EXPLORING MARKETING TO ENGINEERING INFORMATION MAPPING IN MASS CUSTOMIZATION: A PRESENTATION OF IDEAS, CHALLENGES AND RESULTING QUESTIONS

Scott Ferguson
Assistant Professor
North Carolina State University
scott_ferguson@ncsu.edu
(919) 515-5231

Andrew Olewnik
Research Associate
NYS Center for Engineering Design and Industrial Innovation
olewnik@buffalo.edu

Phil Cormier
Graduate Research Assistant
Design of Open Engineering Systems Laboratory
University at Buffalo
cormier@buffalo.edu

ABSTRACT
The paradigm of mass customization strives to minimize the tradeoffs between an ‘ideal’ product and products that are currently available. However, the lack of information relation mechanisms that connect the domains of marketing, engineering, and distribution have caused significant challenges when designing products for mass customization. For example, the bridge connecting the marketing and engineering domains is complicated by the lack of proven tools and methodologies that allow customer needs and preferences to be understood at a level discrete enough to support true mass customization. Discrete choice models have recently gained significant attention in engineering design literature as a way of expressing customer preferences. This paper explores how information from choice-based conjoint surveys might be used to assist the development of a mass customizable MP3 player, starting from 140 student surveys. The authors investigate the challenges of fielding discrete choice surveys for the purpose of mass customization, and explore how hierarchical Bayes mixed logit and latent class multinomial logit models might be used to understand the market for customizable attributes. The potential of using discrete choice models as a foundation for mathematically formulating mass customization problems is evaluated through an investigation of strengths and limitations.

1. INTRODUCTION AND MOTIVATION
Traditionally, design can be considered a multiobjective problem of maximizing value to the consumer while maximizing value to the firm. This traditional approach, while not trivial, is easier to deal with in a pure mass production context where consumer markets are viewed as homogeneous and design is focused more on maximizing market share through satisficing of consumer needs while minimizing production costs.

Over the last two decades however, consumer markets have been recognized to be increasingly heterogeneous, pushing firms to offer increased variety in their product offerings. The need to offer more products that serve the same fundamental purpose (e.g., all models of consumer sedans get you from A to B) increases the complexity of engineering design by pushing decision impact to finer levels of product resolution.

The continuing trend of increasing variety in response to increasing market heterogeneity has raised the profile of the mass customization concept detailed by Davis [1], and Gilmore and Pine [2], more than twenty years ago. This has led to much research across the marketing, engineering and distribution domains toward identifying methodologies that can serve firms in offering appropriate product variety while maximizing financial return [3].

The continuing movement away from pure mass production toward increasing mass customization raises two questions regarding value in product development that firms must answer: (i) What exactly does value mean in a mass customization problem? (ii) How does this definition of value change from how we consider it in a typical mass production problem?

Work toward identifying these questions and determining a path toward answering them began in a literature review of mass customization [3]. A key conclusion in that work is that, along with challenges common to all 21st century product development (e.g., multidisciplinary, globally located, cultural barriers), there is a need to focus on the mapping of information from the marketing to engineering domain for mass customization in order to identify ideal product architectures capable of supporting true mass customization.

1 Corresponding author
This research hypothesizes that focus on this need will lead to a multiobjective problem formulation with competing objectives for maximizing individual consumer value by minimizing sacrifice gap (the gap between the ideal and available product) \[2, 3\] and maximizing firm value by minimizing the cost of producing mass customizable goods in order to ensure profitability in the near and long term (depending on the strategy). Both metrics, sacrifice gap and production cost, are critical to mass customization success with the former representing a key parameter for mapping from the marketing to engineering domain and the latter for engineering to distribution. The focus in this work is on the former and the authors believe that in mass customization, these metrics represent value to the customer and value to the firm, respectively.

Developing a front-end metric for sacrifice gap requires investigating methods capable of modeling consumer utility for a product at a level sufficiently granular to support design decisions that lead to a customizable product capable of sufficiently minimizing sacrifice gap. It is our hypothesis that discrete choice theory can provide a basis for developing such models. However, the application of discrete choice analysis (DCA) is a non-trivial endeavor.

This paper explores the complexity in applying DCA for engineering design of mass customized goods. This exploration is executed through the hypothetical investigation of designing a mass customizable MP3 player. Two design strategies resulting from application of two DCA methods, hierarchical Bayes and latent class multinomial logit are presented. The details of this investigation are reported in Sections 2, 3 and 4 before conclusions and future work are discussed in Section 5. First, relevant background is reviewed in the remainder of this section.

1.1 Hypothetical scenario – a MC MP3 player

The research in this paper examines two approaches toward developing a strategy for designing a mass customized MP3 player. To support this hypothetical development and, more importantly, the basis for a community dialog, the perspective adopted here is that of a firm looking to develop a mass customizable MP3 player. The firm is looking to compete with the existing dominant producers by offering a mass customizable product in an effort to gain market share.

To facilitate this development, the firm utilizes a discrete choice approach to understanding the utility for individual attributes that make up the MP3 player. By leveraging two DCA approaches, two possible product development strategies are identified.

The decision to utilize DCA as a basis for identifying a product development strategy parallels a general trend in engineering design research which has seen increased utilization of discrete choice theory over the past decade. A review of discrete choice fundamentals and its use is offered in the subsequent subsections.

1.2 Discrete choice theory fundamentals

Discrete choice theory is rooted in conjoint analysis, a marketing method that allows for a quantitative assessment of the impact of individual product attributes on overall product demand. Through consumer evaluation of whole products comprised of "conjoined" parts or attributes, conjoint analysis allows for the overall ranking of individual products to be converted through mathematical analysis, to the underlying value system of the individuals purchasing those products \[4-7\].

