Experiential Conjoint Analysis: An Experience-Based Method for Eliciting, Capturing, and Modeling Consumer Preference

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Traditionally, consumer preference is modeled in terms of preference for the aesthetic and functional features of a product. This paper introduces a new means to model consumer preference that accounts for not only for how a product looks and functions but also how it feels to interact with it. Traditional conjoint-based approaches to preference modeling require a participant to judge preference for a product based upon a static 2D visual representation or a feature list. While the aesthetic forms and functional features of a product are certainly important, the decision to buy or not to buy a product often depends on more, namely, the experience or feel of use. To address the importance of the product experience, we introduce the concept of experiential conjoint analysis, a method to mathematically capture preference for a product through experience-based (experiential) preference judgments. Experiential preference judgments are made based upon the use, or simulated use, of a product. For many products, creating enough physical prototypes to generate a preference model is cost prohibitive. In this work, virtual reality (VR) technologies are used to allow the participant an interactive virtual product experience, provided at little investment. The results of this work show that providing additional interaction-based (interactional) information about a product through a product experience does not affect the predictive ability of the resulting preference models. This work additionally demonstrates that the preference judgments of virtual product representations are more similar to preference judgments of real products than preference judgments of 2D product representations are. When examining similarity of modeled preference, experiential conjoint is found to be superior to visual conjoint with respect to mean absolute error (MAE), but with respect to correlation no significant difference between visual and experiential is found. [DOI: 10.1115/1.4027985]

1 Introduction

1.1 Exploring Preference Through Traditional and Visual Conjoint. Armed with meaningful and actionable consumer feedback, designers can create products that directly address consumer needs and desires. The challenge is to obtain such meaningful and actionable feedback in a cost-effective way. Consumer feedback has typically been generated through some combination of focus groups, discrete physical prototypes, or surveys. While these methods all have unique benefits, they neglect to uncover the deeper relationship between preference and variation in specific design elements. Accurate mathematical models of preference, however, provide designers with an understanding of which product features are liked by the consumer, and how changing them affects preference for the overall product, allowing designers to potentially create the ideal product. In this work, the term "preference model" is used to describe a set of utility functions whose inputs are levels of attributes, and outputs are the relative utilities associated with those levels.

Methods, such as traditional conjoint analysis (traditional conjoint), succeed in eliciting, capturing, and modeling preference for the descriptive features of a product, but neglect to capture preference for parameterized form of a product. While descriptive features certainly affect market success, physical form features are a greatly influential factor in a purchasing decision [1]. Visual conjoint analysis (visual conjoint) extends traditional conjoint by allowing participants to judge preference for 2D-static parameterized representations of continuous 3D product forms (static representations) [2]. Visual conjoint and related work has a proven ability to capture aesthetic form preference in a continuous design space and generate accurate preference models using static representations, effectively addressing the limitations of physical prototyping, focus groups, and traditional conjoint [2–5]. While successful, visual conjoint currently presents two shortcomings:

(1) The static representations used as part of visual conjoint to elicit preference are simplifications of the true product form and lack the full 3D interactive experience.
(2) Consumers typically do not make purchasing decisions based upon judgment of a simplified 2D product representation.

In this work, we introduce experiential conjoint analysis (experiential conjoint): a method to elicit, capture, and model consumer preference through experiential preference judgments. As participants are exacted to state preference for various product representations, experiential conjoint is performed with products whose attributes can be evaluated before purchasing (search goods). Experiential preference judgments are made based upon an experience a participant has with a product (product experience). For the purpose of this work, the product experience is defined to be an interaction with a product representation that affects preference for the product. The truest possible product experience is that with the real product; however, there exists a continuum of product experiences. By this definition, static representations and verbal descriptions do not facilitate a product experience.

The product experience is meant to provide the participant with additional interaction-based aesthetic and ergonomic information (interactional information) about a product and allow the

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participant to account for this information when judging preference [6]. Experiential conjoint capitalizes on experiential preference judgments to generate preference models that provide designers with the feedback necessary to directly address the needs and desires of consumers. This paper explores the application of experiential conjoint to capture preference through the use of VR.

1.2 Exploring Preference Through Experiential Conjoint Analysis Using VR. One of the most significant limitations of exploring preference for physical products is the creation of the physical product itself. If preference is desired for a wide range of product configurations, many physical products must be created. This often presents a resource hurdle in time, money, and space. VR technologies provide an opportunity to effectively simulate the interaction with and, in some cases, use of products with far fewer resources.

In this work, the VR environment provides the participant with an understanding of the layout and form of a product. Providing the product experience through the use of VR has unique benefits when exploring preference for both layout and form. For a participant to be able to judge preference for a 3D layout, they must understand the space in which the 3D layout exists. To gain a 3D spatial understanding of a layout of objects, a participant must be able to perceive an object's location both relative to themselves and relative to other objects [7,8]. Depending on the nature of the environment, the 3D spatial understanding might also require the perception of the object's location within the context of a greater environment. A 2D image of a layout, even if the layout itself is 3D, provides a limited amount of interactional information and would not satisfy these requirements. An interactive VR experience provides the participant with additional aesthetic end ergonomic information, meeting the requirements for a 3D spatial understanding. The high quality graphics and interactions currently possible within a VR environment also provide the participant with a detailed understanding of the form of a product. By using the interactive features of a VR environment, the participant can inspect the aesthetic form elements of a product similarly to how they would inspect the aesthetic form elements of a real product. Through the experience provided by the interactive VR environment, participants will be able to gain a deeper understanding of a product and judge preference based upon this understanding.

Section 2 of this paper details the previous work concerning conjoint analysis and VR. Section 3 details the methodology employed in experiential conjoint and the hypotheses of this work. Sections 4–7, respectively, detail case studies, hypotheses, results, and conclusions.

2 Background

2.1 Conjoint Analysis. Conjoint analysis was created to mathematically capture consumer preference in a utility function [9]. As part of a traditional conjoint survey, participants are asked to rank, rate, or choose among product offerings with various textually described discrete-feature combinations, determined using experimental design [10]. These combinations of features are carefully chosen as they largely determine whether participant responses can be used to generate accurate utility functions [10]. When a small number of product features are being explored, it is possible to use a full-factorial experimental design, in which all feature combinations are presented to the participant. For most experiments, a full-factorial experimental design is impractical due to participant fatigue and combinatorics, and a fractional-factorial experimental design must be utilized to provide the participants with a limited but evenly distributed set of product offerings. Fractional-factorial experimental designs have been previously used to successfully predict part-worth utilities [2,9–11].

2.2 Visual Conjoint and Decision Making in Engineering Design. Expanding upon traditional conjoint, visual conjoint captures aesthetic form preference by allowing participants to make preference judgments based upon static representations. As a result, the utility functions generated from visual conjoint represent aesthetic form preference over a continuous design space and allow overall product utilities to be calculated from the continuous variation of product attributes. Orsborn et al. introduced and employed visual conjoint with 2D visual representations of sport utility vehicles (SUV), the form of which was parameterized using Bezier curves. Participants were led through a discrete-choice experiment in which they were asked to choose between different 2D SUV representations. The participants' choice decisions were employed to generate utility functions that mapped consumer preference to the control points of the Bezier curves used to parameterize the continuously varying SUV shapes. The participant's utility functions were then used to generate high, neutral, and low utility vehicle designs that were shown to participants in a follow-up discrete-choice study. In a follow-up study, participants chose high-utility designs over low-utility designs with statistical significance, demonstrating that visual conjoint can accurately elicit, capture, and model aesthetic form preference [2].

Visual conjoint-based methods have been used to further understanding of both form and function. Sylcott el al. [12] created a metaconjoint model that combines both form and function, to elicit and accurately model consumer preference. Reid et al. [4,13] used conjoint analysis with static representations to identify vehicle shape features related to perceived environmental friendliness. Kelly and Papalambros [5] additionally used conjoint analysis with static representations to capture preference for the shape of plastic soda bottles. These works demonstrated the ability of visual conjoint-based methods to elicit, capture, and predict form preference. The methodologies detailed in this paper were previously introduced in part by Tovares et al. [14].

