dryers.

Research work in both psychology and consumer choice theory support this notion. As Miller [29] explored information processing in individuals, he noted asymptotic behavior in the amount of input information that individuals could process. In a product selection context (e.g. selecting a hair dryer from a store shelf) this suggests that individuals are likely to look at a subset of all possible CAs rather than give consideration to the full profile of attributes.

In a decision-theory context this implication has led to research on the heuristic nature of choice models in complex choice problems [30]. From a consumer preference perspective, Lee and Geistfeld [31] found that the type of choice model (compensatory vs. non-compensatory) varies among individuals but non-compensatory choice models (i.e., models in which an individual does not consider tradeoffs among attributes but rather focuses on a subset of the attributes) are the most common. Again, the implication is that consumers focus on a subset of product attributes (CAs) during selection.

Despite the wealth of literature suggestive of heuristics in consumer choice or the "satisficing" nature of human beings [32], the HoQ methodology as presented throughout the QFD literature considers large numbers of CAs for any given product example [16, 33-35]. Accounting for all the potential CAs is important from a product planning standpoint but implementation of the Conjoint-HoQ methodology requires focusing on the subset of CAs that are given the most consideration by consumers. By identifying those CAs that are truly considered at the time of a purchasing decision, the resulting quantitative assessment of the Technical Importance (TA importance) has more meaning in subsequent phases of the design process. That is, the TAs that the designers focus on as a result of the Conjoint-HoQ method are more likely to provide economic payoff when the product goes to market.

For purposes of illustrating the Conjoint-HoQ methodology the most critical CAs for the hair dryer were assumed known and are shown in the HoQ of Figure 4. The component-values (Customer Importance values) for these CAs are determined using Eqn. (3), where b_i is recovered using regression to analyze customer feedback.

$$\alpha_i = b_i \, CA_i \qquad \textbf{(3)}$$

The relationships between CAs and TAs (as determined by designers and represented in the original example [28]) are marked by asterisks and the "Target" and "U/L Limit" settings, which are utilized in creating hypothetical hair dryers for customer rating are shown. The steps necessary to identify the relationship values in the HoQ are described below.

Determination of relevant (technical) attributes

The relevant attributes implied here are those that the designers are interested in, namely the TAs. The TAs to be explored are dictated by those which affect the most critical CAs. In order to obtain ratings, customers are presented hypothetical products in terms of the CAs. Thus it is necessary to have a model for how CAs (or more accurately, the component-values α) are dependent on TAs in the HoQ. The most basic model that can be derived from the HoQ structure is a linear one, which corresponds to the Relationship Matrix in Figure 1. A linear equation for each α (CA value) is a function of only those TAs which affect it (represented by asterisks in Figure 2). A general form of the relationship is provided in Eqn. (4), where C_i corresponds to the set of TAs which affect CA_i.

$$\alpha_i = \sum_{j \in C_i} \beta_{ij} TA_j \qquad i = 1..m \qquad \textbf{(4)}$$

Due to the matrix-based structure of the Conjoint-HoQ, models consisting of higher order polynomial terms are not conceptually supported. For example, adding second order terms for each TA in Eqn. (4) could be accommodated by additional columns in the Conjoint-HoQ matrix (one for each TA^2 term). However, the resulting technical importance of a second order TA term (e.g. "air flow^2") lacks physical meaning. In order to maintain the HoQ structure (which is a primary motivation) the first order form of Eqn. (4) is a forced assumption.

There is justification for accepting this assumption. Though higher order effects are often seen in engineering design, it is well documented that those terms do not necessarily provide great gains in overall knowledge of a meta-model but do require additional experimental observations [36]. Rather, higher order terms support increased model fidelity, which at this early stage of the design process - where uncertainty in information reigns - may not be worth pursuing.

It is noteworthy that the "Correlation Matrix" of the HoQ shown in Figure 1 already attempts to include interaction terms among TAs in a *qualitative* manner. The Conjoint-HoQ methodology may be extended to make this aspect of the HoQ a more *quantitative* design aid but this topic is reserved for future research discussion.

A final aspect of the model represented by Eqn. (4) is important from the consumer-choice theory perspective. Eqn. (4) represents a deterministic, compensatory model [31]. The form is similar to typical additive utility models used in multi-attribute utility theory [37-39]. Here again, it is possible for the users of the Conjoint-HoQ methodology to utilize a different form of consumer choice model (e.g. non-compensatory) [31] when and where appropriate.

