The Effect of Product Representation in Visual Conjoint Analysis

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When most designers set out to develop a new product, they solicit feedback from potential consumers. These data are incorporated into the design process in an effort to more effectively meet customer requirements. Often these data are used to construct a model of consumer preference capable of evaluating candidate designs. Although the mechanics of these models have been extensively studied, there are still some open questions, particularly with respect to models of aesthetic preference. When constructing preference models, simplistic product representations are often favored over high fidelity product models in order to save time and expense. This work investigates how choice of product representation can affect model performance in visual conjoint analysis. Preference models for a single product, a table knife, are derived using three different representation schemes: simple sketches, solid models, and three dimensional (3D)-printed models. Each of these representations is used in a separate conjoint analysis survey. The results from this study show that the choice model based on 3D-printed photopolymer prototypes underperformed. Additionally, consumer responses were inconsistent and potentially contradictory between different representations. Consequently, when using conjoint analysis for product innovation, obtaining a true understanding of consumer preference requires selecting representations based on how accurately they convey the product details in question.
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Introduction

In order to remain competitive in a crowded market, it is important that designers develop a good understanding of their consumers' behavior [1]. One popular approach for gaining this understanding is to construct consumer preference models using conjoint analysis [2]. In conjoint analysis, direct feedback is solicited from consumers in the form of product surveys. These surveys present participants with multiple design alternatives chosen to span the design space without conflating the effects of individual product attributes [3]. By allowing designers to model the preference of their customers and predict responses to new product designs, conjoint analysis has proven to be a powerful tool for product innovation [4–7].

This approach to preference modeling has been used in a wide variety of design contexts including but not limited to, consumer products, health care options, travel packages, food, and engineering [6,8–26]. Although originally used to characterize consumer preference for the functional attributes of a product, over time the method has evolved and extensions have been added to accommodate aesthetic attributes. Still, many preference studies focus on objective product attributes, such as functionality descriptors and feature counts. These types of attributes can be easily described through text or simple images. However, this approach is limited in its ability to convey an accurate depiction of a product's form [27].

With preference modeling being used to tackle more complex product forms, the choice of model parameters, in this case, product representations, becomes a crucial part of the experimental design. Since designers have to generate each of the design alternative representations, survey preparation can require a considerable amount of time and effort. To keep this work manageable, designers have to balance their time and effort with level of detail when choosing a design representation. These representations vary greatly in complexity between rough sketches [28,29], fully realized virtual models [30–32], and real products [16]. Several studies have shown that high fidelity product representations are not a necessity when soliciting consumer feedback [33–38]. Simplified representations are advantageous because they take less effort to both develop and implement. However, some information is lost in representing a three-dimensional object with a simplified two-dimensional representation (even when a 3D model is displayed in a two dimensional environment).

Although many researchers agree that aesthetics play an important role in product design and evaluation [39–46], there is currently no consensus on how detailed aesthetic representations should be when surveying consumer product preference. This work uses conjoint analysis to investigate how a consumer's expressed preference for a single product, a table knife, can vary with different representations. Study participants evaluated a single set of design alternatives in three separate surveys: once as a line drawing, once as a computer-aided design (CAD) drawing, and once as a prototype from a 3D printer. The survey responses were compared to check for consistency between representations and to see if there were any differences in the expressed preference.

Conjoint Analysis

There are many examples of researchers using conjoint analysis and other methods to model consumer preference for shape attributes. Swamy et al. successfully used conjoint analysis to model preference for vehicle headlight shape [47]. The product representation in that work was the outline of the headlight composed of Bézier curves. Headlight shape was also the subject of preference modeling in a separate work completed by Petiot and Dagher [48]. Here, an alternative method to conjoint analysis was shown to be able to capture preference. This method uses multidimensional scaling to build a perceptual space that yields interpretable perceptual dimensions. Reid et al. used a visual conjoint method to quantify the relationship between vehicle profile shape and perceived environmental friendliness [49]. That work had participants' rate two-dimensional vehicle silhouettes on environmental friendliness. The results showed that cars with smoother curves were more likely to be thought of as being inspired by nature

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while boxier cars were less likely. MacDonald et al. used conjoint analysis to model semantic messages of wine flavor associated with different wine bottle shapes [23]. Kelly et al. presented a method for optimizing a product based on shape preference data and engineering performance characteristics [50]. Conjoint analysis is used to capture preference for the shape of a beverage bottle. Shape preference is then plotted along with shape-dependent engineering characteristics to create a Pareto front that illustrates the tradeoffs between aesthetic form preference and functional performance.