With respect to traditional design decision making, Gurnani et al. [15], Ferguson et al. [16], Li et al. [17], and Maddulapalli et al. [18], among others, have developed methods to handle multi-attribute decision making and inform engineering design that account for risk, uncertainty, and preference. In many of these situations, a more robust model of preference that accounts for experience would be beneficial.

2.3 VR. VR technologies have progressed to the point where interactive, immersive, and realistic experiences can be provided with little investment. These advancements have allowed VR to be employed in a variety of situations including to train forest machine operators, pilots, and computer numerical control machine operators; to improve surgical performance; and to provide crowd simulation for military purposes [19–25].

The issues associated with VR environments have also been explored thoroughly. Bowman and McMahan [26] clarifies the difference between immersion—the authenticity of the sensory experience—and presence—the user's response to the VR system—and describes the factors affecting the former. Tasks involving reaching or aimed movements were found to be less effective in VR environments than in the real world [27]. On the other hand, Reuding and Meil [28] attempted to gauge the ability of VR to provide a meaningful ergonomic understanding and found no statistical difference between the efficiency of tasks performed within a VR environment and in a real world setting. To address this, providing either visual or tactile feedback has been found to reduce error in user estimates of distance in VR environments [29].

With respect to product knowledge and VR, Söderman [30] investigated the additional product knowledge provided by realistic VR product representations and found that a participant's understanding of the product is minimally affected. Artacho-Ramírez et al. [31] conversely found that that representation type greatly affects the transmission of product knowledge. There exists no consensus on the effect of VR on product knowledge. We hypothesize that VR will, in fact, provide additional meaningful product knowledge and detail the test for this hypothesis in Sec. 5.

With respect to displaying the VR environment, display size and resolution have been found to significantly affect the completion times of tasks requiring 3D spatial information [26]. Greater realism, through the inclusion of realistic lighting and reflections, has been found to increase user presence [32]. In a VR environment, frame rate and lag have a direct effect on the user's ability to perform a task [33,34]. The results and suggestions of these works are considered in the creation of the custom VR environment and the implementation of the experiential conjoint methodology.

2.4 VR and Conjoint Analysis. While the use of VR within conjoint analysis has previously been explored, our work is differentiated in several ways. Berneburg and Dijkstra et al. performed conjoint studies in which participants judged virtual product representations with categorical form attributes [35–37]. In the experiential conjoint methodology introduced in this paper, product forms are parameterized continuously and product utilities can be calculated for any combination of attribute values. An additional, and critical, distinction is that while participants in the studies performed by Berneburg and Dijkstra et al. were able to evaluate virtual product representations, their experience did not simulate interaction with and/or use of said product. Experiential conjoint aims to provide participants with an experience more similar to the true product experience by allowing for the interaction with and simulated use of a product. Orzechowski et al. [38] performed a study which examined the use of VR when capturing preference for housing layouts. They utilized noninteractive VR representations to provide participants with additional information and found that neither external nor internal validity was significantly affected by the noninteractive VR representations.

3 Experiential Conjoint Methodology

3.1 Summary of Methodology. This section details the methodology for eliciting, capturing, and modeling preference through experiential conjoint. With a product chosen to investigate, its design is analyzed to identify the attributes that, when changed, are most likely to influence a participant's experience. With these attributes identified, design of experiments is performed to determine the specific product configurations to be experienced by the participant during the study. In this work, D-optimal experimental designs are used [2,12,39,40]. Alternative approaches to experimental design have previously been used. [4,5,41]. Once confirmed, the product configurations are created in the medium chosen for presentation to the participant. Next, a survey is conducted in which participants are allowed to interact with and experience the use of the product configurations. The experiential preference judgments provided by the participant in the survey are then employed to generate preference models whose predictive ability is validated using the Pearson product–moment correlation coefficient (PCC) the MAE.

Two studies are presented in this paper. The first study is designed to capture layout preference. The second study is designed to capture form preference. The methodology detailed henceforth is generalized. Issues concerning layout and form are addressed in Sec. 4.

3.2 Determining Product Attributes and Parameterizing the Design Space. In order for experiential conjoint to be performed, a product must be chosen and its design must be broken down into attributes. These attributes represent variable design elements, and typically there are many possible attribute choices. After studying the design of the product and the design space in which the product exists, attributes are chosen that are likely to impact a participant's experience. Attributes can be location of elements, dimensions of elements, or mathematically defined curves representing the shapes of elements [2]. Once the attributes of the product are chosen, those that are continuous must be discretized and their associated levels must be determined to allow for experimental design. Three levels that equally divide the design space should be chosen for each attribute to allow for a nonlinear representation of preference. The process of parameterizing the design space is unique for each product, and additionally each type of preference being explored [42]. In this work, interaction effects were not considered. Pilot studies demonstrated the generation of accurate preference models without accounting for interaction effects. A similar approach was additionally taken by Osborn et al. [2] and Orzechowski et al. [38] and has led to accurate main-effects preference models generated without interaction effects.

3.3 Response Format. In experiential conjoint, the participant is provided with additional interactional information about a product through the simulated interaction and use of that product. If a participant is asked to experience and absorb information pertaining to multiple products, it is easy to imagine a situation in which cognitive overload would impede the ability of the participant to make consistent and meaningful preference judgments [43–45]. Because of this, a ratings-based response format is chosen, in which the participant experiences and judges one product at a time.

3.4 Experimental Design. Experimental design is performed to determine the runs or product configurations, included as part of the experiential conjoint survey. In this study, the number of runs required to perform a full factorial, in which every configuration is explored, is unreasonably large. In order to have a reasonable number of runs, a fractional-factorial design is implemented [10]. For this work, the D-efficiency measure is chosen to evaluate possible fractional-factorial designs [46].

3.5 Functional Form of Preference Model. At its foundation, conjoint analysis is a decomposotional method that uses consumer evaluations of products to estimate the utilities associated with those product's individual attributes. If the attributes explored are continuous, utility values are desired for the entire design space. For the purpose of this work, there are three choices for the functional form: linear, quadratic, and part worth. The linear and quadratic forms yield continuous and differentiable utility functions. The part-worth model generates utilities for the levels examined as part of the study, which are then typically linearly interpolated.

In this work, individual preference models are chosen of quadratic form, remaining consistent with visual conjoint [2]. The individual quadratic preference model states that an individual's preference for a given design can be described using the sum of that individual's quadratic preferences for each of the design's attributes. For the quadratic preference model, two coefficients are estimated for each utility function. Additionally, a global intercept term is estimated. Equation (1), used to calculate the total utility of a design q for participant r with total attributes p, shows the form of the quadratic preference model, in which α_1 and α_2 are the quadratic coefficients of the ith attribute, and X_i is level of the ith attribute

$$y_{r,q} = a_0 + \sum_{i=1}^{p} \alpha_{i,1} X_i + \alpha_{i,2} X_i^2 \tag{1}$$

The linear coefficients of the quadratic utility functions composing the preference model are estimated using standard ordinary least squares regression.