That is, if an individual is presented several products made up of several attributes, and asked to provide a ranking or rating of those products, it is possible to establish the customer importance of each attribute that makes up the product. Further, by understanding a person’s preferences for an entire product it is possible to make predictions on any products with the same attributes \[4-7\] once the individual attribute importance is established. 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 mathematical and statistical modeling. The research and application of conjoint analysis is a rich field of work \[6-9\] which dates back to the work of Luce and Tukey in behavioral psychology in the 1960s and McFadden in the 1970s \[7\]. Since that time, great strides have been made in developing theories and methodologies and conjoint analysis can be thought of as falling into two categories, traditional conjoint analysis and discrete choice analysis (DCA) which is also called "choice-based conjoint analysis" \[7\]. In general, traditional conjoint analysis is simpler to apply but it is limited by assumptions and assessment barriers, both of which DCA methods overcome but at the cost of increased complexity \[7\].

In the marketing literature, data from conjoint choice experiments are typically analyzed using discrete choice models, the most prominent of those being the multinomial logit (MNL) model \[10, 11\]. The overall utility of a product for an individual consumer is modeled as the sum of the component utilities of the attributes that make up that product. The linear-in-the-parameters and additive form is not restrictive, as nonlinearities and non-additivities may be readily accommodated \[10, 11\]. The latent utility model of Equation 1, represents an individual consumer’s underlying preference for products, where \(U_{ik}\) is the \(i\)th consumer's overall utility for the \(k\)th product, \(X_{ijk}\) is the \(j\)th consumer rating of the \(j\)th attribute for the \(k\)th product, \(\beta_j\) is the importance of the \(j\)th attribute, and \(\varepsilon_{ik}\) is an error term accounting for differences in the observed consumer response and that modeled by Equation 1.

\[
U_{ik} = \sum_j X_{ijk} \beta_j + \varepsilon_{ik}
\]  

(1)
Under the assumption that the error term follows an extreme value distribution [9, 12], the MNL choice framework is obtained where, under the assumption of utility maximization, a probability of choice is defined as in Equation 2 [10]. This equation represents the probability of a consumer \( i \) choosing product \( l \) among the alternatives \( k=1,\ldots,K \).

\[
p_i^l = \frac{\exp\left(\sum_j X_{ijl} \beta_j\right)}{\sum_k \exp\left(\sum_j X_{ijk} \beta_j\right)} \quad (2)
\]

The log-likelihood function of the choice model resulting from this simplification is given by Equation 3, where consumer \( i \) selects product \( l \). This equation becomes the objective function to be maximized in estimating the \( \beta \)-values for the aggregate market.

\[
\log L = \sum_i \log(p_i) \quad (3)
\]

The use of the MNL model represented by Equations 1, 2, and 3 is the basic form in discrete choice theory from which other models are derived. Relevant to this work, hierarchical Bayes (HB-ML) and latent class (LC-MNL) models leverage the MNL framework. These extensions of the MNL framework allow for estimating heterogeneity in the preferences of surveyed individuals. Specifically, the HB-MNL provides an estimate of preferences at the level of each individual while LC-MNL provides estimates of preferences for segments of similar consumers [12]. More details of the specifics of both HB-MNL and LC-MNL can be found in numerous references [9, 12].

Recalling the discussion in Section 1, a stated purpose of mass customization is to provide each customer with their ‘ideal’ product in order to minimize sacrifice gap. Thus, in a competitive market designers face the challenge of satisfying both the heterogeneous preferences of a consumer population and their willingness to pay. As mass customization inherently focuses on product design at the level of the individual, it is necessary to represent market preferences in a continuous manner. By nature, all random utility models in the generalized extreme value family include continuous representations of heterogeneity in some form through their stochastic terms. Leveraging the HB-ML and LC-MNL models will allow identification of the heterogeneity in the MP3 player market.

1.3 Discrete choice theory in engineering design

The use of utility and preferences as a basis for driving design decisions has been evolving over the past two decades. An initial focus of utility theory was on designers’ utility for engineering options [13] but quickly evolved to include consumer utilities, as represented in Hazelrigg’s Decision-Based Design framework [14]. This evolution eventually integrated basic conjoint analysis into product development strategies [15].

As the practice of integrating consumer preferences and utilities continued to mature, research began incorporating the more commonly used DCA basis described in Section 1.2. Work of Wassenaar represents some of the earliest efforts in this integration [17, 18]. Continued efforts toward the integration of DCA at the marketing-engineering interface have focused on several facets including, development of efficient experimental methods for profiling the market and mapping to the technical space [19, 20], exploration of demand aggregation model assumptions and their implication on results [21, 22], integration of conjoint analysis and discrete choice theory with existing design-decision tools like the House of Quality [23] and Analytical Hierarchy Process [24], and exploring the role of developing methods capable of representing market heterogeneity [25].

The references listed above, while not exhaustive, provide a representative cross-section of discrete choice integrated methods and research findings in engineering design. The specific focus of the methods lies in the generalization of knowledge capable of supporting information mapping from the consumer to technical space. Typically, the objective of such methods is identification of ideal system architecture or optimal settings of technical attributes that will succeed in the market.

1.4 Marketing methods in mass customization

For those focused on mass customization from marketing backgrounds, research extends broader facets. Of course, significant effort goes toward understanding need and preference assessment, similar to discrete choice application in engineering design.

Liechty and Ramaswamy [26] develop a Bayesian based multivariate probit (MVP) approach for menu-based choice. This methodology is intended to support menu-driven choice scenarios where features, constraints and pricing may be a function of previous features selected (e.g. graphics cards choices are limited by overall PC family at Dell). Comparisons to alternative approaches and to conjoint based approaches show that this method can be superior. This work represents an important combination of traditional market modeling techniques and the IT infrastructure necessary for effective market assessment in the MC paradigm. Similarly, Fogliatto and Silveira [27] focus on developing a method to determine the optimal choice menu design based on consumer segments which leverage traditional market research techniques, cluster analysis and experimental design techniques, use of stated preference models, and logistic regression. Frutos et al. [28] propose a decision support system for facilitating designer and customer collaboration in the process of selecting production configuration in MC environments. The set of technical, aesthetic and financial constraints are defined interactively by designers and customers and multiattribute decision modeling techniques are used to determine the value of customization.
Fung et al. [29] propose a working model of customers' preferences to product styling. In doing so, the work examines the relationships between product style and fashion trends on consumer preferences and the challenge this imposes for MC. The motivation is that by focusing on "pleasure" gained from aesthetic properties in addition to functional properties, the desire for a product can be increased. Furthermore, a particular style can become reusable if it becomes a fashion - which means that it is liked by a critical mass of consumers - permitting greater efficiency by promoting component reuse.