In a work by Tseng et al., a method was presented for capturing preference for stylistic attributes [51]. The subject of that work was a vehicle design represented by line drawing silhouettes. Here, neural networks were used to capture preference, and genetic algorithms were used to create optimal designs based on preference and functional performance. In a work by Turner et al., a conjoint framework was used to model preference for color [52]. The attributes in that study were the red, green, and blue components that make up the color of a backpack, and the levels were the component intensity values. That work showed that preference for something as subjective as color can be captured in a utility function. In a work by Sylcott et al., a method for modeling the relationship between form and function is presented [53]. This work uses the same vehicle representation scheme as Tseng et al. in a visual conjoint analysis study. The work involved using meta-attributes to model how consumers make tradeoffs between form and function.

Representation in Conjoint Analysis

There are a variety of different representations used in conjoint analysis studies. Intille et al. presented a methodology that incorporates images in a storyboard format [54]. This image-based experience sampling technique combines images or short videos taken during tasks with conjoint analysis to design a desirable kitchen. Virtual reality is another alternative for product representation in conjoint analysis that is growing in popularity [55]. Urban et al. presented a conjoint-based method for determining preference for electric vehicles using a multimedia virtual-buying environment [32]. Consumers were able to use the environment to simulate the experience of exploring the product. In a work by Tovares et al., a methodology for experiential conjoint analysis is presented [56]. There, the preference for the layout of a long haul truck console is gathered through a conjoint analysis study conducted in a virtual reality environment. Alternatively, some studies have used real products. In a work by Dominique-Ferreira et al., preference for water bottles is modeled with conjoint analysis [57]. This study highlights the importance of preference modeling as consumer preference was found to counter the intuition of the company's decision makers.

Due to the large variation in the representations used in conjoint studies, the influence representation has on choice consistency and model performance is emerging as an important area of research. Jansen et al. performed a study that looked at preference for housing [58]. In this work, consumers were given different descriptions of housing that included either text only, text and a color image, or text and a black and white image. The results showed the importance of some housing characteristics varied depending on how the information was presented. Vriens et al. compared the use of verbal descriptions and realistic pictorial representations when evaluating stereos [59]. The responses based on the pictorial representations showed increased importance for some of the design attributes while the responses based on the verbal descriptions had higher predictive accuracy. Jaeger et al. compared conjoint results for real packages of apples and photos of the packages [16]. The results from both stimuli were found to be comparable. Reid investigated how choice of representation impacts consumer judgment [60]. Consumers were asked to make different evaluations of vehicles and coffee carafes for four different types of representations: computer sketches and front/side view (FSV) silhouettes or simplified renderings and realistic renderings. Results showed that consumers were inconsistent in their preference judgments and objective evaluations across the different representations. In a work completed by Sahin et al., designers and engineers were asked to evaluate vehicle designs that were presented in three different formats, industrial design sketches, CAD models, and physical prototypes [61]. The participants were found to employ different evaluation strategies for each of the concept design representations.

While the last two examples focus on differences across product alternatives and participant segments, respectively, the work presented here addresses differences in consumer utility part-worths based on different representations. As such, the participant pool was not limited to engineers and designers. This work investigates the influence product representation has on consumer response and whether certain representations elicit more accurate responses from consumers.

Modeling Preference

In general, when making a choice between alternatives, Eq. (1) defines the total utility associated with alternative j out of J total alternatives

$$\begin{aligned} u_j &= \beta' x_j + \varepsilon_j \\ &= v_j + \varepsilon_j \end{aligned} \tag{1}$$

Here, u_j is the total utility associated with the jth design alternative, x_j contains the attribute values for the design alternative (and their combinations, such as interactions), and β is a vector of unknown regression parameters. The quantity $\beta' x_j$, or v_j, accounts for the observable portion of the alternative's utility, while ε_j accounts for the unobservable portion, which is treated as a random variable. When interested in the aggregate preference of a group, the maximum likelihood estimation (MLE) method can be used to solve for β.

Discrete choice models relate the utility of a design and its alternatives to the probability of the focal design being chosen [62]. The probability of an individual selecting product alternative j from choice set k is denoted as P_j. Assuming the error terms from Eq. (1) are independent and follow an extreme value distribution, P_j can be expressed as below [63,64]

$$P_j = \frac{e^{v_j}}{\sum_{k \in J} e^{v_k}} \tag{2}$$

β is found by maximizing the probability that the model will generate the observed data. This likelihood, L, can be expressed as below [63]

$$L = \prod_j P_j^{n_j} \tag{3}$$

where n_j is the number of respondents that choose alternative j. The log likelihood, (LL), is obtained by taking the log of Eq. (3) resulting in the following equation:

$$\mathrm{LL} = \sum_j n_j \ln(P_j) \tag{4}$$

An optimal value for β can be found by maximizing Eq. (4) (a monotonic transformation of Eq. (3)) with respect to β. Once β is specified, the utility model is complete and can then be evaluated for performance.

