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INFORMING EARLY DESIGN VIA CROWD-BASED CO-CREATION

Devarajan Ramanujan[1]*, **Vinayak**[1], **Yash Nawal**[1], **Tahira Reid**[1], **Karthik Ramani**[1,2]
[1] School of Mechanical Engineering
[2]School of Electrical and Computer Engineering
Purdue University
West Lafayette, IN 47907

ABSTRACT

Customer inputs in the early stages of design can potentially lead to completely new outlooks in concept generation. We propose crowd-based co-creation as a means to this end. Our main idea is to think of the customer as a source of initial design concepts rather than a means for obtaining preferences towards designer-generated concepts. For analyzing a large collection of customer-created prototypes, we develop a framework that focuses on generating hypotheses related to customer perception of design attributes. We demonstrate our approach through a web interface to gather design requirements for a computer mouse, a bicycle seat, a pen holder, and a cola bottle. This interface was used in a crowdsourcing study with 253 users who represented potential end users for these products. Results from this study show that web-based co-creation allows designers to capture a variety of form and function-related design requirements from user-created virtual prototypes. We also found that such studies can be instrumental in identifying innovative product concepts, and gaining insights about how user perception correlates with product form. Therefore, we make the case that customer creation through distributed co-creation platforms can reinforce concept exploration in future early design processes.

1 INTRODUCTION

In this paper, we explore the idea of supporting distributed co-design by leveraging web-based interfaces for virtual prototyping. Our goal is to gather customer input to inform product conceptualization and prototyping in the early stages of design. Traditionally, designers use established principles such as voice of customer, focus groups, or immersive design to gather user feedback and translate them to engineering specifications or designs. Our focus is to allow customers to provide direct input to the prototyping stage by creating designs containing form and function-related data. For this, we develop a web interface that allows customers to create designs and express their preferences, perceptions, or ideas. Our work seeks to advance the early design process by leveraging the capabilities of Web 2.0 technologies [1]. Web-based engagement platforms are allowing companies to interact with large user bases and better understand user demographics. From the perspective of the consumer, these web-based tools provide an avenue for shaping the design of future products. These developments have motivated us to explore the usefulness of co-creation in the product design process. Using a crowd-based study, we show that virtual co-creation has the potential to gather a variety of user-related data. We also show that co-creation can generate valuable insights for early design through analysis of user-created prototypes. Two such methods: shape-based and semantics-based clustering, are discussed in this paper.

An important focus of our work is to explore methods that provide useful insights into user perception of design attributes. Previous literature has approached these questions from the point of view of preference elicitation [2, 3, 4, 5]. Such studies discretize the design space through comparisons or rat-

*Address all correspondence to this author - dev@purdue.edu

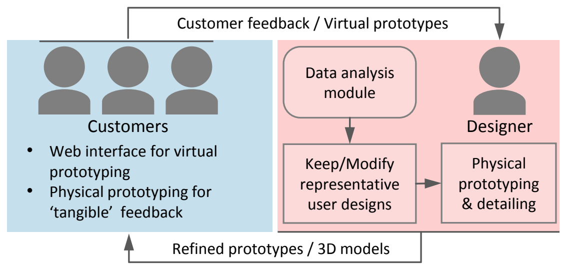

FIGURE 1. Pipeline illustrating our framework for crowd-based co-creation. Customers design virtual prototypes & specify preferences for product attributes using a web-based interface. Designers use the data analysis module to generate insights for the potential market. Subsequently, designers can develop more detailed prototypes for iteratively gathering customer feedback. In this paper, we restrict our focus to methods for user driven of virtual prototypes.

ings of designer-generated prototypes/products. More recently interactive tools for preference assessment have also been proposed [6, 7]. These tools provide better coverage of the decision space by adaptively modifying design concepts using optimization algorithms. A review of such studies can be found in Reid et al. [8]. The focus of these studies is on validating correlations in product attributes through controlled user evaluations. In our work, we approach these questions from the perspective of user-creation. For this, we gather user inputs from direct creation/editing of product form and text-based feedback of desired features. We believe this approach will be useful for product conceptualization as customers can provide insights that may otherwise be misunderstood or entirely missed by designers. This also allows designers to form meaningful hypotheses about product attributes that can be subsequently verified through preference assessment type studies. Therefore, we focus on exploring mixed parameter spaces containing continuously varying shape parameterizations as well as text-based annotations.

Figure 1 illustrates the pipeline for our co-creation framework that supports distributed co-design. Here, design requirements for products are crowdsourced through web interfaces for virtual co-creation. Customers can create virtual/physical prototypes to to express their needs and ideas. Subsequently, user-created virtual prototypes are analyzed by designers in order to understand customer needs as well source design requirements. Designers can also create more detailed prototypes by modifying customer prototypes in order to iteratively gather additional feedback. In this paper, we restrict our focus to methods for user driven of virtual prototypes.