In addition to methodologies that provide firms a basis for assessing the market - in terms of needs and preferences - with regard to what aspects of a product should be made customizable, a number of researchers have looked at establishing whether or not MC is viable as a product development approach ("customer readiness") and the psychology of the customization decision process.

Bardacki and Whitelock [30] put forth a decision framework for establishing "customer readiness" which consists of three components: 1) customer willingness to pay a premium for customization, 2) customer willingness to wait to receive their customized product, and 3) customer willingness to spend time to specify preferences when ordering. Similarly, Guilabert and Donthu [31] focus on the development of a scale which measures 1) consumer sensitivity toward customization in general and 2) differences in customization sensitivity across product/service categories. The motivation lies in overcoming the general lack of knowledge of how MC strategies and market theory (particularly consumer behavior) must be integrated to make MC a successful paradigm. In developing this scale, two dimensions represented by the CCS (Customer Customization Sensitivity) metric are used as a basis: 1) consumers having an inherent preference toward or against customized offerings and 2) consumers preferring more or less customization dependent on product/service under consideration. The authors point out that their scale can be used to examine how consumers feel about customization and assess if potential consumers will be pleased. In addition, firms could easily modify the scale to assess customization sensitivity for specific products/services. Kaplan et al. [32] use base category information (frequency of use and need satisfaction) to identify users most likely to adopt a mass customized product. Surveying allows for perceived usefulness, ease of use, and behavioral intent to be captured. Finally, regarding the psychology of mass customization, Puligadda et al [33] explore the role of consumer knowledge on customization satisfaction, while Levav et al. demonstrate how order of customization influences overall utility for a customized good [34].

Though non-exhaustive, this review of research on the use of DCA in engineering design and mass customization from the marketing literature demonstrates the complexity and multiple facets in understanding human preferences as a driver for product design. These complexities and the inherent challenge they imply makes the integration of DCA and mass customization explored in this paper an interesting point for discussion. The next section begins the discussion on the approach.

2. APPROACH: DISCRETE CHOICE SURVEY

As originally stated in Section 1.1, the context for this experiment revolves around a firm that is interested in fielding a customizable MP3 player. To serve as a representative market for this product, the authors identified 140 undergraduate students (approximately 70 from NC State and 70 from the University at Buffalo) that would serve as respondents. The selected students came from a junior-level aerospace engineering course in orbital mechanics and senior-level mechanical engineering capstone design courses. All students enrolled in each class were allowed to partake in the conjoint study, which led to a predominately male demographic in their early 20s. In a real product development process, the respondent demographic should be expanded to provide a more accurate description of potential customers.

The selection of 140 students is based on the purpose of this research being “investigative”. For such scenarios it is suggested that “30-60 respondents may do” [35]. Identifying an appropriate sample size is highly dependent on the purpose of the study and generally a complex issue [35].

Creating the survey was completed using an academic license of Sawtooth Software’s SSI Web [36] program. For even the most basic surveys, this software suite allows the user to specify the:
- number of attributes;
- levels associated with each attribute;
- number of alternatives (including the ‘none’ option) per choice task;
- number of choice tasks seen by each respondent;
- and, the number of unique questionnaires.

In constructing the choice tasks, the first challenge centered on identifying the proper product attributes and the number of levels to include. This challenge is discussed in the next section.

2.1 Defining the attributes and levels of interest

The academic license limits surveys to 10 attributes and places an upper bound on the number of possible levels per attribute at 15. Initially this limit was not considered to be a significant constraint, as MP3 players are relatively “simple” products. However, identifying ten attributes happened fairly easily and quickly. This was done by surveying the range of MP3 players currently offered by Apple – the Shuffle, Nano, Classic, and Touch – to determine what features / attributes were available and to bound the possible design space. A listing of the considered attributes and their levels are shown in Table 1.
The attributes and levels shown in Table 1 were chosen by the authors as a means of representing today’s available design space region under which an MP3 player would be constructed (note – the touch pad level is available on Microsoft Zune players, not Apple iPods); the attribute ranges are reflective of products currently available in the market. This list is by no means comprehensive. In fact, the level of desired product decomposition can result in well over 10 attributes. A workaround to this problem would have involved combining multiple attributes into the same category. For example, instead of having two binary product attributes (i.e. photo playback and video playback) the survey could be constructed such that both capabilities would be considered in one four-level feature. Under this approach, up to three binary attributes could be combined without exceeding the allowable number of 15 levels. However, enumerating all possible levels when dealing with a combination of non-binary attributes proved increasingly difficult when faced with the allowable level constraint.

For this study, a decision was made to stay within the confines of the academic license while treating each attribute separately. The attributes in Table 1 were selected to provide customization opportunities in hardware, software, physical dimension, aesthetics, and total price. The inclusion of more attributes would not only increase the complexity of the study, but also raises possible concerns about the ability of respondents to rationally process the list of attributes when comparing two or more products. While the authors have experience with discrete choice surveys that exceed 10 attributes [36], the proper presentation of product alternatives becomes a challenge associated with building the actual questionnaire. This is the focus of the next section.

### 2.2 Constructing the questionnaire

Having defined the attributes and levels to be considered in this study, the next step was development of the questionnaire. The authors used Sawtooth Software’s SSI Web to generate pencil-and-paper versions of the questionnaire to ease implementation in the classroom. Based upon a discussion with Sawtooth’s technical support staff, 10 unique questionnaire versions were created. Each version consisted of 12 questions. The first question asked the respondent if they currently owned an MP3 player. If they did, the second question asked them to write in the name and model of the device. The remaining 10 questions were the choice tasks. In each choice task, students were presented with three hypothetical product alternatives and a ‘none of these’ option. To ensure a proper sampling of the design space, a ‘balanced overlap’ design strategy was selected. The SSI Web manual states that a balanced overlap approach is a preferred selection as it is a middle ground between random designs and complete enumeration.