3.6 Evaluating and Comparing Preference Models. In this work, preference models are evaluated on their predictive validity: how well the preference model performs when estimating external preference [46–49]. Preference models must be able to predict preference for designs not used to generate the preference model. In order to validate the predictive ability of the preference model, the PCC and MAE are employed [50,51]. The quantification of the predictive abilities of the preference models is desirable as this quantity is representative of the level of insight that can be obtained from the preference model

$$\mathrm{PCC} = \frac{\sum_{q=1}^{n}\left(y_{r,q} - \bar{y}_r\right)\sum_{i=1}^{n}\left(Y_{r,q} - \bar{Y}_r\right)}{\left[\sum_{q=1}^{n}\left(y_{r,q} - \bar{y}_r\right)^2\left(Y_{r,q} - \bar{Y}_r\right)^2\right]^{1/2}} \tag{2}$$

$$\mathrm{MAE} = \frac{\sum_{q=1}^{n}\left|y_{r,q} - Y_{r,q}\right|}{n} \tag{3}$$

To calculate both the PCC and the MAE, holdout runs are added to the experimental design. The participant experiences and rates holdout runs just as they would any other, but holdout runs' ratings are not used in the generation of the coefficients of the utility functions. In Eqs. (2) and (3), y is the predicted utility for design q for participant r, Y is the provided rating for design q for participant r, and n is the number of designs used as holdout runs. $\bar{y}_r$ is the average predicted ratings for participant r, and $\bar{Y}_r$ is the average provided ratings for participant r. For each participant, the same set of designs is used to calculate both the PCC and MAE. The participant ratings for nonholdout runs are used to generate the preference model. This preference model is used to predict the ratings that the participant would provide for the holdout runs. The PCC and MAE are then used to calculate the ratings given to the holdout runs by the participant and the ratings predicted for the holdouts runs by the preference model. Together the PCC and the MAE provide a robust analysis of the predictive ability of preference models.

4 Experiential Conjoint Case Studies

4.1 Exploring Layout Preference. This study is designed to provide an example of the experiential conjoint methodology and VR experience performed in the context of capturing preference for the positions of the dashboard components of a long-haul truck. This study also serves to compare experiential conjoint and visual conjoint. Drivers of long-haul trucks become distracted when attempting to access the dashboard, and distracted long-haul truck drivers are more likely to be in an accident [52,53]. Taking into account driver preference when designing the layout of the controls of the dashboard would increase usability, decrease on-road distraction, and, in turn, decrease the likelihood of an accident. Further, given the competitive nature of the industry, more highly preferred designs could improve market share for a product. As part of this experiential conjoint study, a series of dashboard layouts, determined through experimental design, are presented to participants on a computer screen. Through the use of the VR environment, participants are able to interact with the virtual dashboards, gaining a 3D spatial understanding of the component layout. Participants make preference judgments based upon this interactive experience that are recorded, and used to generate preference models representing preference for the positions of the dashboard components.

4.1.1 Truck Cab Optimization. Usability, the ease with which a consumer can use a product is greatly affected by the quality of the product's controls [54]. Usability, in turn, greatly affects a consumer's overall satisfaction with a product. However, in many professional settings, the effect of a product's usability transcends satisfaction, affecting factors such as safety or efficiency [52,53]. Layouts of controls/interfaces have previously been optimized and evaluated with respect to anthropometrics and eye-gaze data [55], but it is crucial to consider user feedback, especially in situations where a product's usability affects efficiency or safety [56–58]. VR technologies eliminate the need for physical prototypes and allow users to gain an understanding of and evaluate the layout of controls/interfaces with respect to usability.

Layout optimization has previously been applied to the cab of a long-haul truck. The optimization of the driver package using anthropometric data has ensured that drivers are able to perform critical driving functions without having to engage in poor posture, a behavior that has been known to increase driver distraction [58]. By taking into account individual body characteristics and related preference, further advances were made in ergonomic designs of driver packages [57]. Digital human models have also been used to predict and remove any potential ergonomic issues that might arise while driving a truck [59]. While these optimization methods generate cab designs that ensure general ergonomic usability, individual driver preference is not accounted for.

4.1.2 Determining Product Attributes and Parameterizing the Design Space—Layout Preference. The purpose of this experiential conjoint study is to elicit, capture, and model preference for the positions of the control/interface elements of a product. The control/interface elements chosen for this study are the radio, switch controls, global positioning system, and temperature controls. For this study, each element is given two one-dimensional attributes: an x-position and y-position along the 3D dashboard. Each attribute is discretized at three levels. The minimum and maximum values of the dimensional attributes are determined through examination of the design space. Once the minimum and maximum values for the dimensions are determined, a middle value is also determined. When exploring layout preference, it is best to discretize the design space into a grid pattern. Care must be taken when discretizing the design space to ensure that both an efficient experiment design can be generated for a low number of runs and that preference can be captured for the entire design space [42].

4.1.3 Accounting for Spatial Constraints When Exploring Layout Preference. When designing physical products, in particular layouts, it is critical that two elements not have the same x-position and y-position, as that would cause them to be in the same physical place. If this issue were to be resolved after the generation of the design matrix, heuristics would have to be developed to accommodate participants rating layouts not dictated by the design matrix, inducing error in the parameter estimates. When generating experimental designs, SAS, the software used for this work, allows for the implementation of restriction macros. For this work, the restriction is: in a run, two elements cannot have the same level for the x-position and y-position attributes. Implementation of the restriction macro allows for the generation of optimal experimental designs that bar two elements from occupying the same space, effectively resolving the overlap issue.

4.1.4 Virtual Truck Environment. In this study, the VR environment is used to provide a participant with an understanding of the layout of the dashboard components of a long-haul truck. For creating the VR environment, careful attention was paid to ensure that the interaction was able to provide the participant with meaningful information, and that the resolution of the interaction and the graphics were consistent. The environment includes representations of the dashboard, steering wheel, radio, switch controls, global positioning system, and temperature controls (Fig. 1).

The radio, switch controls, global positioning system, and temperature controls are chosen because truck drivers use them often, and therefore are likely to have a strong preference associated with their position. The dashboard and steering wheel are included to both increase the realism and immersion of the environment and also to provide the participants with a size and position reference. The inclusion of the steering wheel specifically allows the participant to reach for the various dashboard components as though their hand was coming from the normal driving position. The VR environment also includes a representation of the participant's hand (Fig. 2). In this study, participants wear a 5DT data

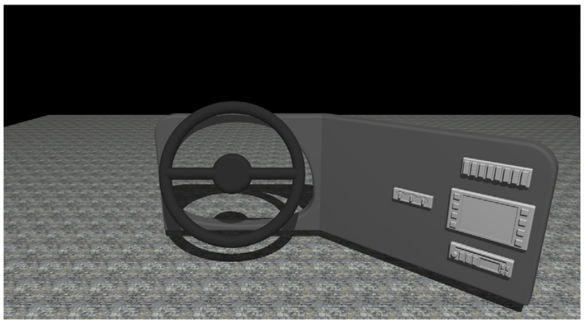

Fig. 1 Virtual dashboard with components

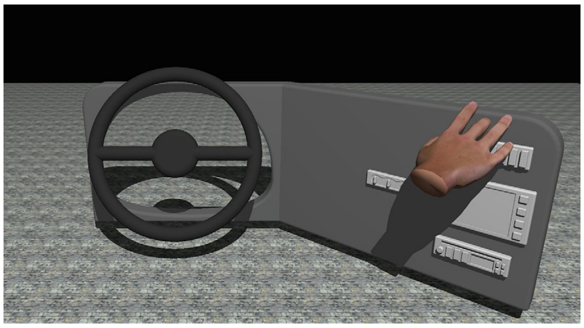

Fig. 2 Virtual dashboard with virtual hand

glove ultra and Polhemus Patriot tracker. Data from these inputs are used to realistically match the motion of the virtual hand to the motion of the participant's hand. Together, the robust motion tracking and high quality graphics allow the participant to explore the layout of the dashboard components and gain the understanding required for experiential conjoint.

4.1.5 Experiential Conjoint Survey I Procedure. Before beginning the experiential conjoint survey, the participants fill out a questionnaire to ascertain their truck driving experience. Once the questionnaire is completed, the general survey procedure is explained. At the beginning of the experiential conjoint survey, the participant sits in front of a computer screen and puts on the 5DT glove. The participant is led through a short structured training exercise in which they are introduced to the VR environment and taught how to use the interactive gestures in order to manipulate the virtual objects (Figure 3). The emphasis of this training activity is the understanding of depth within the VR environment.