Since the customers are presented hypothetical products to rate in terms of the CAs, the CAs represent "surrogate variables" through which the β coefficients for the TAs in Eqn. (1) can be recovered. Essentially, Eqn. (4) represents a meta-model for understanding how the technical aspects of a product affect consumer perception of that product.

The attributes of interest for the designer are represented by the TAs for the hair dryer. Based on Eqn. (4), the relationships between CAs and TAs for the hair dryer are found as in Eqn. (5), where α_1 corresponds to component-value of the first CA "dries quickly" and TA_1 corresponds to the first technical attribute "air flow", etc.

$$\begin{aligned} \alpha_1 &= \beta_{11}(TA_1)+\beta_{12}(TA_2)+\beta_{15}(TA_5) \\ \alpha_2 &= \beta_{21}(TA_1)+\beta_{25}(TA_5) \\ \alpha_3 &= \beta_{32}(TA_2)+\beta_{33}(TA_3)+\beta_{34}(TA_4) \\ \alpha_4 &= \beta_{43}(TA_3)+\beta_{44}(TA_4) \\ \alpha_5 &= \beta_{51}(TA_1)+\beta_{52}(TA_2)+\beta_{55}(TA_5) \end{aligned} \tag{5}$$

Stimulus representation

At this point, it is necessary for the designers to generate a set of hypothetical products for the customers to rate. The hypothetical products are a function of the target level of each TA. For example, setting all the "L/U Limits" to their upper (+1) settings for every TA represents one hypothetical product. It is important to note that the designers must have some knowledge about how the TAs that affect a given CA will impact its performance.

The number of hypothetical products possible is dependent on the number of TAs and the number of levels for each TA. For example, in the hair dryer design, there are five TAs which can each assume two levels (+1 or -1) – assuming the target levels are not used. Thus there are 32 (2^5) possible hypothetical hairy dryer products. It is not necessary to present every possible hypothetical product to a group of customers. Instead an arrangement of hypothetical products utilizing a Taguchi design [40] or similar method could be presented to allow for sufficient design space exploration without too many experiments. This allows designers to minimize the number of hypothetical products necessary to estimate the β coefficients in Eqn. (4). However, there is a tradeoff in the accuracy of the coefficient estimates. The choice to tradeoff accuracy for fewer hypothetical products should be dependent on the resources and time that designers can put toward engaging customers. It is also worth noting at this point that it is important to have multiple customers rate each hypothetical product to ensure that the coefficients represent the "average" of the customer base.

To reduce the number of hypothetical hair dryer designs the designers must account for in terms of CA performance, a Taguchi design is selected. The minimum Taguchi design that can accommodate five factors with two levels per factor is an L8 design. The level settings for each TA using such a design are shown in Table 1.

	Technical Attributes (*settings for hypothetical hairdryers*)				
hypothetical hair dryer	air flow ft^3/sec	air temperature ^oF	weight *lb*	volume in^3	energy consumption *W*
1	1.5	105	0.75	380	1600
2	1.5	105	0.75	480	2000
3	1.5	125	1.25	380	1600
4	1.5	125	1.25	480	2000
5	1.9	105	1.25	380	2000
6	1.9	105	1.25	480	1600
7	1.9	125	0.75	380	2000
8	1.9	125	0.75	480	1600

Table 1. TA settings for hypothetical hair dryers

As the designers must present the hypothetical hair dryers in terms of the CAs to the customers, they must have some insight into how the TA settings affect the performance of the CAs. For instance, the designers should be able to specify how the settings for "air flow", "air temperature" and "energy consumption" affect drying time. Of course the designers can utilize simplistic heat and mass transfer models to determine the time necessary to dry a wet mass of fibers or something similar. The issue is the presentation of this information to the customer. As "dries quickly" is a subjective and relative attribute, customers need to compare several possible designs against some constant that must be dried. Similar issues must be addressed for CAs like "comfortable to hold" and "portable". This may require mock-ups of hypothetical hair dryers that have different weights or conveying to customers how much space in a suitcase a hypothetical hair dryer might take up.

Generally, for any engineered product, representing hypothetical products for customer evaluation is not a simple task. Identifying ways to represent hypothetical products to consumers which can be rated on the merits of the customer attributes is a critical research issue. This stage requires the development of prototypes which are relatively cheap to fabricate yet still represent the consumer attributes appropriately.