Many interesting – and potentially significant – challenges arose during the creation of the questionnaire. The first challenge involved determining how many choice tasks to ask each respondent, as a fundamental tradeoff exists with this selection. A large number of choice tasks provide a more complete picture of an individual’s utility for different product attributes and levels. However, if the survey is too long the results obtained from the participant are subject to greater error. Fewer choice tasks better manage the time required for completion, but the model fits from this data are not as robust to uncertainty. Further studies may look to increase the number of choice tasks to the 15 – 20 range.

A more serious challenge occurred when product attributes began to interact within the survey. As mentioned in the previous section, four Apple products were studied to define bounds on the available design space. Initially, the authors considered offering a diagonal screen size of zero inches to reflect the lack of a screen. However, hypothetical products could then be created that have a touchscreen, or play video, despite the technical infeasibility. While it is possible to define prohibitional pairs within Sawtooth to prevent this from occurring, it destroys the orthogonality of the experiment. This issue raises a more significant question about the interaction of components and their ability to be correctly modeled that is further discussed in Section 5.

Finally, the survey created and fielded in this paper was completely text-based. However, questions should be raised about the ability for a text-based survey to provide the necessary preference information needed to successfully model mass customization problems. Diagonal screen size, for

<table>
<thead>
<tr>
<th>Product attributes</th>
<th>Attribute level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Photo playback</td>
<td>Yes</td>
</tr>
<tr>
<td>Video playback</td>
<td>No</td>
</tr>
<tr>
<td>Web access</td>
<td>Yes</td>
</tr>
<tr>
<td>App capability</td>
<td>No</td>
</tr>
<tr>
<td>Pedometer / Nike+ support</td>
<td>Yes</td>
</tr>
<tr>
<td>Input type</td>
<td>No</td>
</tr>
<tr>
<td>Diagonal screen size (in.)</td>
<td>Dial</td>
</tr>
<tr>
<td></td>
<td>Touchpad</td>
</tr>
<tr>
<td></td>
<td>Touchscreen</td>
</tr>
<tr>
<td>Storage</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>3.0</td>
</tr>
<tr>
<td></td>
<td>3.5</td>
</tr>
<tr>
<td>Storage</td>
<td>2 GB Flash</td>
</tr>
<tr>
<td></td>
<td>8 GB Flash</td>
</tr>
<tr>
<td></td>
<td>16 GB Flash</td>
</tr>
<tr>
<td>Color</td>
<td>Black</td>
</tr>
<tr>
<td></td>
<td>Silver</td>
</tr>
<tr>
<td></td>
<td>Blue</td>
</tr>
<tr>
<td>Price</td>
<td>$76</td>
</tr>
<tr>
<td></td>
<td>$149</td>
</tr>
<tr>
<td></td>
<td>$179</td>
</tr>
<tr>
<td></td>
<td>$229</td>
</tr>
<tr>
<td></td>
<td>$249</td>
</tr>
<tr>
<td></td>
<td>$299</td>
</tr>
<tr>
<td></td>
<td>$399</td>
</tr>
</tbody>
</table>

Table 1. Survey setup
instance, may have been difficult for students to understand in a spatial context. Further, a few questions were raised during the survey asking about what the input level of ‘touchpad’ referred to. Exploring the potential of using pictures or virtual models in discrete choice surveys has been identified as an area of future work.

3. APPROACH: ANALYSIS OF SURVEY DATA

The previous section described efforts to create a choice-based conjoint survey and collect data from a respondent population. Numerous challenges in survey construction were raised that point to necessary areas of future work if this tool is to be reliably used for mass customization (or mass production) problems by practicing design engineers. In this section, we explore how the data from these conjoint surveys can be used to provide insight into the design of customized products. Two model forms are considered: hierarchical Bayes mixed logit and latent class multinomial logit. For each model form, we present both possible insights that could be gained from each model and the challenges associated with assimilating the information into the design process. This effort culminates in Section 4, where the analytics from each model are used to explore product design strategies.

3.1 Hierarchical Bayes information

As previously discussed in Section 1.3, a hierarchical Bayes mixed logit model outputs each respondent’s part-worth utilities for all levels of each attribute. For the purposes of this study, part-worth utilities are calculated using a zero-centered difference scale. In this scale, the part-worth utility summation across all levels of an attribute equals zero. An example of the estimated part-worth utilities for two respondents with respect to the ‘input type’ attribute are shown in Table 2.

Table 2. Sample of respondent part-worth utilities recovered from HB-ML model

<table>
<thead>
<tr>
<th>Respondent number</th>
<th>Dial input</th>
<th>Touchpad input</th>
<th>Touchscreen input</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.36429</td>
<td>0.419963</td>
<td>-0.055672</td>
</tr>
<tr>
<td>3</td>
<td>0.746259</td>
<td>-1.248088</td>
<td>0.501829</td>
</tr>
</tbody>
</table>

By capturing the attribute-level part-worth utilities for each respondent, it is possible to gain insight into what features / components / properties give the greatest changes in overall utility. For instance, the results in Table 2 suggest that for Respondent #1, the selection of a touchpad would increase the probability of the proposed product being chosen. Further, while incorporating a dial decreases the probability of choice, the inclusion of a touchscreen changes the overall utility of the product only slightly. However, as a touchscreen is the most technologically complex level for this attribute it would be expected to correlate with a higher cost. As shown in Table 3, this increase in cost could result in a smaller part-worth utility when considering product price.