The primary contributions of this paper is the development of a co-creation framework for gathering and analyzing user-created virtual prototypes. This framework consists of (1) a web interface for 3D modeling and text input, and (2) an analysis module for making sense of crowdsourced design prototypes. We limit our focus towards developing a co-creation framework for products in which the effect of shape modification is simple enough that it can be easily understood by the customer. Furthermore, our framework is targeted towards a diverse audience with unknown engineering expertise. Therefore, we decided to conduct our studies with commonplace consumer objects such as computer mice, bottles, pen holders, and bicycle seats. Although the methods developed in this paper can be extended to other kinds of objects, the developed design interfaces for these cases might be more specialized, requiring specific kinds of audiences. Based on the analysis of user-created prototypes, our work has led to these outcomes:

- Crowd-based co-creation studies are feasible to conduct, and scalable to a large group of geographically distributed users.
- Our analysis of shape-data shows that co-creation studies provide insights for correlating user perception to product form.
- Semantic analysis of user-created tags can help in identifying innovative/unique user-created product concepts.

An overarching insight of our work is that it is difficult to derive useful insights by standardizing the analysis process for such studies. There is a strong need for a visual analytics-based tool for exploring results from design-related crowdsourcing studies.

2 BACKGROUND

Web-based platforms are increasing engagement between companies and their customers. Easily accessible product reviews, communication forums, and social media are giving everyday consumers a greater influence over products considered for purchase [9]. Simultaneously, companies are developing web-based design platforms for promoting customer-involvement. Examples include web-based customization platforms such as NikeiD [1], jewelery design tools[2] and apparel configurators[3]. In our work, we try to extend the idea of customer-created designs towards co-creation new consumer products.

2.1 Co-designing new products

Methods and tools for co-design have been developed in diverse contexts such as product interfaces [10], apparel design [11], and service design projects [12,13]. Co-designed products can be valuable in gaining a richer understanding of customer needs. Sanders [14] makes the argument for accessing user experience through not only *what they say*, or *what they do*, but also through *what they make*. The author points out that user-generated artifacts are helpful for capturing user experiences, perceptions, and gathering unanticipated needs.

The level of user-involvement in the product design process usually depends on the type of product/service offered, its in-

[1] www.nike.com/us/en_us/c/nikeid
[2] www.n-e-r-v-o-u-s.com/tools
[3] www.z2jeansco.com

tended market, and company policies. Kaulio [15] classifies user involvement in the design process into three categories: (1) *design for* customers, (2) *design with* customers, and (3) *design by* customers. The author also distinguishes user involvement in design, based on the phases of involvement in the product development cycle. Our idea of involving customers in the prototyping stage, uses both *design with* and *design by* customers. We use customer-designed prototypes as a seed point for the design process. Further refinements are made by designers which can be re-sent to customers for validation.

Software for supporting co-design activities are classified by Li et al. [16] into: (1) visualization tools to assist co-design, and (2) co-modeling tools to implement co-design, from the view point of intended function. The authors make the distinction that visualization-related platforms are usually light-weight, easy-deployed, and platform-independent, while co-modeling systems consist of more advanced features such as feature-based modeling, database-type data management, and collaboration capabilities. Advancements in web-enabled technologies makes it now possible for disseminating advanced browser-based co-modeling software to customers. Such software can enable distributed co-design without the need for direct designer involvement. However, this gives rise to the need for designing interfaces that are engaging, easy-to-learn, and usable. Merle et al. [17] point out that companies must pay close attention towards managing *experiential contexts* of customers by facilitating both hedonism and creative fulfillment during co-design. In their study of collaborative customer co-design websites (CCCWs), Son et al. [18] find that perceived playfulness has the largest effect on customer intent to use CCCWs. Shaukat [19] discusses the role of customer demographics and product complexity with regards to co-design. His studies show that customers' interest in co-design varies significantly based on product type and demographic variables such as gender and age. Economic aspects of collaborative prototyping are discussed by Terwiesh & Loch [20]. The authors develop an economic model for exploring questions such as: (1) how many prototypes should be built, (2) who should pay for them, and (3) how they should be priced.

2.2 Crowdsourcing in design

Crowdsourcing serves as an enabler for democratizing innovation for new product development. von Hippel [21] argues that the democratization of innovation is being driven by improvements in: (1) the capabilities of computer hardware and software, and (2) customer abilities to combine and coordinate their innovation-related efforts via new communication media. Poetz & Schreier [22] conducted a study comparing ideas generated by professionals with users through an idea generation contest for baby products. Their results show that crowdsourcing processes can generate user ideas that score significantly higher in terms of novelty and customer benefit. However, these ideas scored lower in terms of feasibility of realization. This work motivates our idea of co-creation in that; refining customer-created prototypes through the practiced eye of a product designer can potentially help generate practical designs that are also cognizant of customer needs.