Continuing with the hair dryer example, how can a design group create prototypes of hair dryers which represent the hypothetical products well enough for consumers to rate them? It may require more than just presentation of hypothetical products on paper, since the designers cannot truly represent all CAs on paper. This is due to the fact that the CAs are subjective elements of a product that consumers rate products on. Even attributes which could be measured, like "dries quickly", are subjective. That is, although two hair dryers currently on the market could be compared by the amount of time each takes to dry hair, the term *quickly* implies subjective assessment. One of the hair dryers could be twice as fast in terms of time but individual customers may still view both hair dryers as "quick enough". The subjective nature of CAs becomes even more difficult to handle when dealing with attributes like "comfortable to hold" or "portable". These two CAs are clearly the type that require "tangible" prototypes that consumers can access in a virtual environment or in reality.

There exist a number of technologies that could accommodate the presentation of (cheaply made) prototypes. Consider the growth of rapid prototyping (RP) technologies, especially 3D printers, which makes possible creation of 3D objects that can be presented to designers and/or customers. Beyond RP, it is also possible to utilize virtual reality (VR) applications to present prototypes for customer rating.

The goal in the Conjoint-HoQ methodology and subsequent research that supports its utilization is to bring these types of design environments to the client-designer interface. The vision of the research necessary to support effective Conjoint-HoQ use is the integration of existing and emerging technologies like CAD/CAM, rapid prototyping, virtual reality, haptic devices, etc., to develop a cyberinfrastructure-based design environment which allows designers to interact with customers and explore design concepts. This type of research and development is critical to the progress and proliferation of design tools, like Conjoint-HoQ, capable of supporting mass-customization.

Response type

The response type proposed for this improvement methodology is a rating by customers in the form of product value, V, in dollars. For each hypothetical product, the customers are asked to assign a value to the product between some specified bounds. The value is intended to represent the question: "How much would you pay for this product?" while providing some bounds which are representative of the product market.

Returning to the hair dryer example, the customers are required to rate the hypothetical hair dryers by assigning a price. Table 2 shows example CA metrics and their values for the eight hypothetical hair dryers of Table 1 (the first row of Table 2 corresponds to the first row of Table 1, etc.) for a *single customer*. This table of metrics and values was generated as a hypothetical set of consumer performance metrics (which are a function of the TA seetings in Table 1) on which customers may evaluate a product. In some cases, the metrics are easily measured (e.g. minutes) while others are "rating metrics" which each customer has evaluated internally. This table of CA metrics is simply meant to lend understanding for the method and example being presented.

Actual presentation of hypothetical products was discussed previously as a critical issue for study. The importance of Table 2 for this example is the column of "Consumer ratings", which represent *customer perceptions* of the hypothetical hair dryers. In reality, multiple customers would rate the same hypothetical products before processing the resulting survey data. As this example proceeds, results for 100 simulated consumers are represented but information from a single customer is displayed to aid discussion.

	Customer Attributes (hypothetical consumer performance)					
hypothetical hair dryer	dries quickly (minutes)	quiet (dB)	comfortable to hold (rating)	portable (rating)	energy efficient ($/use per month))	Consumer ratings ($)
1	8	59	5	5	0.62	27
2	5	65	5	4	0.43	26
3	6	59	2	5	0.43	23
4	2	65	1	3	0.19	24
5	4	69	2	5	0.33	22
6	7	63	1	3	0.54	20
7	1	69	5	5	0.10	30
8	5	63	5	4	0.35	26

Table 2. Hypothetical hair dryers with ratings

Criterion

For the Conjoint-HoQ method detailed here there is no desire to estimate a market share or market size, though the data could potentially lend itself to that type of analysis. Rather, the goal is to identify importance relations between related CAs and TAs so that the relative importance of each TA can be processed through the HoQ methodology. In this context, the criterion driving customer ratings is preference assessment.

Method of data analysis

The method of data analysis utilized for the Conjoint-HoQ method presented here relies on least squares linear regression to recover the β coefficients of Eqn. (4). The data analysis process has two steps for reasons previously discussed.