Table 3. Respondent #1’s part-worth utilities for price

<table>
<thead>
<tr>
<th>Price</th>
<th>Dial Utility</th>
<th>Touchpad Utility</th>
<th>Touchscreen Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>$76</td>
<td>-7.6537</td>
<td>3.3331</td>
<td>3.7795</td>
</tr>
<tr>
<td>$149</td>
<td>0.2502</td>
<td>-3.87</td>
<td>-3.693</td>
</tr>
<tr>
<td>$179</td>
<td>7.453</td>
<td>-1.248088</td>
<td>0.501829</td>
</tr>
<tr>
<td>$229</td>
<td>-1.248088</td>
<td>0.501829</td>
<td>-3.693</td>
</tr>
<tr>
<td>$249</td>
<td>0.501829</td>
<td>-3.693</td>
<td>-1.248088</td>
</tr>
<tr>
<td>$299</td>
<td>-3.693</td>
<td>0.501829</td>
<td>-1.248088</td>
</tr>
<tr>
<td>$399</td>
<td>-7.453</td>
<td></td>
<td>0.501829</td>
</tr>
</tbody>
</table>

The information for in Table 2 demonstrates that customer preferences for a MP3 player are definitely not homogeneous. Here, Respondent #3 gains positive utility for both dial and touchscreen inputs, unlike Respondent #1. This respondent also gains negative utility for a touchpad.

A challenge with the information presented in Table 2 is that it is generally incorrect to compare utilities respondent to respondent. While it is possible to compare attribute utilities for the same respondent (i.e., input type vs. price), the presence of scaling typically prevents a comparison of attribute utilities between respondents. However, as part-worth utilities are calculated on a zero-centered difference scale, it is possible to determine generalized trends about which attribute levels lead to positive increases in utility across the population.

Figure 1 depicts this information for the five binary attributes: photo playback, video playback, web access, app capability, and pedometer. For this data set the ability to access the web and utilize apps would result in a positive utility increase for 133 of the 140 respondents, assuming that price remains constant. This result is not surprising as the surveyed population was undergraduate students who spend a majority of their time on a wired campus. The preference trends are less clear for photo playback and the inclusion of a pedometer, however. While at least two-thirds of respondents would receive a positive utility increase from the inclusion of these capabilities, there is an increased portion of those surveyed that do not desire the inclusion of these attributes.

When exploring the attribute of product color, further interesting insights can be extracted from the part-worth utilities. Again, when price is held constant, the inclusion of a custom color would typically lead to a positive utility increase. This identifies the potential for true innovation in a customization context. However, for the students studied in the survey, pink almost always leads to a negative change in utility. From a customization standpoint, this result tells us that it may be advisable to remove the color pink as a product option.

![Figure 1. Number of respondents with positive part-worth utilities for the binary attributes](image-url)
Finally, Figure 3 shows respondents with a positive part-worth utility for the different prices considered in the discrete choice survey. These results imply that students studied have become desensitized to the fact that an MP3 player could cost at least $200. In fact, an argument could be made that it almost becomes an expectation, as all respondents in the survey received a positive utility increase at the $179 price point. After the $200 price point, the number of respondents receiving positive utility decreases significantly, reaching zero by time price reaches $399. It is also interesting to note that not all respondents received a positive utility increase from the cheapest price. It is hypothesized that this result ties into a respondent’s mental model that a low price may reduce the quality of the product. While quality was not considered in this survey, nor would any of the attributes hint at the quality or brand of the product, it is suspected that respondents may commonly introduce outside factors into their choice task responses. Therefore, a potential area of research is exploring how respondents interact with the survey instrument itself.

### 3.2 Latent class information

Sawtooth has the ability to create up to 30 classes when performing a latent class analysis. For each latent class analysis, a log is produced documenting the convergence of the algorithm. At its core, latent class uses an optimization to develop the class utilities, so multiple starting points are used. Each run is referred to as a replication. Sawtooth then selects the best replication as determined by the strength of fit metrics, and this process is repeated for each number of classes. Table 4 shows a comparison of the evaluation metrics for a five classes run. The “Percent Difference” row compares the best value (Replication 4) to the average value, and it can be seen that there is little difference in the evaluation metrics. However, the classes and their corresponding attribute importance vary significantly. That said, there is no justification not to take the best statistical fit. Further, multiple runs of the software can be used to confirm the best fit. Assuming that the best fit is reliable, it is possible to move on to examine the consumer fit and utility information.

#### Table 4: Strength of Fit Information (5 Classes)

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>Average</th>
<th>Maximum</th>
<th>Membership Probability</th>
<th>Per Cert</th>
<th>Consistent Akaike Info Criterion</th>
<th>Chi Square</th>
<th>Relative Chi Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rep 1</td>
<td>0.9631</td>
<td>36.37</td>
<td>3728.3</td>
<td>1405.6</td>
<td>9.127</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep 2</td>
<td>0.9525</td>
<td>36.17</td>
<td>3736.0</td>
<td>1398.0</td>
<td>9.078</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep 3</td>
<td>0.9695</td>
<td>36.44</td>
<td>3725.5</td>
<td>1408.4</td>
<td>9.145</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep 4</td>
<td>0.9711</td>
<td>36.88</td>
<td>3708.7</td>
<td>1425.2</td>
<td>9.255</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep 5</td>
<td>0.9637</td>
<td>36.06</td>
<td>3740.4</td>
<td>1393.6</td>
<td>9.049</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rep 6</td>
<td>0.9619</td>
<td>35.88</td>
<td>3747.3</td>
<td>1386.7</td>
<td>9.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.9619</td>
<td>36.30</td>
<td>3731.0</td>
<td>1402.9</td>
<td>9.110</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Difference</td>
<td>0.951</td>
<td>1.592</td>
<td>0.599</td>
<td>1.592</td>
<td>1.592</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Latent class models produce a membership probability that indicates the likelihood that the given member belongs to a specific class. Typically there is high membership probability (around 95%), but occasionally a consumer will straddle two classes. Each class has a utility function, and the probability of membership indicates how well the class’ utility function represents the consumer’s utility function. Further, the utilities can be used to determine each attribute’s importance.

**4. APPROACH: UTILIZING THE ANALYTICS**

Based on the results of the two analysis approaches used to process the survey data, hierarchal Bayes and latent class segmentation, two potential “philosophies” regarding the design of a customizable MP3 player are explored. These approaches reflect the resolution of the individual methods.

#### 4.1 Hierarchal Bayes Perspective

The information presented in Section 3.1 provides general insight into which attribute levels correspond to positive part-worth utilities across the students surveyed (when price remains constant) for a HB-MNL model. However, this information...
alone does not provide much help when designing products as product cost is often related to the features / components selected. As the end goal of this work is to minimize a respondent’s sacrifice gap, focus must be placed on designing individually customized products while accounting for changes in components and price.