Once they are familiar with the interactive gestures, the experiential conjoint survey procedure is explained, and the survey begins. The participant is shown a series of layouts of dashboards with varying positions for the radio, switch controls, Global Positioning System (GPS), and temperature controls, determined through experimental design. Before the participant can rate each layout on a scale of 1–10, they must first "touch" the steering wheel to simulate starting from the driving position. They must then reach and "touch" each dashboard component, ensuring that they have experienced the space. Once they have touched all of the components, they can provide a preference rating on the scale of 1–10. The participant rates a total of 40 designs, 27 models, and 13 holdout runs.

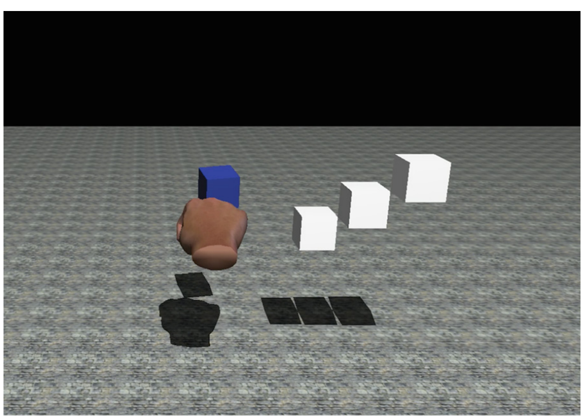

Fig. 3 Training activity

In addition to the experiential conjoint survey, the participant also completes a visual conjoint survey, in which the participant rates the same designs based only on their static representation, and is unable to gain a spatial understanding using the VR environment. Half of the participants complete the visual conjoint survey first, and half participate in the experiential survey first, in an attempt to minimize bias due to survey order.

4.2 Exploring Form Preference. A second study is designed to provide an example of the experiential conjoint methodology and VR experience performed in the context of capturing preference for the form of a product. Additionally, this study is a comparison of experiential conjoint to both visual conjoint and conjoint analysis performed with the identical physical products. Reid et al. [41] showed that the type of representation used can strongly affect the participant's ability to discern preference. In choosing the product for this study, it is important that the form of the representation is convincingly real and producible to specification determined by experimental design. Although creating physical prototypes is often infeasible due to available resources, using 3D printing technology, ceramic objects can be printed and glazed. For this study, ceramic drinking mugs are chosen as the product for which to investigate preference. Unlike with larger or more complex products, the ceramic 3D printing process thus provides the opportunity to create realistic (and usable) product configurations for the mugs according to experimental design using reasonable resources. With real products 3D printed according to experimental design, a preference model can be generated for physical products, enabling a comparison between static representations, 3D VR representations, and real products. Figure 4 shows examples of the 3D printed ceramic mugs.

4.2.1 Determining Product Attributes and Parameterizing the Design Space—Form Preference. The methodology for parameterizing a product for the exploration of form preference is identical to the layout methodology in many ways. Instead of the x- and y-positions of objects, the height, base-width, and a mathematically described curve for the handle shape are chosen to describe the design of the product.

The continuous space is again discretized to allow for experimental design. The radius of the base of the mug, the thick oval in

Fig. 4 Real mug examples

Fig. 5, is given the levels of 40 mm, 60 mm, and 80 mm. The height of the mug is given the levels of 75 mm, 95 mm, and 115 mm. The handle is parameterized using a spline with three defining points (Fig. 6). The x-positions of these points (indicated by the three thick horizontal lines) change to produce varying handle shapes. The design of the mug was based upon a wide survey of available mugs, and the designs generated as part of the experimental design span the ceramic mug design space.

4.2.2 Virtual Mug Environment. The virtual environment used for the mug study employs the same equipment and graphics engine used in the layout study. The participant is able to employ a "grabbing" gesture to manipulate the position and orientation of the virtual mug, allowing for the visual inspection of the interactional aspects of the mug.

4.2.3 Experiential Conjoint Survey II Procedure. As in the first study, the participant sits in front of a computer screen and dons the 5DT glove and Polhemus Patriot tracker. The participant is led through a short structured training exercise in which they are introduced to the VR environment and taught how to use the interactive gestures in order to manipulate the virtual objects. While the emphasis of the training activity for the first experiment is the understanding of depth within the VR environment, the focus of this training activity is on the interaction with and manipulation of virtual objects.

Once the participant is familiar with the interactive gestures, the experiential conjoint survey procedure is explained, and the survey begins. The participant is shown a series of mugs with varying aesthetic features. The participant is asked to interact with the mug and visually inspect the design before providing a rating on a scale of 1–10. The participant rates a total of 21 designs, 9 models, and 12 holdout runs. Nine runs were chosen to generate the model as creating additional mugs was cost prohibitive. In addition to the experiential conjoint survey, the participant also completes a visual conjoint survey, in which the participant rates the same designs but is unable to interact with the mug, and a real conjoint survey, in which the participant rates a series of real mugs that they are able to touch and hold with their hands. By definition and design, the real conjoint survey is an experiential conjoint survey; however, to minimize confusion, the three types of surveys will be referred to as visual conjoint, experiential conjoint, and real conjoint. Bias related to the evaluation sequence is again minimized by randomizing the order in which the participants take the experiential and visual surveys. All participants completed the real conjoint survey after completing both the experiential and visual surveys. Additionally, the order of the design presented within each survey was identical.

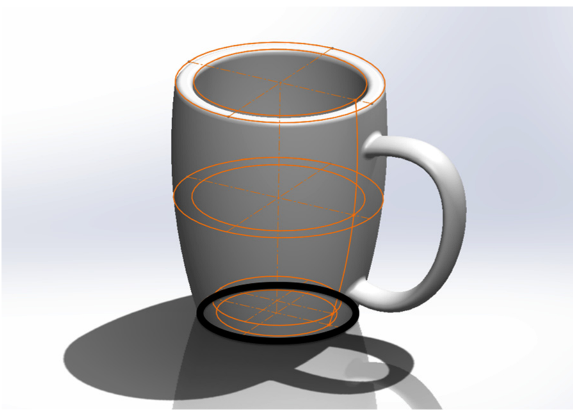

Fig. 5 Mug design parameterization

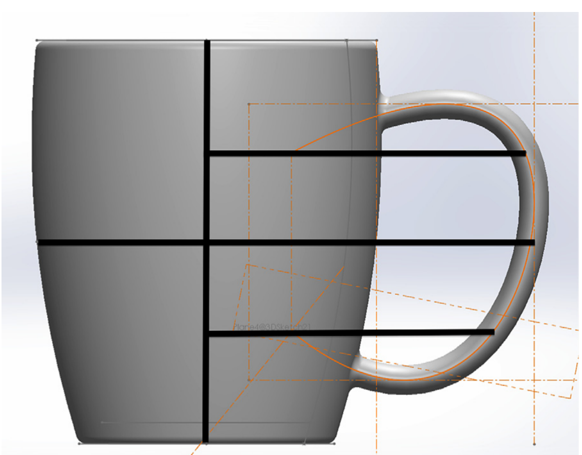

Fig. 6 Mug handle parameterization

4.3 Study Summary. Tables 1–3 provide a summary of the studies performed.

5 Hypotheses and Tests

Three hypotheses are presented concerning the provision of additional interactional information to the participant and the comparison of experiential conjoint and visual conjoint. Two types of hypothesis are presented. The A-hypothesis determines if any significant difference exists between two sets of data. For all A-hypotheses, the null hypothesis corresponds to no difference between the two sets of data, and the alternative hypothesis corresponds to a significant difference between the two sets of data. The B-hypothesis determines both if a significant difference exists between two sets of data and if experiential conjoint is the superior method. For all B-hypotheses, the null hypothesis corresponds to no difference between the two sets of data, and the alternative hypothesis corresponds to both a significant difference

Table 1 Overview of studies

Study type	Number of attributes	Levels per attribute	Parameters estimated
Layout	8	3	17
Form	3	3	7

Table 2 Attributes used for layout study

Attribute	Definition
1	X-position radio
2	Y-position radio
3	X-position switch controls
4	Y-position switch controls
5	X-position GPS
6	Y-position GPS
7	X-position temperature controls
8	Y-position temperature controls

Table 3 Attributes used for the form study

Attribute	Definition
1	Height of mug
2	Bottom radius or mug
3	Handle shape

between two sets of data and experiential conjoint being the superior method.