Model Evaluation

Utility models are typically evaluated based on how well they can predict consumer responses on holdout samples. One of the most common metrics used to describe this performance is hit rate (HR). HR is calculated by comparing the observed selections with the predicted selections for each choice set [65]. The predicted selections are determined by calculating the utility associated with each choice option using the attribute β coefficients. The choice option with the highest utility is the predicted choice for each set. Each time the observed selection matches the predicted choice counts as a hit otherwise it is a miss. The HR is calculated using the below equation

$$\mathrm{HR} = \frac{1}{N \cdot k} \sum_{k} n_h \tag{5}$$

where n_h is the number of respondents who selected the highest predicted P_j for each choice set. In this work, HR is used to evaluate the group preference models. The additional performance metrics used in this work are the LL, equivalent average likelihood (EAL), and mean absolute share error (MASE). These values are all calculated at the optimal β and are also used to evaluate the performance of the group preference models.

EAL simply normalizes L with respect to the size of the data set by assessing the geometric mean likelihood per question. EAL is calculated using the below equation

$$\mathrm{EAL} = L^{\frac{1}{N}} \tag{6}$$

MASE is used to evaluate how well the observed choice shares line up with the predicted choice shares. It is calculated by taking the average of the absolute difference between the observed and predicted choice shares for each design alternative as shown in the below equation [66]

$$\mathrm{MASE} = \frac{\sum_{j=1}^{J} |S_{j,\mathrm{PRED}} - S_{j,\mathrm{OBS}}|}{J} \tag{7}$$

$s_{j,\mathrm{PRED}}$ is the predicted choice share, and $s_{j,\mathrm{OBS}}$ is the observed choice share. Together these metrics are used to evaluate the overall performance of the utility models in this work.

Study Methodology

Participants. There were a total of 36 participants in this study (15 female; 21 male; mean age 30 years). Written consent from all the subjects was obtained prior to the experiment. Subjects were instructed prior to the actual experimental session. The focus of the study was varying representations of flatware (table knives). The subjects were recruited from Carnegie Mellon University, Pittsburgh, PA, and the surrounding community over the Internet. Participation was limited to subjects who were graduate school aged or older. The likelihood that these subjects would have some opinion about flatware aesthetics was greater than undergraduates who may have never owned their own flatware. Subjects were compensated with $5.00 for their participation.

Survey. In this work, conjoint analysis is used to build preference models for table knives such as the one shown in Fig. 1. This product was chosen because of its simplicity and its familiarity to consumers. The CAD model of the knife was developed in SOLIDWORKS (Dassault Systèmes S.A., Concord, MA). The model allows for the dimensions of three of the major product features to vary continuously between the upper and lower bounds that were

Fig. 1 Typical table knife

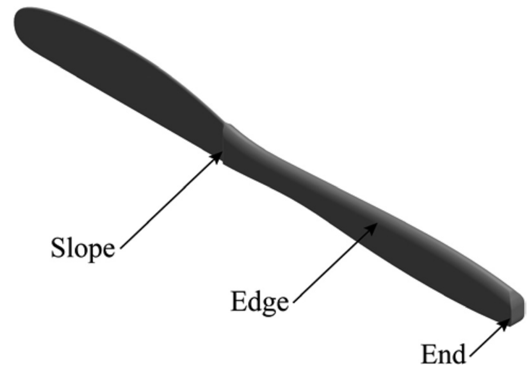

Fig. 2 Perspective view of knife model

selected. These attributes were selected based on a review of knives presently on the market and pilot testing to ensure the model appearance was deemed realistic to consumers. The three attributes, slope, edge, and end, are depicted in Fig. 2.

The slope (Fig. 3), edge (Fig. 4), and end (Fig. 5) attributes describe the height of the handle-blade transition, the curvature of the edges, and the curvature of the end, respectively. Each of the attributes has three levels leading to 27 design alternatives. These designs were used to populate the survey questions presented to study participants.