Involving a large number of potential users presents challenges towards gathering meaningful data and consolidating them into useful design insights. Koyama et al. [23] present a general technique to analyze high dimensional parameter spaces in order to obtain a distribution of crowdsourced preferences. Their method is suitable for design spaces formed by the variation of a set of continuous parameters. Chaudhuri et al. [24] utilize crowds to learn the semantic attributes of 3D design components. This learning is used to develop an interface for exploring multiple combinations of the design components. On similar lines, Orbay et al. [25] use cars as an example to understand relationships between product form and consumer emotions. The authors generate multiple levels of abstraction of 3D models through visual deconstruction to show that emotional responses evoked by coarse products are strongly correlated with those evoked by final production models. These results allow us to hypothesize that, customer responses during co-creation low fidelity models can be correlated to anticipated responses to final designs.

Previous research has also looked into methods for validating responses from crowdsourcing surveys. Burnap et al. [26] show that crowdsourced evaluations may fail for simple engineering design evaluation tasks, due to the distribution of experts in the crowd. The authors conclude that further research is needed to develop practical methods to find experts, if they are a small subset of the crowd, or when there are numerous clusters of consistent yet incorrect evaluators. Kittur et al. [27] caution that special care is needed while formulating tasks for micro-task markets (such as Amazon mTurk). Strategies suggested by the authors include: (1) having explicitly verifiable questions as a part of the task, (2) reducing the effort required for accurate task completion, and (3) incorporating multiple checks to filter out suspect responses.

3 METHODOLOGY

For facilitating end users to participate in the design prototyping stage, we developed a framework for crowd-based co-creation. Our goal was to allow a large number of geographically distributed users to directly participate in the product prototyping cycle. For this, we developed a virtual prototyping interface that allows end users to interactively manipulate an object's shape and provide text feedback related to attributes such as material, usage scenario, and color. Our design goals for developing the web interface are detailed below.

3.1 Design goals

- Minimal user training required for learning the interface.

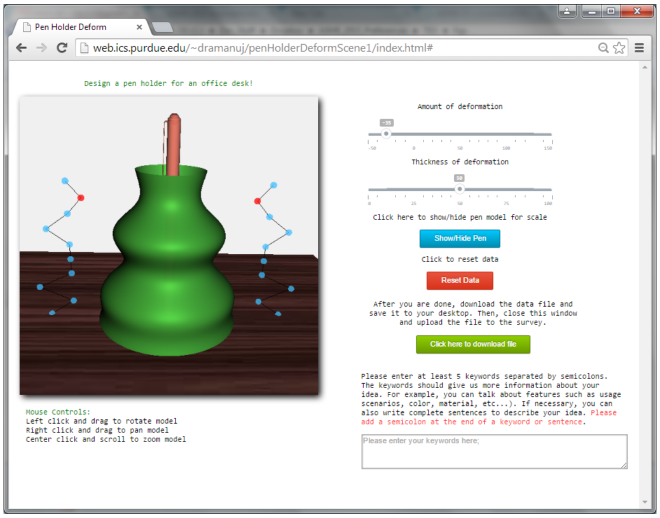

FIGURE 2. Screen capture of the web interface developed for crowd-based co-creation. This interface was used to gather form-related feedback through shape deformations of seed products. Text-based input related to material, color, usage scenario was gathered using the comment box shown bottom-right. We developed one interface for cage-based deformation of generalized objects, and another one for axisymmetric objects. A video tutorial for the interfaces can be accessed here: http://goo.gl/KLezXs. The two types of interfaces can be accessed through these links: http://goo.gl/2ObyjM and http://goo.gl/4CrVC9
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- A simple set of interactions should allow users to create a reasonable variety of 3D shapes. An important consideration is to keep the modeling process relatively unaffected by the geometric complexity of the object.
- Maintain a consistent representation of the 3D object and interactions across different tasks using the interface.
- Allow users to provide input through shape manipulation and textual input. The structure of the gathered data should allow for quantitative and qualitative comparisons.
- Ability to distribute the interface to a large demographic of geographically distributed users.

3.2 Implementation

We designed two web-based interfaces (see Fig. 2) to allow users to express their design choices through two distinct geometric representations: (1) triangle mesh and (2) simple homogeneous generalized cylinder (SHGC). The main idea here was to allow users to explore designs in a variety of contexts. For instance, we used triangle meshes for designs such as a computer mouse and SHGC for symmetric shapes such as bottles. In our implementation, we used ThreeJS[4], an open source JavaScript library for 3D computer graphics. We followed an editing-based approach wherein the users started with a *base model* and modified the model by displacing a set of *control points* provided in the interface (akin to free-form deformation). Our rationale was informed by a pilot study wherein we found that untrained users from a wide academic background could quickly learn the interface controls. They were also able to intuitively conceptualize several shapes to their satisfaction. Below we briefly describe the deformation methods for the triangle mesh and SHGC.