The ***first step*** is to find the component value (α) for each CA based upon the customer ratings. This is done by first solving Eqn. (6) for the b values using least squares linear regression (Eqn. 7) on the ratings from 100 customers. For this example, the matrix of CA values from Table 2 and the consumer ratings for all customers are normalized from 0 to 1. The resulting b matrix is of size (5 × 100 – number of CAs by number of customers) in this example. The b values for the single customer of Table 2 are shown in Table 3.

$$V = \sum_{i=1}^{m} b_i CA_i \tag{6}$$

$$b = (CA^T \bullet CA)^{-1} (V \bullet CA^T) \tag{7}$$

dries quickly (minutes)	quiet (dB)	comfortable to hold (rating)	portable (rating)	energy efficient ($/use per month))
-0.45966	0.030117	0.52816	0.070606	0.83063

Table 3. Resulting *b* for customer of Table 2

The rational for keeping this information for *each* customer (rather than finding a single set of coefficients b) is that such information could prove valuable in identifying multiple product profiles. That is, finding a single set of b coefficients would assume that all consumers perceive the hair dryer CAs with the same component values. Of course, preferences can vary widely among customers – preference heterogeneity [20]. A complete set of information of all surveyed customers preserves a level of design freedom which could eventually lead to multiple hair dryer designs. This would be accomplished by identifying potential market segments through exploration of the b values. For example, designers may identify three distinct market segments which would lead to three distinct hair dryer designs (i.e., three sets of β coefficients could be identified).

In this hypothetical design scenario it is assumed for purposes of demonstrating the methodology that a homogenous market segment has been identified. Based upon this assumption, the ***second step*** is to identify a single set of β coefficients based upon this consumer data using Eqns. (3) and (4). Using Eqn. (3) and the b values previously identified for each customer, it is possible to estimate the component values for each CA, for each customer, for each hypothetical hair dryer. The result is a set of equations in the form of Eqn. (5), for each customer, for each hypothetical hair dryer.

The form of the equation upon which regression is performed is given by Eqn. (8). The matrix of β coefficients represents the relationship matrix of the hair dryer HoQ and Conjoint-HoQ in Figure 3 and Figure 4 respectively. The zeros correspond to locations where relationships are presumed non-existent. In the case of the HoQ of Figure 3, the β coefficients are presumed known, and are represented by the 1-3-9 ratings. The Conjoint-HoQ method relies on the consumer preference data from Table 2 in order to identify the β coefficients through regression.

$$\begin{bmatrix} \beta_{11} & 0 & \beta_{13} & 0 & \beta_{15} \\ 0 & 0 & \beta_{23} & \beta_{24} & \beta_{25} \\ 0 & \beta_{32} & 0 & \beta_{34} & 0 \\ 0 & 0 & 0 & 0 & \beta_{45} \\ \beta_{51} & 0 & 0 & \beta_{54} & \beta_{55} \end{bmatrix} \times \begin{bmatrix} HP_{11} & & HP_{k1} \\ HP_{12} & & HP_{k2} \\ HP_{13} & \cdots & HP_{k3} \\ HP_{14} & & HP_{k4} \\ HP_{15} & & HP_{k5} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & & \alpha_{k1} \\ \alpha_{12} & & \alpha_{k2} \\ \alpha_{13} & \cdots & \alpha_{k3} \\ \alpha_{14} & & \alpha_{k4} \\ \alpha_{15} & & \alpha_{k5} \end{bmatrix} \tag{8}$$

The matrix of hypothetical products (HP) represents the TA level settings for each of the k hypothetical products rated. For example, the first column of the hypothetical product matrix corresponds to row one of Table 1. The matrix of component values (α) represents the value of each CA for each of the k hypothetical products calculated using Eqn. (3).

As it is desirable to have the same hypothetical products rated by multiple customers, the number of columns for the hypothetical products and component values matrices (α) is equal to the product of hypothetical products and number of customers rating each product. For example, if there are ten hypothetical products and five customers rating each product, both these matrices would have fifty columns.

As both the hypothetical products and component values matrix have values from the customer ratings, it is possible to use least squares linear regression to estimate the β coefficients. The resulting solution of coefficients represents the relationships between the corresponding CAs and TAs in the "Relationship Matrix" of the Conjoint-HoQ. The relationship is based upon the data from the customer responses and represents a "best fit" of the β coefficients for Eqn. (4), since this equation represents a case of more observations than coefficients. This is the case as long as there are more columns in the hypothetical products and component values matrices (i.e. more products rated) than unknown β coefficients. Based upon these values the relative importance of each TA can be identified in the same fashion as if 1-3-9 were utilized as the relationship scale, like in the HoQ of Figure 3.