Random designs have been previously suggested for use in visual conjoint studies [67]. In a random design, each survey participant receives a randomly generated set of questions. This approach was not followed here because the number of 3D-printed prototypes necessary to produce a unique survey for each individual participant was impractical. Additionally, the impact of interaction effects was found to be relatively small in comparison to the main effects and had a negative impact on holdout sample performance. It is possible that this is the result of increased variance in the regression coefficients [68]. As it has been showed that main effects designs can perform well in visual conjoint studies [67], interaction effects were not included in this design. Instead, the SAS software package (SAS Institute Inc., Cary, NC) was used to develop a D-efficient main effects survey from the 27 possible knife designs. The survey design consisted of 18 questions with three options each. The survey included an additional five questions that were used as a holdout sample for a total of 23 questions. The same set of knife designs was presented in each of the three representation surveys. MATLAB

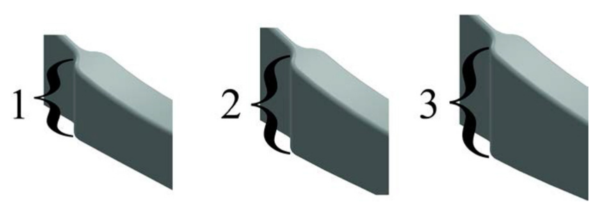

Fig. 3 Slope attribute levels

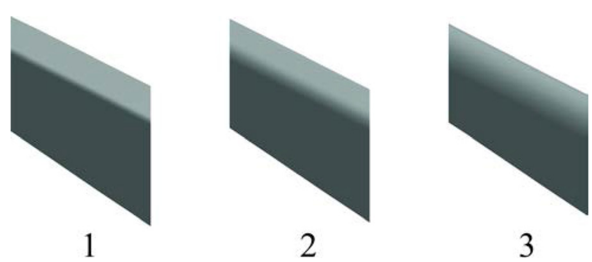

Fig. 4 Edge attribute levels

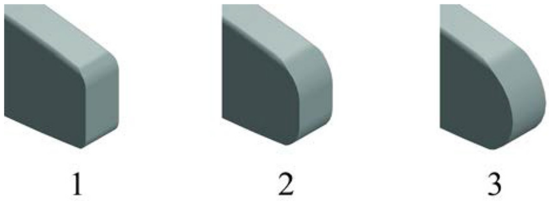

Fig. 5 End attribute levels

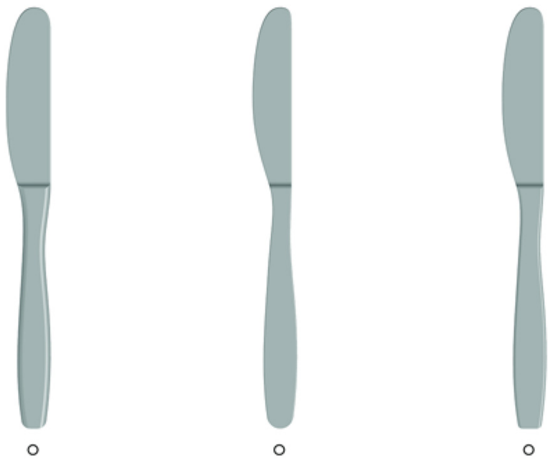

Fig. 6 Screenshot of CAD trial

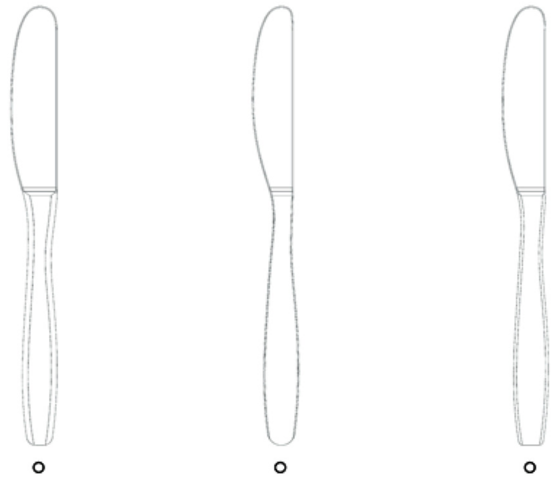

Fig. 7 Screenshot of sketch trial

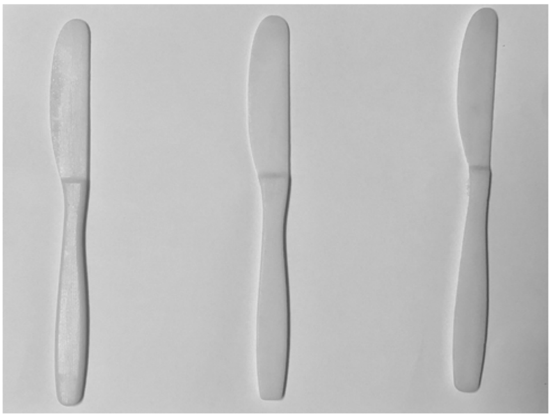

Fig. 8 Photograph of prototype trial

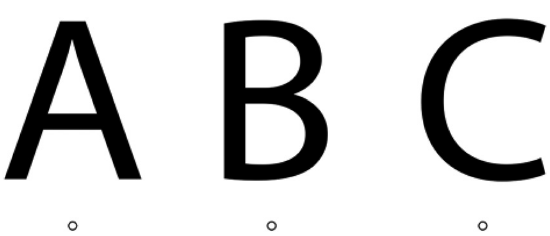

Fig. 9 Screenshot of prototype trial

(The MathWorks Inc., Natick, MA, 2000) was used to present each of the CAD trials in pseudorandom order, on a 19-in. monitor. The knife images were orientated on the screen to resemble how they appear in place settings. Participants used a mouse to select the option they preferred aesthetically. A screenshot from the survey with the CAD representation is shown in Fig. 6.

In addition to the CAD representation trials, participants also evaluated the knives represented as line sketches. These representations were based on the wire frames of the CAD models. The line sketch trials were also presented in pseudorandom order using MATLAB. A screenshot from this representation survey is shown in Fig. 7.