[4]http://threejs.org

Cage-based mesh deformation: In this case, the shape of the object is represented as a triangle mesh $M(V,T)$. Here, $V = \{v_i\}$ is the set of vertices, and T is the set of triangular faces. Our deformation strategy was to define a rectangular *cage* C around the mesh where each vertex $c_j \in C$ was a control vertex which the user could select and displace in order to deform the mesh. We propagated the displacement δ_j of c_j to each of the 8 vertices v_i according to a smooth weight matrix given by $w_{ij} = e^{-\gamma\|c_j - v_i\|^2}$. Here, γ can be adjusted to a specific smoothing bandwidth. Subsequently, the deformed vertices are computed using the equation given below:

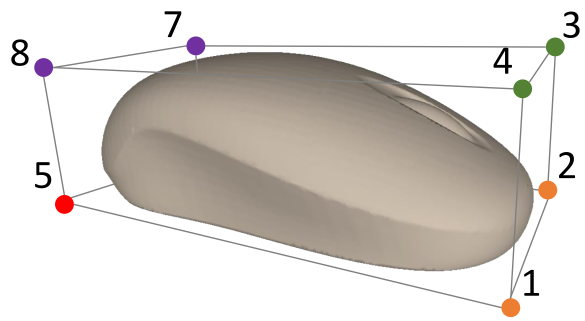
$$v_i = v_i + \sum_{j=1}^{8} w_{ij}\delta_j \tag{1}$$

We initialized the cage as the bounding box of the given mesh. Users could select any vertex on the cage and displace the vertex using three sliders to provide the displacements along the X, Y, and Z axes.

Cylinder-based modeling: In this case, the shape of the model is defined as a vertical stack of circular sections of radii r_i at heights h_i $(1 \leq i \leq n)$. Here, the sequenced list of pairs (r_i, h_i) is the *profile function* of the shape. We model the profile of the shape by representing it as a convex combination of a set of vertically aligned control points R_j at heights H_j $(1 \leq j \leq m)$, as given by:

$$r_i = \frac{\sum_{j=1}^{m} e^{-\gamma_j\|H_j - h_i\|^2} R_j}{\sum_{j=1}^{m} e^{-\gamma\|H_j - h_i\|^2}} \tag{2}$$

For a selected control point, the user could deform the shape by controlling two parameters: (1) the deformation bandwidth (γ_j) and (2) the radius of control point (R_j). We provided sliders for



$$\mathbb{R}^{24} \ni (x_1, y_1, z_1, \ldots, x_{24}, y_{24}, z_{24}) \rightarrow (x_1, y_1, z_1, \ldots, x_{12}, y_{12}, z_{12}) \in \mathbb{R}^{12}$$

FIGURE 3. Symmetry constraints that were specified for cage-based deformation of the computer mouse. Each design is parametrized using the X,Y, & Z coordinates of the 8 bounding box vertices. Pairs of vertices on which the symmetry constraints are applied, are shown using the same color. Due to these constraints, the 24 dimensional data representing the design (8 vertices $\times$ 3 coordinates) can be reduced to 12 dimensional data (4 vertices $\times$ 3 coordinates) without information loss.

the users to specify the values for the parameters.

Constrained interaction: We constrained the magnitude and the type of deformations possible using the interface. This is because we wanted to (1) limit possible shapes to a feasible set that are physically realizable, and (2) prevent artifacts such as self-intersections or singularities that can potentially confuse the user. Although these constraints prevent users from exploring the entire design space, these measures helped us ground the designs to real world constraints such as material limitations and manufacturability. In the current interface, these constraints are implemented through (1) deformation thresholds that are set through slider limits, and (2) symmetry constraints applied to a select pair of vertices. For the cage-based deformation tasks, the applied symmetry constraints are shown in Fig. 3. These constraints allow the design to be parametrized using 12 dimensional data without any loss of information. For the cylindrical objects, symmetry constraints were applied onto the control points to maintain axisymmetric deformation. Additionally, the height of each control point remained fixed.

Simplicity & Consistency: Our interface was targeted at a wide demographic in which a majority of users did not have experience with 3D modeling software. Therefore, we restricted the number of controls in the interface to the least amount with which users could create a reasonable variety of shapes. Although a richer feature set would generate higher fidelity designs, we were curious to see if users could express their ideas through a limited set of controls. To test this hypothesis, we conducted a pilot study with 6 university students. Among them, 5 participants had no previous experience with 3D modeling software. Participants were given two design tasks that required creating a design using the web interface. Before starting the tasks, we made each participant watch a 5 minute video tutorial. They also had the option of exploring the interface for another 5 minutes before starting the tasks. The survey moderator recorded user behavior as well as usability comments at the end of each task. Feedback from the pilot study confirmed that the interface was easy to learn. Additionally, five out of size users felt that they were able to convey their idea using shape deformation and text feedback. A significant concern pointed out was the lack of *a scale* to judge the overall size of the object. Therefore, the interface was modified to display a reference object that provided a sense of scale.

4 CROWDSOURCING STUDY

The research goal of our crowdsourcing study was to explore the idea of crowd-based co-creation as a means of gathering design requirements in the early design stage. For this, we created a survey containing design tasks which required a combination of shape manipulation as well as text feedback. The web interface discussed in the previous section was used for these tasks. The setup of the survey, specific tasks, and user demographics are detailed below.

4.1 Participants

The study was conducted with anonymous participants recruited through Luth Research[5], a third-party service provider. Participation was entirely voluntary and we did not enforce any prerequisites with regards to demographics. However, participants were required to have access to a computer with a web browser that supported both WebGL and JavaScript.