A trivial solution to minimizing the sacrifice gap would give each customer exactly what they want at the prices with the greatest part-worth utility (typically the lowest prices). Despite maximizing the utility of the consumer, such pricing strategies are often not financially viable from the perspective of the firm. In response to this challenge, this section introduces an approach that provides initial insight toward understanding the maximum price at which a customized product may be offered. This maximum price effectively becomes a constraint during the rest of the design process. If the customized good is offered above this price, the individual will choose to purchase a mass produced good currently on the market, or walk away from the purchase altogether.

Step 1: Determination of Ideal Product (Excluding Price).
To begin this approach, the level corresponding to the highest part-worth utility for each non-price attribute is selected. Relating to the design of a customizable MP3 player, the first nine product attributes are selected. These attributes correspond to the capability and appearance of the product. Once the ideal attribute levels have been identified, the selected part-worth utilities are added to create a Price Excluded Product Utility. This result for Respondent #8 is shown in Table 5.

Table 5. Customized Product for Respondent #8

<table>
<thead>
<tr>
<th>Attribute</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selected Attribute Level Utility</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>8</td>
<td>18.067 (utils)</td>
</tr>
</tbody>
</table>

Completing this process for the entire population yields 140 products customized to maximize each respondent’s part-worth utilities. It should also be noted that in this formulation of the approach, there is no interpolation between attribute levels, even for those components that are effectively continuous – screen size and storage. In analyzing these 140 products, 113 unique products are identified. From these 113 products, even greater detail can be learned about the true preferences of the market in the context of mass customization. While the figures in Section 3.1 depict which attribute levels correspond to positive part-worth utilities, the information gained from the 113 “ideal” products can be used to understand aspects of market size. When looking at desired input type, for example, 13 respondents ultimately preferred a dial input. Further, while the Apple iPod brand has a dominant market share (roughly 72% in 2008) [38], 38 respondents received the greatest part-worth utility from a touchpad input. This is particularly interesting since none of the iPod brands have a touchpad. Finally, 62 respondents prefer a touchscreen input.

Table 6 depicts the attribute levels that obtain the highest part-worth utilities for the six storage options. From this information, it is possible to gain insight into what options should really be offered. While 13 respondents get the greatest part-worth utility from a 16 GB Flash Drive, most respondents gained the most utility from larger storage sizes. Anecdotal, as Figure 1 demonstrated that most respondents gained positive utility from the inclusion of video playback, a preference toward larger hard drive sizes is not surprisingly.

Table 6. Occurrence of Storage Size Options on the 113 Customized Products

<table>
<thead>
<tr>
<th>Storage size</th>
<th>Number of Occurrences</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 GB Flash</td>
<td>0</td>
</tr>
<tr>
<td>8 GB Flash</td>
<td>1</td>
</tr>
<tr>
<td>16 GB Flash</td>
<td>13</td>
</tr>
<tr>
<td>32 GB Flash</td>
<td>1</td>
</tr>
<tr>
<td>64 GB Flash</td>
<td>51</td>
</tr>
<tr>
<td>160 GB Hard Drive</td>
<td>47</td>
</tr>
</tbody>
</table>

Step 2: Determination of Maximum Allowable Product Price. Next, utilities can be calculated for products currently available in the market. For this study, all available versions of selected Apple product models – the Nano (8 and 16 GB), Classic, and Touch – are mapped to the attribute levels identified in Table 1. These products represent the mass produced products currently available and on the market. Seven versions of the 8 GB and 16 GB iPod Nano, two versions of the Classic, and three versions of the Touch are considered in this paper. For Respondent #8, the versions of each product with the highest utility are shown in Table 7. Further, the value of the ‘none’ option from the HB model fit is 6.6236 utils.

Table 7. Available Products with the Highest Utility for Respondent #8

<table>
<thead>
<tr>
<th>Product</th>
<th>Attribute</th>
<th>Price</th>
<th>Utility (utils)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nano 8 GB</td>
<td>1 2 2 1 3 1 2 5</td>
<td>$149</td>
<td>11.9541</td>
</tr>
<tr>
<td>Nano 16 GB</td>
<td>1 2 2 1 3 1 3 5</td>
<td>$179</td>
<td>-8.9915</td>
</tr>
<tr>
<td>Classic</td>
<td>1 1 2 2 1</td>
<td>$249</td>
<td>-1.8770</td>
</tr>
<tr>
<td>Touch</td>
<td>1 1 1 1</td>
<td>$229</td>
<td>15.5841</td>
</tr>
</tbody>
</table>

These results indicate that in a First Choice scenario, Respondent #8 would select the iPod Touch from Table 7. If for some reason the Touch product line were not available, this respondent would then choose to walk away from this purchasing scenario, as the ‘none’ utility is greater than the utility for the remaining available products. While Share of Preference provides a probabilistic rule under which each alternative has a non-zero probability of selection, First Choice
is more immune to IIA effects and is a deterministic rule in which the highest utility is chosen with certainty.

At this point, the design firm is faced with the challenge of setting a price for the customized product such that its utility is greater than that of the highest available alternative (or the ‘none’ option). For this respondent, the remaining available utility is 2.4829 utils. Attention now must return to the respondent preferences for price, in order to find the product price that negates the remaining available utility. This price value can be found by linearly interpolating between surveyed levels of price. For Respondent #8, a price of $314.20 corresponds to the maximum allowable product price. Therefore, if the firm can produce the customized product at a price less than $314.20, Respondent #8 will choose the customized product under a first choice rule.

This procedure can be followed for the entire population of 140 respondents. A histogram representation of the maximum allowable cost for all respondents is shown in Figure 4. These results show that a firm looking to customize an MP3 player may be able to target price points at the upper end of the surveyed range. The last column in the histogram represents respondents who are willing to pay at least $399 for a customized MP3 player. As part-worth utilities cannot be extrapolated beyond the range of the survey, this is the only representation possible. Respondents in this bin still have remaining utility available for the firm to increase the price of the product. However, to understand how much people would be willing to pay would require the survey to be re-fielded with increased price bounds.