5.1 Hypothesis 1. The additional interactional information provided to the participant in experiential conjoint will not significantly affect the predictive ability of resulting preference models.

It is important to determine whether providing participants with additional interactional information about a product affects the predictive ability of the resulting preference models. The PCC and MAE, calculated using holdout data, are used to measure the predictive ability of a preference model. The Wilcoxon signed-rank test is used to compare the distributions of PCC and MAE values from the visual surveys and the experiential surveys, in which the users were given additional interactional information about the product.

H1.1A$_0$: There is no significant difference between:

- PCC values calculated in the visual conjoint
- PCC values calculated in the experiential conjoint

H1.1A$_A$: There is a significant difference between:

- PCC values calculated in the visual conjoint
- PCC values calculated in the experiential conjoint

H1.2A$_0$: There is no significant difference between:

- MAE values calculated in the visual conjoint
- MAE values calculated in the experiential conjoint

H1.2A$_A$: There is a significant difference between:

- MAE values calculated in the visual conjoint
- MAE values calculated in the experiential conjoint

5.2 Hypothesis 2. Experiential preference judgments, in experiential conjoint, will be more similar to preference judgments of real objects than visual preference judgments.

We hypothesize that judging a VR product representation is more similar to judging a real product than judging a 2D representation is. Because of this, we hypothesize that preference judgments of VR product representations will be more similar to preference judgments of real products than preference judgments of 2D representations will be. The PCC and MAE are calculated between the experiential ratings and real ratings and between the visual ratings and real ratings. The Wilcoxon signed-rank test is used to compare the distributions of previously described PCC and MAE values. Hypothesis 2.1 and 2.2 will be tested separately for the designs used to generate the preference model and the designs used to validate the preference model.

H2.1B$_0$: No significant difference exists between:

- PCC values between ratings provided in the experiential and real surveys
- PCC values between ratings provided in the visual and real surveys.

H2.1B$_A$: The median of the distribution of PCC values between ratings provided in the experiential and real surveys is significantly higher than the median of the distribution of PCC values between ratings provided in the visual and real surveys

H2.2B$_0$: No significant difference exists between:

- MAE values between ratings provided in the experiential and real surveys
- MAE values between ratings provided in the visual and real surveys.

H2.2B$_A$: The median of the distribution of MAE values between ratings provided in the experiential and real surveys is significantly lower than the median of the distribution of MAE values between ratings provided in the visual and real survey

5.3 Hypothesis 3. Preference models based upon experiential preference judgments will be better able to model preference for real products than preference models based upon visual preference judgments.

Using the ratings provided during the conjoint surveys, preference models are generated. Using the preference models, predicted utilities are calculated for all designs; they will differ because the model fits data but does not replicate the exact value of that data. To determine which method, experiential or visual conjoint, is better able to model real preference, the PCC and MAE are calculated between the predicted experiential ratings and predicted real ratings and between the predicted visual ratings and predicted real ratings. The Wilcoxon signed-rank test is used to compare the distributions of PCC and MAE values. Hypothesis 3.1 and 3.2 will be tested separately for the designs used to generate the preference model and the designs used to validate the preference model.

H3.1B$_0$: No significant difference will between:

- PCC values between ratings predicted in the experiential and real surveys
- PCC values between ratings predicted in the visual and real surveys.

H3.1B$_A$: The median of the distribution of PCC values between ratings predicted in the experiential and real surveys is significantly higher than the median of the distribution of PCC values between ratings predicted in the visual and real surveys

H3.2B$_0$: No significant difference exists between:

- MAE values between ratings predicted in the experiential and real surveys
- MAE values between ratings predicted in the visual and real surveys.

H3.2B$_A$: The median of the distribution of MAE values between ratings predicted in the experiential and real surveys is significantly lower than the median of the distribution of MAE values between ratings predicted in the visual and real surveys.

6 Results

The Wilcoxon signed-rank test is employed to investigate all the hypotheses presented in Sec. 5. The Wilcox signed-rank test is used in the place of a paired *t*-test, as PCC and MAE values are not normally distributed. When the Wilcoxon signed-rank test is used, a hypothesis value of 0 indicates that the null hypothesis is not rejected, and a hypothesis test value of 1 indicates that the null hypothesis is rejected with 90% confidence (*), 95% confidence (**), or 99% confidence (***). The A-hypotheses are tested using a two-tailed Wilcoxon signed-rank test. The B-hypotheses are tested using one-tailed Wilcoxon signed-rank tests. When using the one-tailed tests, the superior distribution is dependent on the type of data being compared. A PCC distribution with a higher median is considered superior and an MAE distribution with a lower median is considered superior.

In the following tables, "Data Type" indicates the origin of the data: designs used to generate the preference model (Model) or the designs used to validate the preference model (Holdout). "Variable" indicates the type of data being analyzed: PCC or MAE. "Hypothesis" indicates the hypothesis number, which can be referenced in Sec. 5. "Hypothesis test" indicates the result of the hypothesis test performed according to the corresponding method detailed in Sec. 5.

6.1 Results for Layout Study. The population for this study was truck driving professionals who ranged in ages from 19 to 66. Of the 19 participants, 17 were male and 2 were females. All of the participants were affiliated with a professional truck driving school. The surveys were conducted in person.

In this study, each participant rated 80 dashboards: 40 as part of the experiential conjoint survey and 40 as part of the visual conjoint survey. In each survey, the ratings of the 27 nonholdout runs were used to generate eight unique quadratic utility functions, as

Table 4 Hypothesis test results from the layout study. Hypothesis test: 0 indicates null hypothesis is not rejected and 1 indicates null hypothesis is rejected with 90%*, 95%**, or 99%*** confidence.

Data type	Holdout	
Variable	PCC	MAE
Hypothesis	H1.1A	H1.2A
Hypothesis test	A: 0	A: 0

Table 5 Hypothesis test results from the form study. Hypothesis test: 0 indicates null hypothesis is not rejected and 1 indicates null hypothesis is rejected with 90%*, 95%**, or 99%*** confidence.

Data type	Holdout	
Variable	PCC	MAE
Hypothesis	H1.1A	H1.2A
Hypothesis test	1*	0

detailed in Sec. 3.5. For each of the four design elements, two utility functions are generated: one representing preference for the x-position and one representing preference for the y-position. The PCC and MAE, Eqs. (2) and (3), were calculated as detailed in Sec. 3.6. The full results from the layout study can be found in Table 11 of Appendix.

Table 4 contains the results of the Wilcoxon signed-rank hypothesis tests performed on the results from the layout study. The failure to reject the null hypothesis for, H1.1A, H1.2A, suggests that providing the participant with additional interactional information does not significantly affect the predictive ability of the resulting preference models. The full results from the layout study can be found in Table 11 of Appendix.

6.2 Results for Form Study. The population for this study was 18 currently enrolled full-time students. This study was conducted in person. In this study, each participant rated 63 mugs: 21 each as part of the visual, experiential, and real conjoint surveys. In each survey, the ratings of the nine nonholdout runs were used to generate three unique quadratic utility functions, as detailed in Sec. 3.5. One utility function is used to represent each of the following: preference for the height, base radius, and handle shape of the mug. The PCC and MAE, Eqs. (2) and (3), were calculated as detailed in Sec. 3.6. The full results from the form study can be found in Table 12 of Appendix.