We received a total of 253 complete responses during the time that the survey was kept open. The participant pool was diverse with regards to age ($18-25$: 28%, $26-40$: 41.5%, $41-60$: 27% , $61+$: 3.5%) and gender (60% male, 40% female). Among them, 74% reported that they have a 2-year or a 4-year college degree, 14% of the users were graduates, 10% had a high school degree, and 2% did not attend high school. A majority of users (78%) reported that they did not have any previous experience with creating/editing 3D models. Also, 89% of all users had not previously participated in any kind of focus groups or user studies for products.

4.2 Survey & Design tasks

The survey questions were designed on Qualtrics® and distributed to potential participants through Luth Research. Participants were recommended to set aside a block 20-30 minutes to

[5] www.luthresearch.com

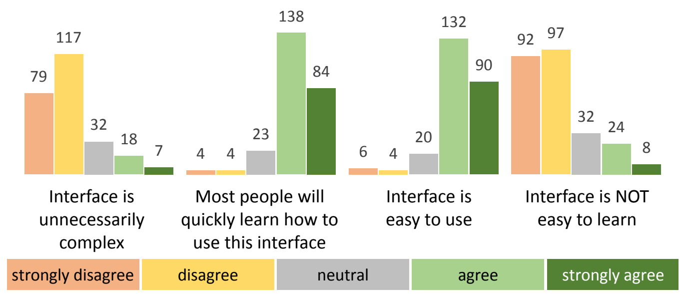


FIGURE 4. Self-reported results for usability-related questions.These questions are adapted from the system usability scale [28].

complete our survey. However, we did not enforce a strict time limit. Users were free to take breaks and continue working on the study throughout the period that it was kept active. Each participant was paid $1 upon completion of the survey. We designed the survey to contain of four types of questions:

User demographics: All questions pertaining to user demographics were voluntary. Questions in this section included participant age, gender, profession, educational background, geographic location, and previous experience with 3D modeling or product surveys.

Design tasks: After answering demographics-related questions, participants were instructed to watch a 3 minute tutorial video about the web interface. Following this, they were given the option of performing practice tasks before proceeding to the actual design tasks. The complete list of design tasks along with corresponding seed shapes is shown in Fig. 5. In this survey, participants performed two design tasks. The first task was randomly chosen from the set of design tasks related to the mouse and the seat. The second task was randomly chosen from the set of design tasks related to the bottle and the pen holder. Users submitted a file containing: (1) the parameterized shaped data, and (2) tags specified on the interface, as a part of the survey.

Feedback about the design process: After completing each design task, participants were asked to provide feedback about the process. We asked them if they had an idea for a design in mind before they started the modeling process and if they were successful in conveying their idea. We also asked them to provide a brief description of the design process that they followed.

Usability-related feedback: After finishing the design tasks, users were asked to rate the usability of the web interface. The specific questions were based on the System Usability Scale (SUS). SUS is a subjective scale which is useful for obtaining a global view of usability with regards to the tested interface [28]. We chose specific questions within the SUS that were relevant in the context of our web interface.

5 RESULTS

In the next subsections, we discuss the results of our analysis of user-created prototypes in order to derive insights that could be useful for early design. Our entire data set consists of 506 user-created prototypes (253 users $\times$ 2 design tasks/per user). While performing our analysis, we removed incorrect responses due to wrongly uploaded, or corrupt design files. The number of filtered responses for each design task is shown in Fig. 5. The methods presented in the next sections are discussed in the context of one specific design task. Our goal is to highlight the utility of performing such analyses in the early stages of product development. Please note that these methods are directly applicable to all design tasks from our survey.

5.1 User performance

Since we were largely unaware of the familiarity of the survey participants with 3D modeling or design tools, we chose to design a simple and easy-to-use web interface. Therefore, in spite of sampling a diverse population, usability results for our web-interface were highly positive. The corresponding questions, and their results are illustrated in Fig. 4. Interestingly, 81% of users for the cage-based deformation interface, and 83% of users for the cylinder-based deformation interface reported that they were able to successfully convey their idea using the corresponding interfaces. Additionally, only 6% and 7% of users for the respective interfaces reported that they were not able to get close the idea that they had in mind. These results show that simple design interfaces can be useful in gathering user-created designs for co-creation. We did not find any significant differences in time taken for creating the designs based on tasks, products, or the type of interface. The median completion time for all users was 3 minutes and 33 seconds per task.

5.2 Shape-based clustering of user designs

The procedure for shape-based clustering of user-created shapes is described below:

Dimensionality reduction: The cage for each shape is represented by a 24 dimensional vector (8 vertices $\times$ 3 coordinates). First, we reduce dimensionality of this vector to 12 dimensions, without any loss of information (due to symmetry).

k-means clustering: Next, we use the k-means clustering algorithm with a Euclidean distance metric to find n cluster centers in the low-dimensional data space. For this, we used CVAP [29] to compute the silhouette index over a range of $n = [2, \sqrt{n}]$ cluster centers. Here n is the size of the dataset. The silhouette index measures cluster consistency and provided us with a basis for determining the natural number of cluster centers.