The final representation used in this work was a prototype of the CAD model produced using a 3D printer. An example trial is shown in Fig. 8. The prototype knives were printed using an Objet30 Pro desktop printer and made out of a photopolymer. The prototype knives were affixed to white cardstock and organized in a binder. MATLAB was used to provide on screen prompts and record participant responses. The order of these trials was not randomized but it was reversed between participants (i.e., for half of the participants, the question order was 1–23 and for the other half, the question order was 23–1). The participants selected either A, B, or C corresponding to the options in the binder as shown in Fig. 9.

The participants were not allowed to interact with/touch the knives, only to view them. The participants saw one of the three representations in each condition. The order was counterbalanced across subjects. After completing the conjoint surveys, the participants responded to questions about their product experience and provided demographic information. An example of the experimental procedure is illustrated in Fig. 10.

Results

As stated previously, each of the 36 participants completed three 23 question surveys. If representation does not matter, it is expected that consumers would answer the questions the same way in each survey. The chart in Fig. 11 shows the average number of times participants answered consistently for all the three surveys, for two out of the three surveys, and not at all. These values are plotted alongside the potential results from answering all the questions at random.

The participants answered each of the 23 questions three times: once in the sketch survey, once in the CAD survey, and once in the prototype survey. For each question, the answer selected in each of the three surveys is treated as an independent event. As such, the probability that selections will match in all the three events is 1/9, the probability that two of the selections will match is 6/9, and the probability that none of the selections will match is 2/9. Out of the 23 opportunities, on average, at random, 2.56