Table 5 contains the results of the two-tailed Wilcoxon signed-rank hypothesis tests performed on the results from the form study. The failure to reject the null hypothesis for H1.1A shows that there is a significant difference in ability of preference models from experiential and visual conjoint to predict holdout design ratings. Additionally, one-tailed Wilcoxon signed-rank tests performed on the PCC data show that the median PCC for visual conjoint is significantly ($p = 0.08$) higher than the median PCC for

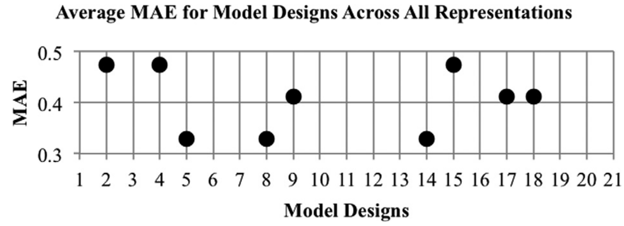

Fig. 7 Average MAE for the nine model designs (designs 2, 4, 5, 8, 9, 14, 15, 17, and 18)

Table 7 Hypothesis test results from the form study. Hypothesis test: 0 indicates null hypothesis is not rejected and 1 indicates null hypothesis is rejected with 90%*, 95%**, or 99%*** confidence.

Data type	Holdout	
Variable	PCC	MAE
Hypothesis	H1.1A	H1.2A
Hypothesis test—original	1*	0
Hypothesis test—removal	0	0

experiential conjoint, suggesting that preference models generated from visual conjoint are better able to predict preference for within-sample holdout designs. Surprisingly, for Hypothesis H1.2A, the null hypothesis is not rejected, showing no significant difference in the MAE data between visual and experiential conjoint.

Table 6 contains the results of the one-tailed Wilcoxon signed-rank hypothesis tests performed on the results of the comparison between the visual and real surveys, and the experiential and real surveys. Examining first the data for the designs used to generate the preference model, the null hypothesis is rejected for H2.2B, H3.1B, and H3.2B. This demonstrates that for the predicted ratings PCC, actual ratings MAE, and predicted ratings MAE, experiential conjoint is a significantly superior method. When examining the data for the holdout designs, the null hypothesis is rejected only for H2.2B.

The results in Table 6 contain several inconsistencies that warrant further investigation. Hypothesis H2 is not fully supported for either the model or holdout designs. Additionally, Hypothesis H3, but not Hypothesis H2 is fully supported for the model designs. For further investigation, the MAE was calculated for each design after sorting the designs by the order in which the participant rated them: 1 being the first design and 21 being the last design. Nine of the 21 designs were used to generate the model, and the specific MAEs for those designs are plotted in Figure 7. When examining the average MAE across all representations for the designs used to generate the preference model, the average MAE after the fourth design (0.39) is less than the average MAE before and including the fourth design (0.47). We hypothesize that whereas the large error in designs 2–4 is attributed to the participant become acclimated to the representation and confident in their preference the large error in design 15 might be due to the difficulty in the evaluation of the design itself.

Table 6 Comparing visual and experiential-VR to experiential-real. Hypothesis test: 0 indicates null hypothesis is not rejected and 1 indicates null hypothesis is rejected with 90%*, 95%**, or 99%*** confidence and that experiential is the superior method.

Data type	Model				Holdout			
Variable	Actual ratings PCC	Actual ratings MAE	Predicted ratings PCC	Predicted ratings MAE	Actual ratings PCC	Actual ratings MAE	Predicted ratings PCC	Predicted ratings MAE
Hypothesis	H2.1B	H2.2B	H3.1B	H3.2B	H2.1B	H2.2B	H3.1B	H3.2B
Hypothesis test	0	1**	1*	1**	0	1**	0	0

Table 8 Comparing visual and experiential-VR to experiential-real with error reduction. Hypothesis test: 0 indicates null hypothesis is not rejected and 1 indicates null hypothesis is rejected with 90%*, 95%, or 99%*** confidence and that experiential is the superior method.**

Data type	Model				Holdout			
Variable	Actual ratings PCC	Actual ratings MAE	Predicted ratings PCC	Predicted ratings MAE	Actual ratings PCC	Actual ratings MAE	Predicted ratings PCC	Predicted ratings MAE
Hypothesis	H2.1B	H2.2B	H3.1B	H3.2B	H2.1B	H2.2B	H3.1B	H3.2B
Hypothesis test—original	0	1**	1*	1**	0	0	1**	0
Hypothesis test—removal	1**	1**	1**	1*	1**	1**	0	1**

Table 9 Hypothesis 1 test results using form data with removal treatment. X indicates the hypothesis supported by data.

Hypothesis type	Null hypothesis	Alternative hypothesis
Hypothesis 1.1A	X	
Hypothesis 1.2A	X	

In effort to remove potential error, a revised set of data is generated. In this set the first four designs are discarded entirely, a new nine-design matrix using the remaining runs with the highest D-efficiency chosen, and the results recalculated: the designs discarded are the first four designs that the participant saw, these four designs are the same across all participants and the D-optimal design used after the removal is identical for each participant. The number four was chosen as the first four designs had a higher average MAE than the remaining designs. In the revised treatment, the remaining eight designs are used as holdouts. Tables 7 and 8 contain the results original and removal treatments. The full results from the removal treatment can be found in Table 13 of Appendix.

Table 7 contains the results of the two-tailed Wilcoxon signed-rank hypothesis tests performed on the results from the original and removal treatments of the form data. In the removal treatment, for Hypotheses H1.1A and H1.2A, the null hypothesis is not rejected, suggesting that providing the participant with additional interactional information does not significantly affect the predictive ability of the resulting preference models.

Examining first the data for the designs used to generate the preference model, in the removal treatment the null Hypothesis is rejected for all hypotheses, meaning that with respect to both the MAE and PCC for the ratings provided and predicted by experiential conjoint are closer to the ratings provided and predicted by real conjoint than the ratings provided and predicted by visual conjoint are. When examining the data for the holdout designs, with respect to the actual ratings PCC, actual ratings MAE, and predicted ratings MAE experiential conjoint is superior to visual conjoint. The failure to reject the null hypothesis for H3.1B can be interpreted to mean that the model is having difficulty predicting preference for designs not used in the generation of the preference model. This can possibly be addressed by increasing either the number of data points used to calculate the PCC or the number of designs used to generate the model. Tables 9 and 10 provide a summary of the hypothesis tests.

6.3 Summary. The data from the layout and form study, for the holdout removal treatment, supports Hypothesis 1, demonstrating that additional interactional information provided to the participant does not affect the predictive ability of the resulting preference models. With respect to the model designs, in the holdout and removal treatments, the data from the form study strongly support Hypotheses 2 and 3, demonstrating that experiential preference judgments are more similar to real preference judgments and that preference models based upon experiential preference judgments are better able to model preference for real products. With respect to the holdout designs, in the removal treatments, the data from the form study strongly support Hypothesis 2 but only part of Hypothesis 3. This work demonstrates that experiential conjoint analysis can be used to provide designers with greater understanding necessary to create products that directly address the needs and desires of customers.

Table 10 Hypotheses 2 and 3 test results using form data with removal treatment. X indicates the hypothesis supported by data.

Data type	Model		Holdout	
Hypothesis type	Null hypothesis	Alternative hypothesis	Null hypothesis	Alternative hypothesis
Hypothesis 2.1B		X		X
Hypothesis 2.2B		X		X
Hypothesis 3.1B		X	X	
Hypothesis 3.2B		X		X

7 Conclusion

This paper introduced experiential conjoint methodology in which a product is chosen and its attributes parameterized, design of experiments is performed to determine the product configurations experienced by the participant, a study performed in which participants experience and rate product configurations, and a preference model generated based upon the ratings. Two case studies demonstrated the ability of experiential conjoint to capture preference and provided a basis to compare experimental conjoint to visual conjoint and conjoint with real products. This work was framed through four hypotheses, each of which was supported either in full or in part by the data gathered during the case studies. The results demonstrate that providing the participant with additional interactional information about a product does not affect the predictive ability of the resulting preference models. Additionally, when comparing visual and experiential conjoint, preference judgments provided during experiential conjoint are found to be more similar to real preference. The methodology detailed in this paper builds upon the existing preference modeling and decision literature to provide designers with a new method for eliciting meaningful design feedback from consumers. If utilized during the early stages of the design process, designers can gather actionable feedback leading to a more efficient use of critical resources. This work additionally demonstrates the value of using VR to provide in interactive product experience. Future work will address ways in which the VR experience can be improved to increase realism and will explore how the methodology presented in this paper applies to design problems of increasing complexity.