Cage reconstruction and visualization: Next, we reconstruct the 24-dimensional vector for the cluster centers in order to compute their respective cages. Finally, we deform the seed mesh model using the cages representing the cluster-centers in order to visualize these shapes.

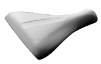
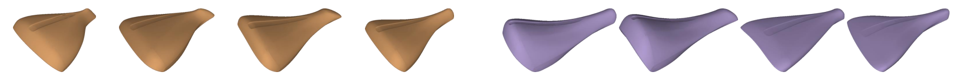
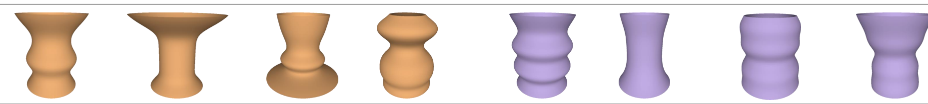
Seed Shape	Design Task	Sample Results
	• Design a mouse that you think is comfortable to use ($n = 37$) • Design a portable computer mouse for a laptop ($n = 61$)	
	• Design a bicycle seat that is comfortable for long rides ($n = 55$) • Design a bicycle seat for a sports bicycle ($n = 71$)	
	• Design a cola/soda bottle that you think is environmentally friendly ($n = 59$) • Design a cola/soda bottle that you think is NOT environmentally friendly ($n = 58$)	
	• Design a pen holder for an office desk ($n = 56$) • Design a pen holder for a desk in an elementary classroom ($n = 55$)	

FIGURE 5. List of seed shapes, design tasks, and example results from the crowdsourcing study conducted with 253 participants. Here, the color of the design task corresponds to the color of the object in the results column. The total number of designs (n), after filtering out incorrect user responses is shown beside each design task.

We applied this procedure to user-created prototypes for the mouse and the bicycle seat. We also tried clustering results from the cylinder-based tasks but found that there was considerable variance between the designs. Therefore, we opted against generating representative cluster centers for the latter designs. Interestingly, for all design tasks with the mouse and the seat, k-means clustering resulted in 3 cluster centers. Results from this analysis are illustrated in Fig. 6. From a company's perspective, a small number of cluster centers may indicate that relatively few product platforms can satisfice a large portion of the potential market. Conversely, if the data does not provide significant representative cluster centers (as in the case of the pen holder and the bottle), mass customization may be a more viable option. Clustering the data also helps us visualize questions such as: *what a comfortable bike seat looks like* for different sets of users. For example, in Fig. 6 in the row of comfortable seat, we see that one set of users prefers really wide seats. In all cases, we observe that users proceeded to increase the rear width of the seat. However, we see no such patterns for the other two dimensions. Such observations can allow us to form hypothesis such as: *the perceived comfort of a bike seat is only dependent of its rear-width.* Results for a *comfortable mouse* show that customers perceive comfort to be correlated with the shape of the mouse near the base of the hand. Follow up studies via methods such as preference elicitation, and eye-tracking can be used to test such hypotheses.

5.3 Semantic analysis of tag data

In the case for the design of the pen holder and the bottle we observed a large variance in the kinds of shapes produced by users. Shape-based clustering did not result in significant representative clusters. Therefore, we decided to look at similarities in user responses based on the list of tags that were provided. Text-based analyses for design data has been shown to be useful for deriving design insights [30]. Our procedure for computing pairwise similarities between users is described below:

Preprocessing user tags: First, we remove non-English or non-numeric words from user-generated tag data and perform stop word removal. This was necessary as the tag data contained a mix of words, phrases, and sentences. Next, the tag data is lemmatized in order to remove inflectional variance. This gives us a list of tags $(R : r_1, r_2, \ldots, r_m)$ that have more information content. Here, each row r_i represents the list of tags for the i^{th} user. Using R, we generate a list of unique words $(U : u_1, u_2, \ldots, u_n)$ for all user responses.

Mapping user tags to unique words: Each participant's list of tags was mapped to the list of unique words to generate a incidence matrix $(A : a_{ij};\ i : 1 \rightarrow m, j : 1 \rightarrow n)$. Here, each row (a_i) represents an incidence vector representing unique words present in the i^{th} user response.