It is important to note that under this proposed approach any form of price endogeneity is ignored. For instance, Train and Winston [39] found that consumer choices were more strongly influenced by vehicle attributes, brand loyalty, and dealerships when purchasing an automobile than product line characteristics. As attributes like brand and the concept of supply and demand were not included in the model fit, the likelihood exists that the part-worth utilities for price interact in some way with the model’s error term (which also encompasses unmodeled attributes). This challenge highlights the necessity of including the appropriate and necessary attributes in the models, and raises questions about the independence of errors. However, in its current form, this procedure provides a first-cut analysis at characterizing a general price point at which a consumer would purchase a customized product.

### Step 3: Incorporation of Engineering and Distribution Domains

To build upon the results from the previous step, the firm must now explore what customization options they want to offer by managing technical considerations, supply chains, and component costs. To formulate this as a mass customization optimization problem, the maximum allowable price for each respondent can now be used as constraints in a multiobjective optimization like that described in Section 1. These constraints can be used to help identify what attribute offerings should be removed from customization consideration, or what opportunities should be explored in the development of a product platform.

#### 4.2 Latent Class Perspective

In order to determine the appropriate number of segments to consider as a starting point for developing a mass customizable MP3 player platform, the perspective taken here is to utilize the individual attribute importance as an indicator of where customization should be applied. That is, by identifying product attributes that are most important to all customers (or at least appropriate numbers of segments), it is expected that a basis for answering the question – Which attributes should be customizable? – can be found.

The approach to this perspective starts from latent class analysis results for the 140 survey respondents, reviewed in the previous section. Latent classes ranging from two to 30 segments were analyzed. The first question facing any producer using latent class attribute importance as indicators – whether they are designing MC or static products – is how many segments should the respondents be divided into?

An output of the Sawtooth analysis package is a set of statistics intended to guide the selection of number of segments. Summary statistics for all explored segmentations are shown in Figure 5. These stats are intended to serve as a guide to determining the appropriate number of selections and a full discussion can be found in the Sawtooth technical paper [40]. In brief, CAIC (Consistent Akaike Information Criterion) is a...
“less-is-better” indicator and Percent Certainty, Chi Square and Relative Chi Square are “more-is-better” indicators. However, in all cases, it is suggested that the use of such statistics should be based on relative comparisons, rather than absolute values [9, 40].

Figure 5. Latent class segmentation statistics

Based on the CAIC statistic – which penalizes improvement in the model fit when it relies on additional data or increasing parameters for estimating the model (i.e., increasing the number of segments) [9] – two segments is the “best” solution. Similarly, the Relative Chi Square statistic suggests two segments as the best solution. However, these statistics are not presented as definitive indicators.

Further clouding the issue, the Chi Square and Percent Certainty statistics contradict, to a degree, the other statistics. Using the notion of relative changes, the idea is to look for the point where the statistic approaches asymptotic behavior. In that instance, Chi Square and Percent Certainty suggest that an appropriate number of segments lie between 15 and 22.

It is worth noting that both of these statistics are expected to improve as the number of segments increases since they are indicators of “goodness of fit” in the underlying model. So, again the suggested solution is not definitive.

Since the objective in this treatment is to suggest a possible approach to identifying a segmentation basis that aids mass customization, it is argued that identifying more distinct segments is critical to designing a customizable MP3 player that minimizes the sacrifice gap in individual consumers. Therefore, a selection of segments between 15 and 22 seems a more rational approach that can, in part, be supported by some of the statistics.

In order to determine the precise number of segments to utilize the approach is to identify the point where the segment membership approaches a “uniform distribution” (i.e. equal number of members per segment). This is proposed as a market derived foundation from which an ideal customizable product platform that minimizes sacrifice gap can be created.

Segment membership across the 29 cases is explored (2-30 segments) in Figure 6. The figure supports that, generally, as the number of segments increase, specifically, as it approaches 20 segments, the membership distribution is increasingly uniform. To analytically determine which of these segment options is closest to a uniform distribution, a Euclidean distance is utilized (Equation 4).

$$D_j = \sqrt{\sum_{i=1}^{I} (M_j - m_{ij})^2}$$

(4)

$$M_j = \frac{N}{I_j}$$

(5)

where $D_j$ = aggregate “distance” between the actual number of members per segment and the ideal number of members

$M_j$ = ideal number of members for the $j^{th}$ segmentation option

$m_{ij}$ = number of members for the $i^{th}$ segment in the $j^{th}$

$N$ = number of survey respondents

$I_j$ = total number of segments for $j^{th}$ segmentation option

Figure 6. Membership across latent class segments
This distance is calculated for each of the potential segment options (i.e., 2 to 30 segments) and the one which minimizes this distance is selected. For example, with the 140 respondents participating in this survey, for the first segmentation option \( j = 2 \) segments, the ideal number of members in each segment is 70. The first segment \( i = 1 \) has 97.5 members and the second segment \( i = 2 \) has 42.8 members, resulting in a distance, \( D_2 \), of 38.9. The results for all segmentation options are shown in the radar plot of Figure 7 and based on this approach the segmentation option which breaks respondents into 20 segments is determined to be the appropriate number.

From the figure some generalizations can be made relevant to setting a strategy for designing a customizable MP3 player. First, price is a significant consideration for selection across all segments, with the arguable exception of segment 2 (8%). In designing a customizable MP3 player, it would be beneficial to provide customizations that lead to “cost cushioning” (i.e., turning off discrete features or reducing the level of continuous features reduces cost). The utility trends for price across all 20 segments are shown in Figure 9.

These utility trends (and all others) were created by using simple trend lines (linear, 2nd order polynomial or logarithmic) with the best fit based on \( R^2 \) value. Such utility curves can be utilized for optimization purposes, supporting identification of between-level variable settings that were not presented as options in the survey for continuous attributes.