Acknowledgment

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Appendix

See Tables 11–13.

Table 11 Full results from the layout study

Participant	Visual				Experiential-VR			
	R^2	PCC	PCC p-value	MAE	R^2	PCC	PCC p-value	MAE
1	0.59	−0.18	0.55	3.41	0.88	0.67	0.01	2.51
2	0.73	0.57	0.04	1.39	0.85	0.78	0.00	0.81
3	0.81	0.66	0.01	1.01	0.86	0.31	0.30	1.60
4	0.83	0.64	0.02	1.81	0.96	0.73	0.00	1.57
5	0.69	0.75	0.00	0.79	0.86	0.38	0.20	1.45
6	0.88	0.72	0.01	0.99	0.81	0.50	0.08	2.29
7	0.93	0.67	0.01	1.11	0.93	0.50	0.08	1.15
8	0.82	0.36	0.23	1.98	0.85	0.84	0.00	1.15
9	0.92	0.69	0.01	0.87	0.89	0.72	0.01	0.79
10	0.96	0.71	0.01	0.69	0.89	0.49	0.09	0.77
11	0.82	0.81	0.00	0.89	0.95	0.66	0.01	0.99
12	0.90	0.85	0.00	0.54	0.83	0.82	0.00	0.82
13	0.94	0.41	0.16	1.84	0.74	0.69	0.01	1.22
14	0.84	0.34	0.25	2.51	0.82	0.55	0.05	1.64
15	0.87	0.56	0.05	1.60	0.80	0.86	0.00	0.81
16	0.81	0.64	0.02	1.79	0.84	0.52	0.07	1.42
17	0.91	0.66	0.01	1.13	0.84	0.78	0.00	0.69
18	0.73	0.58	0.04	1.49	0.88	0.69	0.01	1.49
19	0.89	0.77	0.00	0.47	0.81	0.62	0.03	0.50
Average	0.84	0.59	0.07	1.38	0.86	0.64	0.05	1.25
Standard deviation	0.09	0.23	0.14	0.73	0.05	0.16	0.08	0.54

Table 12 Full results from the original form study

Participant	Visual				Experiential-VR				Experiential-real			
	R^2	PCC	PCC p-value	MAE	R^2	PCC	PCC p-value	MAE	R^2	PCC	PCC p-value	MAE
1	0.72	0.74	0.01	0.6	0.92	0.45	0.14	0.83	1	0.18	0.58	1.03
2	0.94	0.71	0.01	1.05	0.88	−0.15	0.63	1.98	0.95	0.27	0.39	1.52
3	0.63	0.66	0.02	1.26	0.99	0.5	0.1	1.36	0.97	0.88	0	1.08
4	0.96	0.64	0.02	0.61	0.83	0.38	0.22	0.86	0.45	0.8	0	0.7
5	0.85	0.68	0.02	0.88	0.61	0.49	0.11	0.99	0.77	0.7	0.01	0.86
6	0.61	0.28	0.39	0.92	0.87	0.67	0.02	0.79	0.86	0.19	0.56	1.14
7	0.99	0.46	0.13	1.3	0.89	0.41	0.18	1.51	0.92	0.82	0	0.69
8	0.93	0.72	0.01	0.67	0.98	0.65	0.02	0.8	0.81	0.74	0.01	0.58
9	0.93	0.71	0.01	0.83	0.92	0.5	0.1	0.9	0.71	0.39	0.21	1.31
10	0.95	0.88	0	1.15	0.98	0.73	0.01	1.25	0.94	0.8	0	0.89
11	0.97	0.67	0.02	1.57	1	−0.02	0.96	2.67	0.9	0.55	0.07	2.12
12	0.95	0.13	0.69	1.7	0.93	0.43	0.17	0.99	0.72	0.42	0.17	1.12
13	0.85	0.66	0.02	0.91	0.78	0.37	0.24	1.25	0.94	0.81	0	0.9
14	0.84	0.49	0.1	0.9	0.53	0.91	0	0.44	0.81	−0.34	0.29	1
15	0.79	0.49	0.11	1.6	0.95	0.15	0.63	2.05	0.93	0.65	0.02	1.31
16	0.91	0.7	0.01	0.88	0.87	0.46	0.13	1.33	0.81	0.44	0.15	1.56
17	0.97	0.65	0.02	1.83	0.96	0.84	0	1.21	0.98	0.76	0	1.4
18	1	0.54	0.07	0.44	0.86	0.09	0.78	0.54	0.97	0.61	0.04	0.55
Average	0.88	0.6	0.09	1.06	0.87	0.44	0.25	1.21	0.86	0.54	0.14	1.1
Standard deviation	0.89	0.59	0.1	1.09	0.87	0.44	0.25	1.23	0.85	0.56	0.11	1.1

Participant	Actual model ratings						Predicted model ratings					
	Visual			Experiential-VR			Visual			Experiential-VR		
	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE
1	0.35	0.36	0.78	0.14	0.71	0.89	0.41	0.28	0.90	0.15	0.70	0.96
2	0.39	0.31	1.89	0.31	0.41	1.89	0.38	0.32	1.89	0.26	0.50	1.89
3	0.59	0.09	1.56	0.63	0.07	1.11	0.65	0.06	1.46	0.65	0.06	1.11
4	0.13	0.73	1.11	−0.07	0.85	1.44	0.22	0.56	0.96	0.33	0.39	1.00
5	0.37	0.33	1.44	0.45	0.22	1.00	0.23	0.55	1.44	0.38	0.32	1.10
6	0.31	0.42	1.33	0.51	0.16	1.33	0.32	0.40	1.11	0.44	0.23	1.36
7	0.56	0.12	1.22	0.76	0.02	1.00	0.59	0.09	1.22	0.76	0.02	0.95
8	0.85	0.00	0.44	0.52	0.15	0.78	0.91	0.00	0.44	0.53	0.14	0.90
9	0.19	0.63	2.78	0.73	0.02	2.78	0.34	0.37	2.78	0.72	0.03	2.78
10	0.81	0.01	1.33	0.80	0.01	0.89	0.91	0.00	1.33	0.86	0.00	0.89
11	0.11	0.77	2.56	0.72	0.03	1.22	0.16	0.69	2.56	0.76	0.02	1.32
12	0.19	0.63	1.22	0.23	0.55	1.11	0.12	0.76	1.22	0.15	0.70	1.04
13	0.56	0.12	1.00	0.45	0.22	1.22	0.52	0.15	1.05	0.39	0.30	1.27
14	0.23	0.56	2.89	0.40	0.28	2.00	0.07	0.87	2.91	0.47	0.20	2.00
15	0.16	0.67	2.00	0.42	0.26	1.56	0.24	0.53	2.02	0.46	0.22	1.58
16	0.73	0.02	1.00	0.66	0.05	1.00	0.71	0.03	1.00	0.85	0.00	0.78
17	0.81	0.01	1.44	0.82	0.01	1.56	0.84	0.00	1.49	0.83	0.01	1.56
18	0.34	0.37	0.78	0.45	0.22	0.67	0.35	0.36	0.78	0.43	0.25	0.67
Average	0.43	0.34	1.49	0.50	0.24	1.30	0.44	0.33	1.48	0.52	0.23	1.29
Standard deviation	0.43	0.34	1.53	0.52	0.21	1.33	0.44	0.34	1.51	0.54	0.20	1.30

Participant	Actual model ratings						Predicted model ratings					
	Visual			Experiential-VR			Visual			Experiential-VR		
	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE
1	−0.01	0.98	1.50	0.23	0.48	1.00	0.40	0.19	0.80	0.04	0.90	0.97
2	0.37	0.23	1.75	0.00	1.00	1.75	0.39	0.21	1.41	0.28	0.38	1.92