Compute inter-participant similarity: The similarity between two participants is calculated using the incidence matrix. Given two participants i, j we compute the cosine similarity measure between the two rows a_i and a_j as: $S(i,j) = \frac{a_i \cdot a_j}{||a_i|| * ||a_j||}$

Fig. 7 visualizes user responses that had the highest pairwise similarities based on the cosine measure. No significant correlations between shape data and text-based tags was observed. The only cases that did have correlations were instances where the tags described the actual shape of the object. There was significant *noise* in the tag data as most users chose tags that were already a part of the task description or obvious extensions of it. However, the tag data proved to be a valuable resource while looking at outliers. User responses with uncommon words

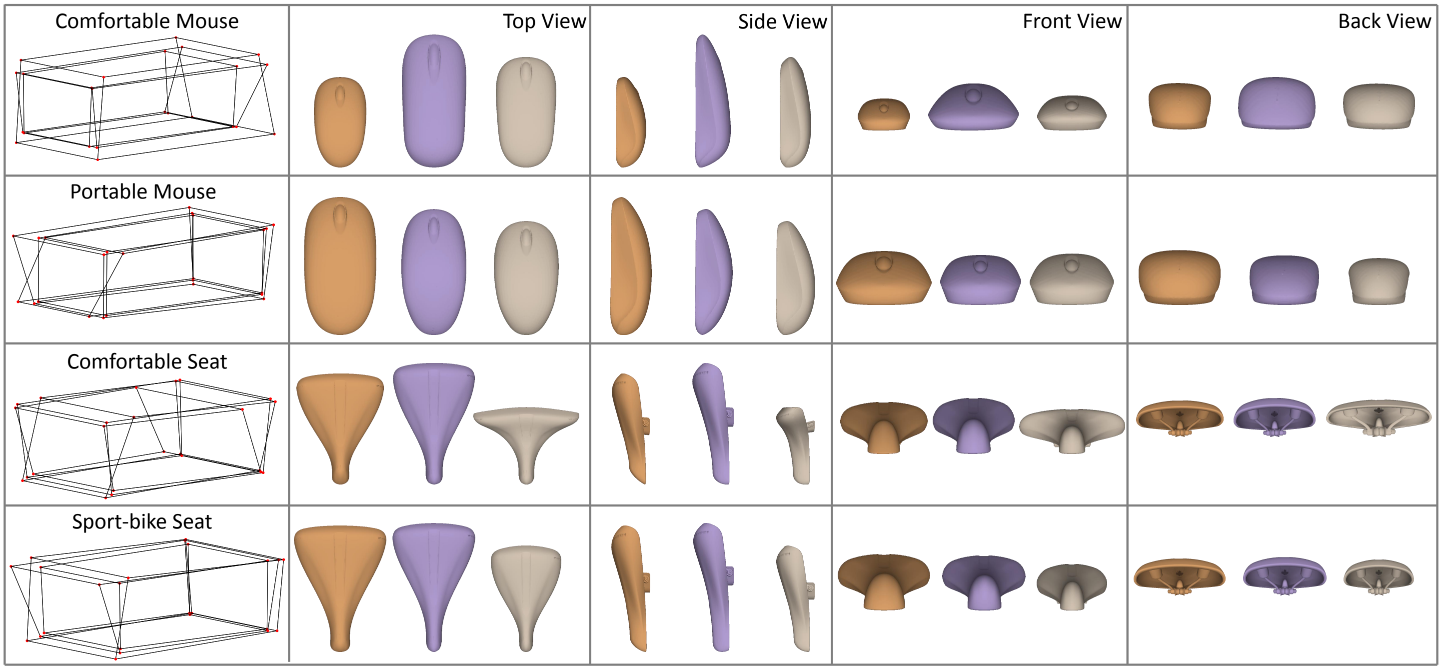


FIGURE 6. Results derived from shape-based clustering of designs for the cage-based deformation task. In each case, the best value of the silhouette index using k-means clustering was obtained for 3 cluster centers. The representative shapes for each design task and their corresponding bounding cages are shown. The cluster centers for each design task are distinguished by color. Please note that figures for a product are shown in the same scale.

seemed to produce interesting design ideas. We found that users with tags such as *oxymoron*, *native-American*, *carbon*, or *boring* seemed to have unique shapes and ideas. This observation presents the possibility of using tag data as a means to discover unique/innovative designs from crowd-based surveys. Although we see this to be a beneficial tool for guiding early design, further work is required to reveal more meaningful correlations.

6 DISCUSSION

Based on the insights developed by analyzing user-created designs from the crowdsourcing survey, we discuss the relevance of co-creation for early design.

6.1 Insights for early design

Results from the crowdsourcing survey show that co-creation platforms can be beneficial for developing new ideas, understanding user perception of product attributes, and benchmarking potential customers. We found that co-creation platforms can be especially useful for hypothesis generation with regards to preference elicitation methods. Allowing the customer to create physical prototypes from virtual models can help in gathering customer perceptions related to tangibility. Physical prototyping can also create a means for companies to perform usability testing with customers spread across geographies. Performing such iterations early in the design process with low-fidelity prototypes can prove to be both economical and insightful.

One important insight from our study is that the process of generating insights for user-created designs is heavily dependent on several environmental variables. Therefore, it is challenging to standardize the analysis process or to develop summative statistical measures. An exploration-based approach that helps the analyst visualize results though multiple lenses, seems to be the way to go. Given the multi-modal and multi-dimensional nature of the data, we felt the need for an interactive exploration tool to reduce the cognitive load on the analyst.