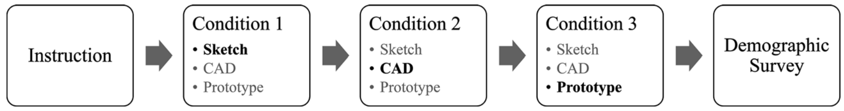

Fig. 10 Experimental procedure example

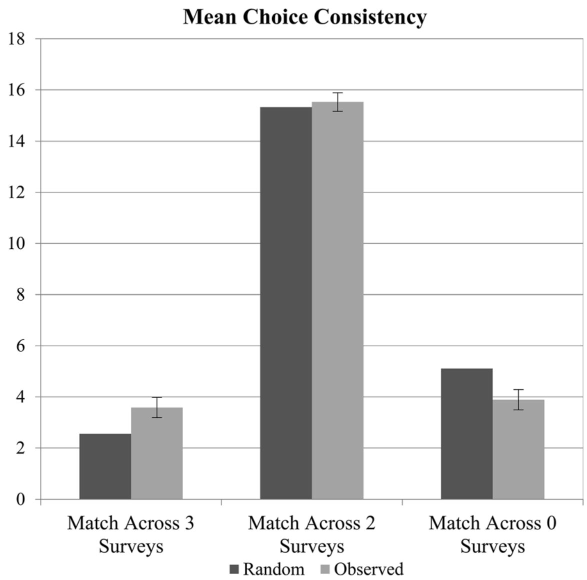

Fig. 11 Mean participant choice consistency

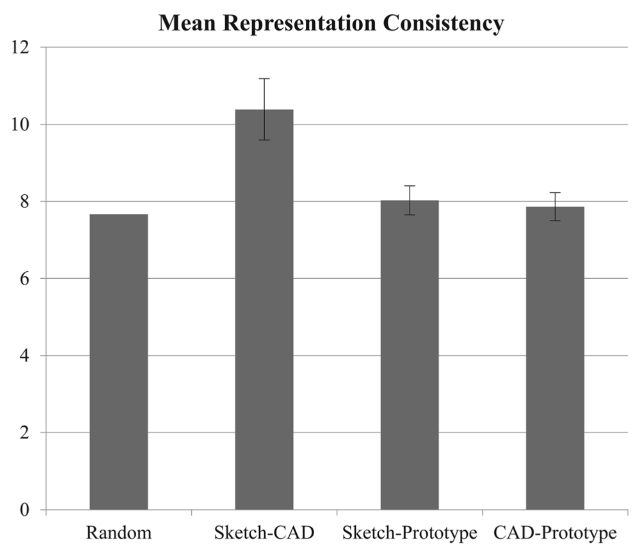

Fig. 12 Mean pairwise representation consistency

questions would be answered consistently across all the three representations, 15.33 questions consistently across two of the representations, and 5.11 questions differently across all the three representations. On average, participants answered 3.58 (standard error = 0.39) questions consistently across all the three representations, 15.53 (0.36) questions consistently across two of the representations, and 3.89 (0.4) questions differently across all the three representations.

Since the average number of times consumers answered consistently across two representations was fairly close to what would be expected from random selection, the number was broken down further to determine if consumers answered consistently more often across any particular pair of representations. The chart in

Table 1 Frequency of selection of each product attribute

	Level	Sketch	CAD	Prototype
Slope	1	231	235	266
	2	290	284	285
	3	307	309	277
Edge	1	344	185	287
	2	271	267	251
	3	213	376	290
End	1	300	296	291
	2	286	274	280
	3	242	258	257

Table 2 Representation model fit results

	B	Null model	Sketch	CAD	Prototype
	$Slope_1$	0	−0.30 (0.10)[a]	−0.31 (0.11)[a]	−0.09 (0.10)
	$Slope_3$	0	0.02 (0.10)	0.13 (0.09)	0.02 (0.10)
	$Edge_1$	0	0.29 (0.09)[a]	−0.32 (0.11)[a]	0.12 (0.10)
	$Edge_3$	0	−0.71 (0.11)[a]	0.38 (0.09)[a]	−0.01 (0.10)
	End_1	0	−0.10 (0.10)	−0.03 (0.10)	−0.01 (0.10)
	End_3	0	−0.02 (0.10)	−0.03 (0.10)	0.01 (0.10)
In sample	LL	−711.90	−663.27	−674.60	−710.10
	EAL	33%	36%	35%	33%
	HR	27%	47%	46%	37%
	MASE	11%	4%	4%	7%
Hold out	LL	−197.75	−184.02	−184.47	−198.88
	EAL	33%	36%	36%	33%
	HR	39%	46%	46%	39%
	MASE	12%	5%	6%	10%

[a]$p \leq 0.01$.

Fig. 12 shows the results of this analysis. With two independent events, the probability that the two selections will match is 1/3. Out of the 23 opportunities, on average, at random, 7.67 questions would be answered similarly between two representations. On average, the participants answered the sketch and CAD representation trials the same way 10.39 (0.79) times, the sketch and prototype trials 8.03 (0.38) times, and the CAD and prototype trials 7.86 (0.37) times, indicating that the sketch and CAD representations have a significantly different selection to random and a more consistent selection to each other, while the physically printed prototype representation does not.

Each product level was seen 23 times by each of the 36 participants. Table 1 summarizes the frequency of selection for each product attribute level. A higher frequency of selection indicates a greater preference for the attribute to be seen at a particular level. The sketch and CAD representations show a large variation in the frequency with which each of the slope and edge attribute levels was chosen while the prototype selection frequencies are closer together. The variation in selection frequency directly impacts the magnitude of the part-worths for each of the attribute levels shown in Table 2. Small variations in the selection frequency imply a lack of strong preference for any particular attribute level. Here, this resulted in the model based on the prototype representation underperforming relative to the sketch and CAD models. The regression coefficients for each discrete choice model were found using the modified quasi-Newton method implemented in MATLAB's *fminunc* function. Dummy variables were used to code the survey design matrix. Level 2 was chosen to be the base level and omitted. The model fit results are listed in Table 2. The first column in Table 2 lists the attribute effects. For each model, the estimated coefficients are listed with the standard error in parentheses and indication of statistical significance. The table also shows in sample and holdout sample performance metrics. Higher LL and EAL values indicate a higher degree of good fit with the data. HR can only reach 100% if all of the respondents choose the highest utility option in all the choice sets. That is unlikely to happen if the choice sets include multiple options with the same utility and respondents split their decisions over those options. As MASE approaches 0% so does the difference between the observed and predicted choice shares. A null model in which the utility of all the alternatives is taken as zero (no information) is included as a reference.

