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VISUAL CONJOINT – FROM DISCRETE TO CONTINUOUS

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Abstract

One goal of designers is to find what users most likely appreciate and translate that into successful product designs. Over the past 15 years, the efficacy of visual conjoint analysis as a means to assess the visual preference of users has been explored and has demonstrated immense potential for product development and aesthetic design. Visual conjoint started within marketing but was adopted by engineering design due to its ability to map visual product attributes to quantifiable mathematical representations. Conjoint studies initially presented only discrete verbal options, which severely limited types of feedback that designers could acquire. As conjoint evolved and was adopted by engineering design, it began to include discrete imagery with verbal representations. This provided more information without requiring more cognitive processing by respondents. Engineering design then realized the advantage of having purely visual conjoint studies in that mathematically represented images could contain immense amounts of information in simple representations. Continuous visual conjoint leverages imagery that represents mathematical models of continuously variable design attributes.

Keywords: New product development, Design methodology, Industrial design, Continuous visual conjoint, conjoint analysis

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1 INTRODUCTION

Conjoint analysis is a method in which measurable variables, both dependent and independent, are presented to respondents in a way that analysis with statistical methods provides useful information regarding the preferred levels of the variables and the potential relationships between those variables (Green and Srinivasan, 1978, 1990). The term *visual conjoint* was coined by Dahan and Srinivasan in 2000. In their marketing paper, an extension of traditional conjoint methodology, they use static images of existing products in concert with verbal descriptions of attributes, like price, to leverage the research of Holbrook and Moore (1981), Berkowitz (1987), and Bloch (1995), which showed that consumers are much more likely to respond well to visual descriptions of products as opposed to purely written descriptions of products.

While presented within the context of design for manufacturing and analytical target cascading, Michalek et al. (2005) leverage the power of visual conjoint to determine the visual layout for bathroom scales. Over the past decade others within the field of design theory and methodology began to ask questions about the efficacy of visual conjoint and whether it might be a tool that could prove valuable for engineering design and product development. The rest of this paper describes the journey visual conjoint has taken from marketing through engineering design and from discrete to continuous attributes.

2 FROM VERBAL TO MIXED TO PURELY VISUAL

At this point, the term visual conjoint has clearly evolved to take on a whole new meaning from its original definition, though possibly subtly different to the outsider. In marketing, visual conjoint meant visual representations of discrete levels of a product example. In turn, the analysis of such studies would produce a discrete result, a selection from the pre-determined set of potential options. For example, Dahan and Srinivasan (2000) show a set of bicycle pumps that vary their physical attributes at different levels but they do not interpolate their results to generate designs beyond the original set. As visual conjoint was adopted by engineering design, each visual option began to represent a set of discrete variables, not discrete options. Michalek et al. (2005) were the first to co-opt the visual conjoint method to engineering design. In their study a respondent chose from various line drawings that represented a bathroom scale (Figure 1). These drawings would accompany verbal descriptions, much like prior marketing studies. But, rather than simply showing discrete images of options, they choose to vary the shape and form of the images based upon the discrete attribute levels represented within the conjoint analysis. One option might show a short and wide scale where another might show a tall and narrow scale, both visual representations of the platform's aspect ratio.

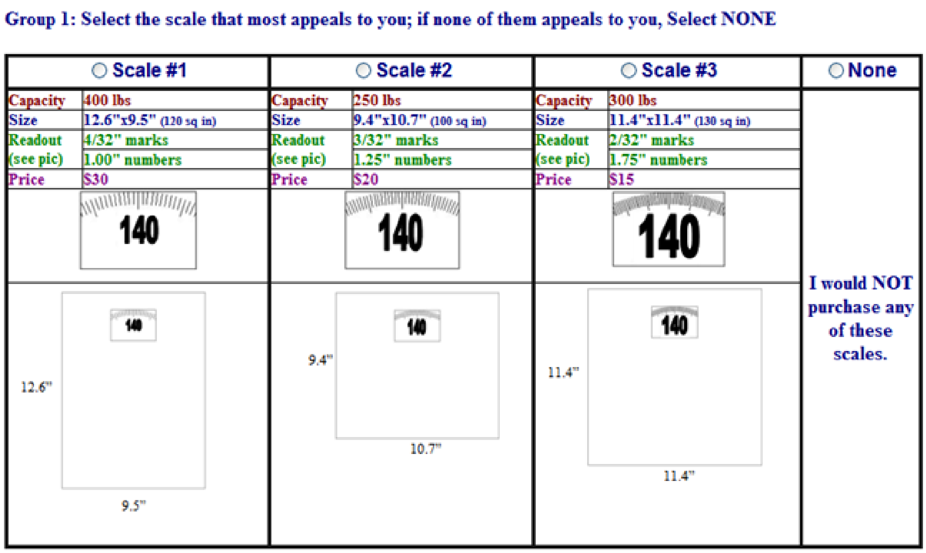

Figure 1. Discrete visual conjoint and verbal conjoint (from Michalek et al., 2005)