6.2 The ideal co-creation platform

In the current study, we observed that a small set of participants wanted the interface to be more feature rich. Also, asking users to provide tags in an unstructured fashion resulted in noisy data. Not surprisingly, we received more detailed responses from users who reported that they enjoyed using the interface. These observations have helped us realize that an ideal co-creation platform should: (1) allow researchers to gather high-fidelity multi-modal data related to user ideas, (2) let users with high proficiencies create complex designs without penalizing the experience of novices, (3) let users (immediately) validate perceptions related to their design through affordances such as rapid prototyping or

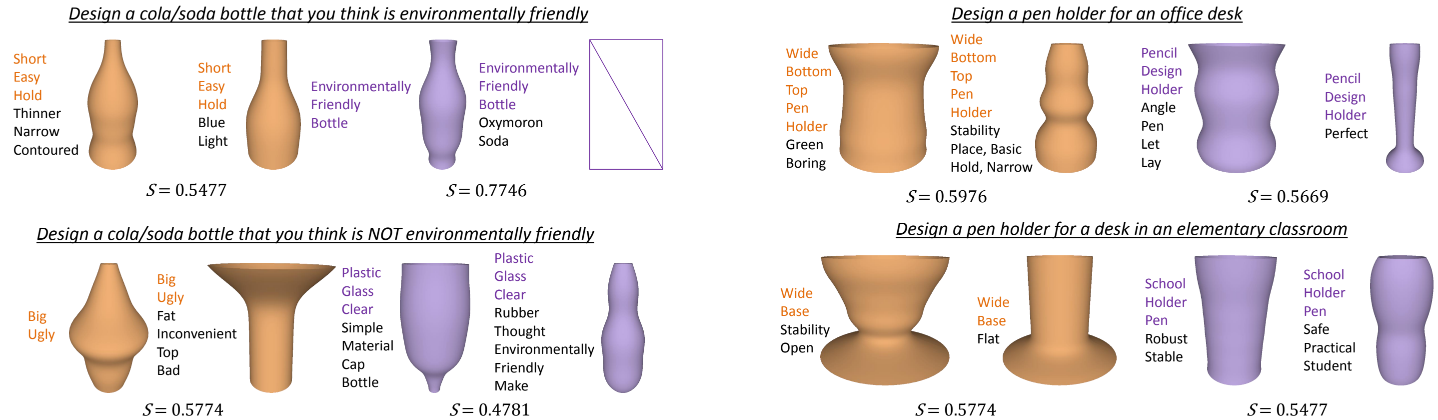


FIGURE 7. Results derived from semantic analysis of tag data. Designs with the highest pairwise similarity (based on tag-co-occurrence) are shown for cylinder-based tasks. The cosine similarity measure is shown below each pair of designs. Here, S=1 represents a completely similar set of tags. Interestingly one user (shown by an empty box)did not submit a design as he felt that the most sustainable cola/soda bottle is the one that does not exist.

immersive simulations, and (4) make creation engaging through gamification.

6.3 Designers Vs. Customers

We are in the process of repeating this survey with a large number of engineering students in the School of Mechanical Engineering. Preliminary results seem to indicate that there is a large difference in how designers and end customers view the co-creation platform. These results are consistent with previous studies [31] that have also found differences in in designers' and users' perceptions of objects. A large number of users from the former group specified that a more complex interface was required for expressing their ideas. This means that either: (1) designers express the same perceptions in higher detail, requiring feature-rich interfaces, or (2) there is a disconnect in perceptions of artifact features between designers and end-users. Both these scenarios are worth exploring, as errors in understanding and articulation can cause a gap in the user experience [32]. We believe that, one possible way to bridge this gap is through iterative co-creation.

Another interesting point that co-creation brings into the forefront is the changing roles of designers and customers. The numbers of connected, technologically-proficient, and hobbyist customers is rapidly rising through efforts such as the Maker Movement [33]. In response, the process of early design needs to be adapted to leverage increased the richness of user experiences. This does not imply that the role of the consumer product designer will become redundant. However, his/her role will have to transition to a mediator that helps companies and users find a common ground. In this process, the designer will help manage real world constraints companies have and help users refine their design embodiments through co-design.

6.4 Limitations and Future work

Our study was conducted with anonymous participants on a crowdsourcing website. Although we took several precautions in designing and analyzing the data, it is not possible to claim that all users provided genuine inputs. There were some cases where we received ever so slightly perturbed models and we could not be certain if this was intentional. Also, providing users with a constrained interface did result in cases where we could not capture user ideas with high fidelity. Our analysis of the data and its utility to designers is biased by the nature of the parts that were used. We cannot tell if providing a very different set of seed parts would change the outcomes significantly. We have tried to address some of the above limitations by surveying a considerably large population. Results from this study have provided us with a good measure of confidence that scaling the study to a larger population is feasible.

In our future work, we will look at expanding our study using diverse product types and user populations. We are in the process of analyzing results from the same version of this study conducted with student engineers. An interactive analytics tool for analyzing crowdsourcing surveys in design is a necessary step for improving our understanding of such studies. Therefore, we will work towards the development of a web-based analytics tool in the near future.

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