The resulting solution (i.e., β coefficients) for 100 "simulated" customers, is shown in the Conjoint-HoQ in Figure 5. The 100 customer ratings are "simulated" by using utility functions with various "risk attitudes" which are randomly selected using uniform distributions for each of the eight hypothetical hair dryers of Table 2. This simulation is simply used to demonstrate the Conjoint-HoQ methodology.

Through the Conjoint-HoQ approach the designers now have *quantitative* relationship levels between CAs and TAs and these relationships can be utilized to determine the importance of each TA based upon the potential customer base. In determining the importance of each TA the designers can utilize the absolute values of the relationships (β coefficients) to identify the relative importance of each TA using (2). The raw score for each TA is found by simply summing each column.

Customer Attributes	Technical Attributes					Customer Importance
	air flow	air temperature	weight	volume	energy consumption	
dries quickly	-0.0444	-0.1109			-0.1627	α_1
quiet	0.0334				0.0501	α_2
comfortable to hold		0	-0.2799	-0.436		α_3
portable			-0.0312	-0.0637		α_4
energy efficient	0.0484	0.121			0.1278	α_5
Technical Importance	-	-	-	-	-	raw score
	-	-	-	-	-	relative weight
	1.7 ft^3/s	115° F	1 lb	430 in^2	1800 W	TARGET
	1.5/1.9	105/125	0.75/1.25	380/480	1600/2000	L/U LIMIT

Figure 5. Conjoint-HoQ for hair dryer with recovered coefficients

Customer Attributes	Technical Attributes					Customer Importance
	air flow	air temperature	weight	volume	energy consumption	
dries quickly	0.0444	0.1109			0.1627	α_1
quiet	0.0334				0.0501	α_2
comfortable to hold		0.0000	0.2799	0.4360		α_3
portable			0.0312	0.0637		α_4
energy efficient	0.0484	0.1210			0.1278	α_5
Technical Importance	0.1262	0.2319	0.3111	0.4997	0.3406	raw score
	8%	15%	21%	33%	23%	relative weight
	1.7 ft^3/s	115° F	1 lb	430 in^2	1800 W	TARGET
	1.5/1.9	105/125	0.75/1.25	380/480	1600/2000	L/U LIMIT

Original HoQ results for hairdryer					
26.5%	18.9%	12.5%	15.5%	26.5%	relative weight

Figure 6. Conjoint-HoQ results for hair dryer compared with original HoQ results

The relative weights for the hair dryer TAs based upon the Conjoint-HoQ methodology are shown in Figure 6 along with the relative weight results for the original hair dryer HoQ, (shown in grey) from Figure 3. As might be expected, the resulting importance of TAs when customer information is integrated (even hypothetically) is quite different from the results generated using a meaningless, qualitative (1-3-9) scale as in Figure 4.

Along with an ability to assess TA importance based upon actual customer data, the Conjoint-HoQ method provides opportunity for other insights based upon the recovered β coefficients. Looking at the results for the hair dryer in Figure 5, one notices that the β coefficients carry both positive and negative signs. It is in the positive/negative relationships represented that a number of insights can be made by the designers (e.g. is more or less of a TA preferred). Speaking to the hypothetical results of the hair dryer example, those insights might include:

- Looking at the results of Figure 5 the coefficient signs for "weight" and "volume" are all negative. This indicates that "the less the better" for this TA with respect to both CAs, "comfortable to hold" and "portable", which it affects. This type of result makes sense with intuition and supports the notion of validation from a *logical* perspective [6, 41]. At the same time, the coefficients for TAs affecting "dries quickly" are all negative which does not agree with intuition. This may suggest some error in analysis or consumer data used for modeling the process.

- The CA "comfortable to hold" is not affected by "air temperature" which seems counter intuitive. That is, the hotter the hair dryer shell, the less comfortable it would be to hold. Thus, designers must account for the increase in the shell temperature when representing the hypothetical products to customers which was not accounted for in the ratings presented in this example. Of course, it is entirely possible that the "air temperature" would not significantly increase the shell temperature in the vicinity of the "handle". In that case, the designers should question whether a relationship exists between the CA "comfortable to hold" and the TA "air temperature". This type of insight is critical in making the results of the Conjoint-HoQ meaningful. In this case, the method results suggest that "comfortable to hold" is not affected by "air temperature" supporting the idea that the temperature of the handle is unchanging.