There are certainly benefits to combining verbal and visual descriptions in a conjoint study. For example, a study that combines both modes of presentation can determine how consumers might respond to a particular product shape while also taking into account attributes that are not easily represented with visual descriptions, like price. Swamy et al. (2007) realized the potential of unlocking purely visual conjoint analysis. They took advantage of the fact that product concepts are often represented with line drawings and these can be distilled down to the mathematical geometry that represents the fundamental shapes (Figure 2). In their study, the outline of vehicle headlights represented in 2D from the front of the vehicle were drawn with 4 curves. The curves themselves could be represented in a variety of ways, 4-control point Bezier curves in this instance. Then each control point is simply a geometrically located point in space that can be moved continuously to effect the overall shape of the headlight. By atomizing the visual elements into discrete mathematical attributes they enables a conjoint study to be created in which respondents viewed different visual representations of the numerical levels.

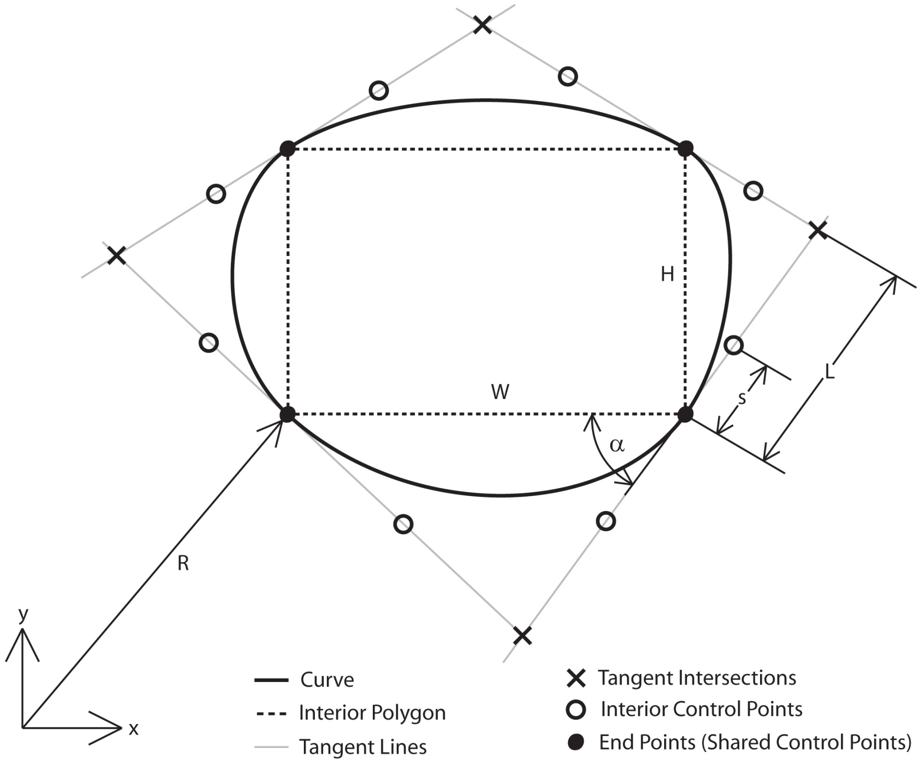

Figure 2. Parameterization of a closed shape with four 4-control point Bezier curves

Herein lies the two-fold power of *continuous visual conjoint*: First, the product attributes and their associated levels are constructed to represent continuous visual features but respondents only see varying imagery. Respondents are shielded from the complexity of the design space. A simple explicit image can represent an enormous amount of implicit information. It is this resultant information that can then be used to inform design decisions. Secondly, since the discrete levels of visual information can represent continuous variables, the extracted preference models can, and often do, result in concept designs that were not presented to the respondents but are interpolated from within the design space. These emergent concept designs match consumer and user preferences but have not yet been seen or assessed by said users and consumers.