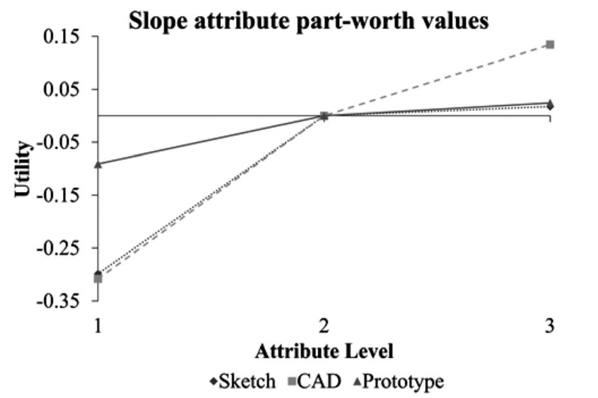

Fig. 14 Slope attribute part-worth values for each representation

Discussion

The chart in Fig. 11 describes how consistent the choices of each participant were across the three representations. The participants were consistent across all the three representations for an average of 3.58 out of the 23 questions (only 15.6% of the time). This is slightly more than random guessing at 11%. On average, the participants answered differently for all the three representations for 3.89 out of the 23 questions (16.9%). The participant selections varied from representation to representation at a lower rate than the 22% expected if the participants answered at random. These results suggest that the participants were not making selections at random and that preference judgments differed relative to the representation choice. Still, there was some consistency as participants answered a majority of the questions the same way for two out of the three representations. As shown in Fig. 12, the average choice consistency between the sketch and CAD representations was significantly higher than the sketch to prototype ($t = 2.69$ and $p < 0.01$) and CAD to prototype comparisons ($t = 2.89$ and $p < 0.01$). This average was also higher than what would be found if the participants were making selections at random. The sketch-prototype and CAD-prototype consistencies were comparable to those expected from selecting at random, suggesting that the prototype representation was not analogous to the sketch and CAD representations. These findings show that the sketch and CAD representations were more comparable for the participants. Additionally, selections based on the photopolymer prototypes were not much more consistent with the other representations than random selection. This indicates that the prototype representation was not well suited for this application. The results from the preference models reinforce this conclusion.

Figure 13 shows the part-worth utilities for the end attribute. None of the beta values for this attribute were found to be significant. The utility function shapes are consistent across the three representations. These results suggest that consumers did not prefer any level of the end attribute substantially more than any other.

Figure 14 shows a plot of the part-worth utilities for the slope attribute from each of the three representations. Although the magnitudes of the beta values are different, the shapes of the utility functions are similar. As such, the effect this attribute has on overall utility follows the same pattern in each representation. Level 1 is least preferred and utility increases with level 2 and further with level 3.

Figure 15 shows the part-worth utilities for the edge attribute for each of the three representations. Unlike with the slope attribute, the utility function from each representation has a different shape. The beta values for the sketch and CAD representations are almost the inverse of each other suggesting that the two representations communicated different information to the participants. Using the sketch representation, level 1 is preferred most followed by level 2 and finally level 3. The result from the CAD model is the exact opposite. Level 3 is preferred most followed by level 2 and then level 1. Although the responses to the sketch and CAD surveys were more likely to be the same, there was enough inconsistency present to result in conflicting preference models. Unlike the slope and end, the edge attribute has depth. This depth is represented with perspective lines in the sketch representation and with shading in the CAD representation. The different methods led to different aesthetic judgments.

These findings agree with those of previous work suggesting that preference judgments are not consistent across different