Table 12. *Continued*

Participant	Actual model ratings						Predicted model ratings					
	Visual			Experiential-VR			Visual			Experiential-VR		
	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE
3	0.63	0.03	1.50	0.65	0.02	1.00	0.64	0.02	1.29	0.60	0.04	1.30
4	0.53	0.08	0.83	0.21	0.51	1.08	0.31	0.33	0.94	0.44	0.15	0.83
5	−0.08	0.80	1.67	0.23	0.47	1.25	0.08	0.80	1.50	0.30	0.34	1.08
6	0.16	0.62	1.33	0.30	0.35	1.25	0.48	0.11	1.06	0.48	0.12	1.16
7	0.73	0.01	1.17	0.75	0.01	1.08	0.61	0.03	1.03	0.75	0.01	0.95
8	0.39	0.21	0.83	0.80	0.00	0.42	0.92	0.00	0.25	0.47	0.12	1.02
9	0.81	0.00	1.50	0.28	0.38	2.00	0.41	0.19	2.75	0.73	0.01	2.83
10	0.77	0.00	0.92	0.88	0.00	0.67	0.92	0.00	1.03	0.87	0.00	0.82
11	0.54	0.07	1.92	0.33	0.29	2.42	0.18	0.58	2.41	0.75	0.00	1.70
12	0.63	0.03	0.92	0.86	0.00	0.67	0.05	0.89	1.28	0.11	0.74	1.28
13	0.38	0.22	1.25	0.70	0.01	0.75	0.56	0.06	1.15	0.47	0.12	1.14
14	−0.11	0.74	2.50	−0.02	0.95	1.67	0.00	0.99	2.58	0.33	0.30	1.67
15	0.41	0.19	1.50	0.56	0.06	1.42	0.23	0.48	1.70	0.43	0.16	1.81
16	0.35	0.26	1.50	0.57	0.05	1.17	0.72	0.01	1.11	0.85	0.00	0.79
17	0.81	0.00	1.25	0.86	0.00	1.25	0.78	0.00	1.52	0.75	0.00	1.58
18	0.18	0.57	0.58	0.22	0.48	0.58	0.27	0.39	0.76	0.32	0.31	0.72
Average	0.42	0.28	1.36	0.47	0.28	1.19	0.44	0.29	1.36	0.50	0.21	1.31
Standard deviation	0.44	0.24	1.35	0.48	0.27	1.20	0.44	0.30	1.40	0.52	0.17	1.33

Table 13 Full results from the removal form treatment

Participant	Visual				Experiential-VR				Experiential–Real			
	R^2	PCC	PCC p-value	MAE	R^2	PCC	PCC p-value	MAE	R^2	PCC	PCC p-value	MAE
1	0.75	0.67	0.07	0.98	0.84	0.75	0.03	0.65	0.30	−0.27	0.51	1.11
0.99	0.50	0.21	1.58	0.98	0.35	0.39	1.10	0.61	0.09	0.83	2.04	
3	0.93	0.60	0.12	1.23	0.75	0.78	0.02	0.92	0.99	0.90	0.00	0.69
4	0.92	0.40	0.32	0.90	0.75	0.48	0.23	0.83	0.98	0.09	0.83	1.07
5	0.85	0.83	0.01	0.81	0.97	0.78	0.02	0.65	0.94	0.37	0.37	1.42
6	0.90	0.26	0.53	1.14	0.90	0.24	0.56	1.03	0.68	0.30	0.46	0.85
7	0.74	0.53	0.18	0.67	0.30	−0.21	0.62	0.95	0.86	0.44	0.28	0.67
8	0.93	0.76	0.03	1.15	0.93	0.69	0.06	0.67	0.94	0.83	0.01	0.56
9	0.75	0.86	0.01	0.75	0.88	0.49	0.22	1.02	0.61	0.67	0.07	1.08
10	0.96	0.84	0.01	0.92	0.85	0.87	0.01	0.80	0.93	0.81	0.01	1.10
11	0.97	0.40	0.33	2.08	0.84	0.28	0.50	2.19	0.63	0.49	0.21	2.00
12	0.69	0.48	0.23	0.90	0.82	0.56	0.15	0.85	0.71	0.80	0.02	0.99
13	0.94	0.23	0.59	1.48	0.91	0.08	0.85	1.40	0.96	0.58	0.13	1.48
14	0.79	0.17	0.68	0.73	0.91	0.83	0.01	0.78	0.32	0.11	0.80	0.89
15	0.95	0.45	0.27	1.33	0.96	0.45	0.26	1.98	0.99	0.60	0.12	2.02
16	0.94	0.87	0.00	0.67	0.85	0.49	0.22	1.29	0.73	−0.28	0.50	2.11
17	0.91	0.73	0.04	1.36	0.92	0.94	0.00	0.69	0.94	0.90	0.00	1.06
18	0.89	0.73	0.04	0.33	1.00	0.06	0.89	0.69	0.94	0.73	0.04	0.53
Average	0.88	0.57	0.20	1.06	0.85	0.50	0.28	1.03	0.78	0.45	0.29	1.21
Standard deviation	0.88	0.57	0.21	1.06	0.85	0.48	0.29	1.05	0.81	0.49	0.28	1.21

Participant	Actual model ratings						Predicted model ratings					
	Visual			Experiential-VR			Visual			Experiential-VR		
	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE	PCC	PCC p-value	MAE
1	0.11	0.79	1.25	0.54	0.17	0.75	0.44	0.27	1.27	0.06	0.89	0.96
2	0.24	0.56	2.00	0.14	0.74	1.88	0.21	0.61	2.54	−0.35	0.40	1.90
3	0.64	0.09	1.13	0.68	0.06	1.13	0.36	0.38	1.77	0.37	0.37	1.27
4	0.44	0.28	1.00	0.13	0.75	1.25	0.26	0.54	0.97	0.61	0.11	0.85
5	−0.20	0.64	1.88	0.65	0.08	0.75	−0.25	0.56	2.19	−0.25	0.55	2.00
6	−0.17	0.68	1.75	0.46	0.25	1.13	0.85	0.01	1.06	0.32	0.44	1.38
7	0.25	0.55	1.38	0.25	0.55	1.13	0.41	0.31	1.04	0.62	0.10	1.31
8	0.54	0.16	0.75	0.62	0.10	0.63	0.41	0.31	1.17	0.93	0.00	0.31
9	0.82	0.01	1.75	0.28	0.51	2.50	0.44	0.28	1.08	0.83	0.01	1.02
10	0.68	0.07	1.13	0.89	0.00	0.63	0.96	0.00	0.44	0.77	0.03	1.04
11	0.25	0.55	2.38	0.60	0.11	1.50	0.37	0.37	1.96	0.45	0.26	1.63
12	0.43	0.29	1.00	0.87	0.01	0.75	0.67	0.07	1.02	0.51	0.20	1.04
13	−0.03	0.94	2.00	0.29	0.48	1.38	0.97	0.00	0.83	0.86	0.01	0.63
14	−0.24	0.57	3.00	−0.16	0.70	1.75	0.75	0.03	3.69	0.91	0.00	1.90
15	0.24	0.56	2.13	0.60	0.12	1.63	−0.16	0.70	1.72	−0.70	0.06	1.58
16	0.32	0.43	1.75	0.48	0.23	1.50	0.44	0.28	0.69	0.75	0.03	0.74
17	0.87	0.00	1.13	0.84	0.01	1.38	0.82	0.01	1.38	0.83	0.01	1.27
18	0.38	0.36	0.50	0.43	0.29	0.50	0.37	0.36	0.59	−0.08	0.84	0.76
Average	0.31	0.42	1.55	0.48	0.29	1.23	0.46	0.28	1.41	0.41	0.24	1.20
Standard deviation	0.32	0.40	1.57	0.47	0.29	1.26	0.46	0.28	1.42	0.43	0.20	1.21

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