These results show the importance of having basic engineering models that reflect realistic CA performance based upon the TA settings. Further, finding ways to represent all CAs to customers like "comfortable to hold" that represent appropriately all effects of the technical variables is important to the credibility of the results.

The steps laid out in this section provide a method for identifying meaningful, reliable (read: quantitative) information for assessing the importance of TAs in the HoQ. The relationships (β coefficients) are viewed as meaningful and reliable now because they are based upon the customer base for which the product is being designed, rather than arbitrary, qualitative scales applied by designers. The next section highlights the value of this methodology and identifies areas of future work associated with implementation.

4 CONCLUSIONS AND FUTURE WORK

The introduction of the Conjoint-HoQ shows the potential for the HoQ framework to support design-decision making in a *quantitative* way. In utilizing customer data to assess relationships between CAs and TAs, the resulting TA importance calculations have a more rigorous foundation which can support a number of insights by designers and provide information for design-decisions which are consistent and valid in ways that satisfy the engineering design community.

Introducing this methodology is further motivated by pragmatic ends. The HoQ and QFD in general are popular design tools in industry and designers are increasingly utilizing these tools to support engineering activities. By integrating a consumer preference modeling tool like Conjoint Analysis into a design tool which is already widely utilized, there is increased probability for adoption of more valid design-decision aids in industry.

A final motivation for introduction of the Conjoint-HoQ methodology is the imperative for a shift to a "mass-customization" paradigm. Remaining competitive in the development of consumer products will necessitate companies to design for "markets of one" [15]. Since the Conjoint-HoQ method is built upon customer preferences and survey, it is possible to identify cross-sections of markets based on demographics, allowing companies to develop product families capable of increasing market share while keeping design costs down.

As with any methodology, there are a number of difficulties that must be overcome in applying Conjoint-HoQ. The first of these is the expected increase in time and resources in applying the methodology. Development of hypothetical products and survey of customers will require additional time and resources and makes the *engineering specification* and *concept generation* phases of design necessarily concurrent. However, the payoff is better customer-centric information for design-decision making, which has the potential to improve product development for multiple cross-sections of a given market. This improved market analysis is tied directly to the technical attributes of a product, decreasing the need for arbitrary designer interpretation. Further, this increased information can lead to better product family profiles which are capable of handling requirement changes in future generations without a need for significant iteration in the latter stages of the design process when the cost of iteration is greater.

Other barriers to implementation take the form of a number of critical issues identified in Section 3. These critical issues are expected to provide a source of motivation for continued fundamental design research (e.g. DBD research) as well as motivation for the development of cyberinfrastructure-based applications for interaction with consumers.

The first of these issues is the need to develop an understanding of the *most critical CAs* as seen by the customers. This will likely require designers working more closely with marketing entities and applying selection tools like HEIM [42] in order to understand the most critical needs. This work could also lead to a more definitive measure of "Customer Importance" for CAs (i.e., attribute weights) rather than reliance on ratings in the form of the 1 to 5 scale as is typically seen in the current HoQ implementation. Other issues in modeling consumer preferences, like homogeneity,

Of a more critical nature is the need to *represent hypothetical products* to customers. As described, this issue represents a major opportunity for research, especially in the development of client-designer evaluation environments that extend beyond an "on-paper" approach. Such an environment would make use of CAD/CAM, virtual reality applications, visualization, haptic devices, rapid prototyping, etc. in order to support customer assessment and preference modeling.

There is also opportunity to extend the Conjoint-HoQ methodology to other aspects of the traditional HoQ. For example, it may be possible to support more quantitative assessment of TA interaction in the "roof" of the standard HoQ shown in Figure 1. The presentation of the Conjoint-HoQ in this paper only focused on the most basic function of the HoQ tool i.e., determination of the "Relationship Matrix" values, however extending the methodology is a topic of future study.

Finally, the work in this paper is presented as a preliminary step to improving a critical design-decision tool and the function it serves (designing based on consumer preferences). A number of critical aspects that must be researched were also identified and discussed in detail. Given the introductory nature of this work it is expected that other difficulties will be uncovered as development of this methodology continues. The next logical step in this research is application of the Conjoint-HoQ method to a real product example to support further deliberation on the approach.

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