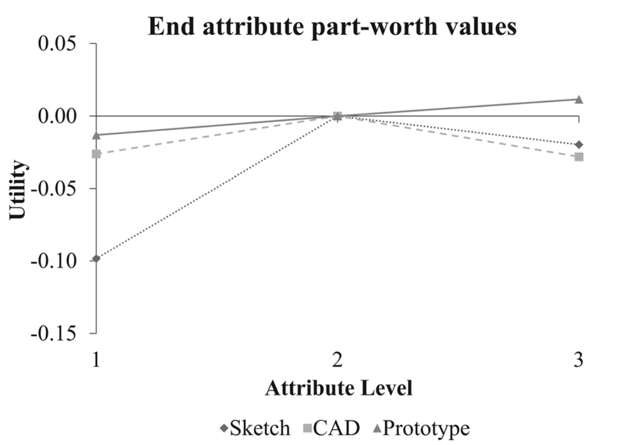

Fig. 13 End attribute part-worth values for each representation

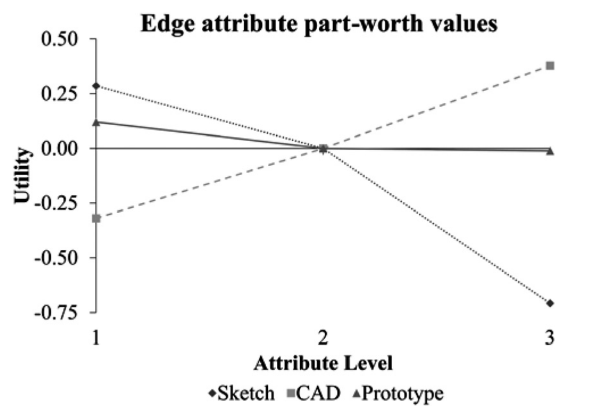

Fig. 15 Edge attribute part-worth values for each representation

representations [56,60]. This work goes a step further by demonstrating how the variation in response to different representations affects utility models and can ultimately lead to conflicting preferred designs. Despite the contradictory differences in preference indicated by the sketch and CAD representations, the HRs for the holdout sample predictions were comparable and both were better than the null model. The MASE was relatively small indicating that there was good agreement between the predicted and observed share values. Unexpectedly however, the prototype representation did not perform as well as the other two models and only slightly better than the null model.

From previous work, it was expected that the prototype representation model would perform as well as or better than the sketch and CAD models [36]. Although the majority of participants in the poststudy survey cited the prototype model as the preferred representation, the model did not perform as well as the sketch and CAD models. One potential reason for this departure was the evaluation criteria used by the participants. Despite being instructed to evaluate the models based on aesthetics, when asked how they went about making their decisions many participants said their choices were based on inferences about functionality. Two of the concerns mentioned most often were how comfortable and how strong (i.e., would not break when cutting) the product would be. The added detail from the prototypes gave participants more information to consider, adding additional variance to their inferences. For example, when evaluating a simple representation such as a sketch consumers can focus on the aesthetics while the more detailed models bring other considerations to the forefront. Some participants commented about the ease with which they made decisions based on the sketch representation, while having a more difficult time comparing the prototypes. Along the same line, although the prototype representation contained more detail than the sketch and CAD models, it was still not a one-to-one depiction of a real knife. As such, the participant feedback indicated that they allowed accidental details [58] such as the material and finish of the prototype to play into their decisions, adding additional variance to the prototype model. In particular, the 3D-printed knives were made out of a photopolymer with limited resolution. Had the prototype been made out of metal instead of plastic, the possibility of breaking would mostly likely have been less of a concern.

As individual products vary greatly in the number and relative importance of aesthetic attributes, it is unlikely that one type of representation will work best in all the cases. While the findings from this study are limited to a single product, they demonstrate the need for careful consideration when selecting a representation to solicit user feedback. Methodology for determining the appropriate representation for a specific product will be the subject of future work. Another limitation in this work is the choice of the product. A relatively simple product was selected so that consumers would be more likely to focus mainly on aesthetics. It is unclear how consumers will respond to more complex products. Additionally, it is necessary to select a product whose form can be reasonably approximated by a 3D-printed model. Doing so will facilitate the addition of an external validation task that will compare evaluations of product representations to those of the actual products. This issue will be investigated further in future work. Finally, the sample that participated in this study was widely diverse. This work did not explicitly account for preference heterogeneity. Doing so in the future may improve the results [69].

Conclusion

In an effort to leverage the potential aesthetics have to positively influence product success, several researchers have turned to conjoint analysis in order to gain insight into consumer preference for aesthetic product attributes. In these studies, a variety of different product representations are used. This work illustrates how preference judgments of aesthetic attributes can vary with choice of product representation. The results showed that aesthetics judgment not only differed but could also be contradictory. Such choice discrepancies directly influence preference models. Researchers are cautioned to take care when selecting a form of product representation. This work demonstrated that in addition to the attributes of focus, physical prototypes that are meant to approximate real products must be made with the specific traits that communicate realism to consumers. Adding general detail to a representation is not alone sufficient to provide accurate predictions. Representations should be selected based on how well they communicate the important attributes to consumers.

The results and participant comments suggest that details of the representation, such as material and finish, can have a significant impact on consumer decisions. Consumers can focus on these representation details and factor them into their decision, adding additional variance to preference models and reducing predictive accuracy. The simple product used in this study may have not garnered a strong preference response from participants, and the subtle attribute variations may have been difficult for consumers to distinguish. In future work, a product that consumers feel more strongly about could be used to garner more pronounced attribute preference variation.

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