Storage space is another attribute that appears to be generally important across most segments (except segments 2, 8, and 12) according to Figure 8. The utility curves for storage space shown in Figure 10 demonstrate that utility maximization for this particular attribute may occur at levels not currently offered. This suggests that potentially offering storage space as a customizable attribute – perhaps by decreasing the discrete steps offered – may be a necessary product development strategy in order to minimize sacrifice gap.
The display size attribute is a significant consideration for about half of the segments (1, 2, 3, 7, 9, 12, 13, 16, 17, 18, 19) but not for the remaining segments (4, 5, 6, 8, 10 11, 14, 15, 20) in Figure 8. Examination of the utility curves for this attribute, shown in Figure 11, leads to a similar argument as made for storage space. Offering customizable display size may be an important product development strategy for a mass customizable MP3 player.

Turning attention to the discrete variables, the color attribute is an important consideration for every segment and a dominant factor for a significant portion - segments 2, 3, 4, 5, 7, 10, 13, 15 all have this attribute accounting for 20% or more in Figure 8. Based on the utility breakdown of Figure 12 however, it is difficult to draw conclusions about which colors should definitely be offered and which should not.

Further, since the custom color option has generally positive utility, it is possible that allowing for true customized color options would be a product strategy important to the success of the customizable MP3 player.

For the remaining attributes, the importance can vary by a wide margin in some cases (e.g. web access) but these attributes are discrete in nature. From this analysis focused on attribute importance as a driver of development strategy, these represent features of a product that could be reduced in the number of levels offered without necessarily increasing the sacrifice gap by a significant margin. Identifying product features that can hold a static set of options is important to managing overall manufacturing costs in mass customizable products.

This strategy is similar to the HB discussion from Section 4.1 in that the goal is to determine the product configurations that lead to maximum consumer utility. The exception here however, is that rather than developing insights based on analysis at the level of individuals, a more macro-level of fidelity is represented by the 20 segments. Where 140 ideal products were identified with HB, the latent class approach will yield 20 ideal products, one for each segment, from which to base the product design around.

The key difference in these approaches is that with the HB based approach, it is possible to move immediately to a utility maximization analysis to identify the ideal product foundations. With a latent class based approach the extra stages of determining the appropriate number of segments, as previously discussed, is required. Further, the latent class approach leveraged both utility functions and attribute importance as an approach to determining mass customization strategy (this is not necessary but is offered to represent the complexity of discrete choice data interpretation).

5. CONCLUSIONS AND FUTURE WORK

The fundamental purpose of this paper is to offer “food for thought” in the realm of mapping information from the market to engineering space in the design of mass customized goods. In order to accomplish this, the research considers the design of a
mass customizable MP3 player and utilizes discrete choice theory as a basis for determining approaches to a product development strategy.

In this sense, the proposed methods are hypothetical approaches that a firm might take. Based on the market derived strategies that result from the discrete choice treatment provided here, the next step is to formulate an optimization model to drive design decisions. Specifically, the goal is to minimize sacrifice gap of the individuals while providing financial gain to the firm.

These competing objectives are the basis for a multiobjective problem formulation and represent a starting point for bridging the marketing-engineering gap in mass customization presented in previous work [3]. Future work from this research will focus on developing this formulation using discrete choice theory as a basis, as presented here.

In pursuing this future work a number of critical issues revealed through the execution of this study must also be considered. The issues include:

- The contradictory statistical indicators in the latent class approach discussed in Section 4.2 require investigation. It is unclear whether these indicators are suggestive of bad data, too little data or a poorly designed survey. Understanding how designers can effectively use the discrete choice approach to guide design strategy and learn from these statistics is critical.

- Survey creation and execution could be improved. Specifically, with regard to a mass customized product, asking the right questions is difficult. For example, a realization after the survey was executed is the inconsistency in presenting actual color options and an option for a custom color. In retrospect, it may be more appropriate to present options as custom color or “select from three colors”.

- Understanding the sometimes inexplicable nature of the utility data is important. There are many instances where the utility function for individuals and latent class segments follow W-shaped curves rather than smooth trends. It is unclear whether this is a result of poor survey design and responses, the zero-centered basis of analysis or if there is more complex consumer psychology that is not modeled by this approach.

- Rather than a paper based survey, in the case of mass customized products it may be more appropriate to have computer based surveys. The digital medium would allow for more complex question representation without increased cognitive load. For example, it may be possible to provide a “color tuning” feature which allows the respondent to vary the RGB color characteristics until they find the color they desire. The resulting data would be in a better form for analysis regarding appropriate color options. Further, by providing a survey environment which is closer to online purchasing environments, uncovering intent to buy information may be possible.

- For most cases of product selection, consumers usually only consider a few attributes – a facet of product selection represented by Miller’s work in human capacity for information processing [41] – rather than the ten associated with the MP3 player in this work. It would be beneficial to use partial profile or adaptive choice based conjoint, methods which may be more effective in capturing true preference.

- Utility models created in this work are linear additive (compensatory) with no interaction terms. It would be assumed that in a mass customization environment, interaction between components will play a particularly significant role. Future work should investigate more complex model forms (non-linear, non-compensatory) as a means of more effectively representing true consumer preference.

- In this work, there is no consideration given to modeling the uncertainty of stated respondent preferences. Uncertainty is always a factor in modeling of engineering systems and decisions and must be considered in future work.

- Determining a sufficient level of granularity for assessing consumer preferences is a critical issue. As this paper explored, it is possible to resolve preferences at the level of the individual or at the level of nearly-homogeneous segments. Understanding which level is appropriate requires further study that considers the specific market scenarios, engineering capability and manufacturing constraints, as well as the development of metrics that guide appropriate selection.

- In Section 4.1, designing “idealized” products for all 140 respondents led to 113 unique configurations. If this method is scaled to thousands or millions of customers, does the number of unique configurations reach a plateau that is below the full factorial of possible product configurations? Additionally, does this number plateau below the number of respondents considered? If so, this could lead to the identification of a core product architecture that permits customization for the masses. These research questions will be addressed in future work.

The number of issues to be addressed in continuing this research effort speaks to the complexity of integrating marketing based tools in engineering design.
REFERENCES