Since the first exploration, continuous visual conjoint has been used to quantify consumer preference in a variety of design contexts. Orsborn, Cagan and Boatwright (2009) continued to explore how consumer preference models might be used to accurately determine consumer preference for the aesthetic shape of products, vehicles in their study. Reid et al. (2010) determined which shapes of vehicle silhouettes seemed to be most environmentally friendly according to consumers, linking non-aesthetic consumer preference with visual attributes (Figure 3). While many researchers using visual conjoint were attempting to break away from verbal descriptive associations, MacDonald et al. (2009) effectively linked discrete visual conjoint to product semantics and demonstrated that visual representations can be correlated to consumer responses. These two works provided an important transition in that researchers focusing just on visual conjoint could be confident that their representation was not completely divorced from semantic research but could still stand independently if used appropriately. Petiot and Dagher (2008, 2011) leveraged continuous visual conjoint to explore the potential for attractive vehicle headlights. Kelly et al. (2011) explored how to model consumer preference for the shape of products through continuous visual conjoint. Sylcott et al. (2013a) pushed beyond simple aesthetics responses and created a two-tiered visual conjoint analysis that took into account consumer preference for both functional and visual attributes in consumer products. Tseng et al. (2013) combined visual conjoint with Likert scales to demonstrate that product shape, perceived functionality, and other implicit attributes are all closely intertwined. Goucher-Lambert and Cagan (2014) combined visual and function-based conjoint along with price preference and the environmental impact (as a dependent variable) to understand how sustainability impacts the trade off between form, function and price preference.

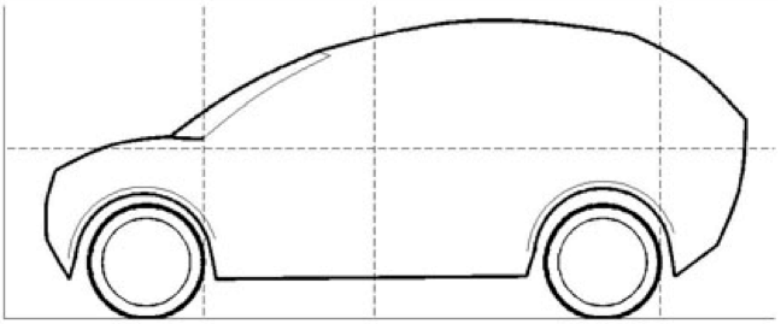

Figure 3. Environmentally friendly vehicle silhouette

Orsborn and Talecki (2011) extended continuous visual conjoint beyond shape representations to product colour options. In their study, rather than representing shape geometry with attributes, they represented each of the three colours of the Red-Green-Blue (RGB) colour space with an attribute. They were able to demonstrate that consumer product colour preference could easily be determined despite it being a prohibitively large design space with over 16.5 million options. More recently, Tovares, Cagan, and Boatwright (2014) have pushed beyond 2D imagery to assess consumer response to product layout through virtual environments (Figure 4).

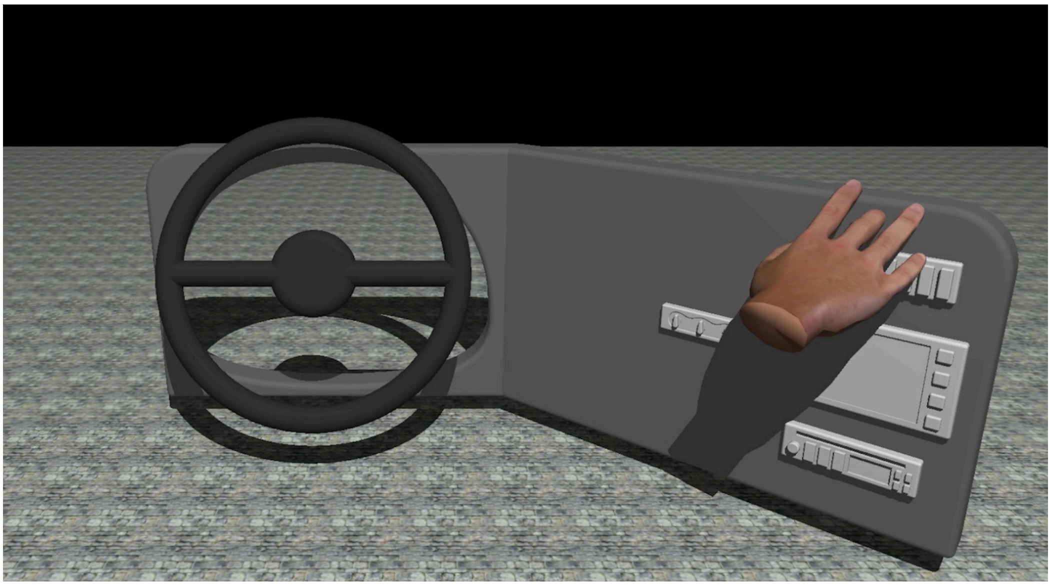

Figure 4. Visual conjoint in virtual environments (from Tovares et al., 2014)

Additionally, other design researchers have begun to understand the value of visual representations of design concepts. While not explicitly using continuous visual conjoint, they are still reliant upon visual representations for valuable design insights. Lai, Chang, and Chang (2005) conducted a Taguchi experiment in which they determined how consumers might project feelings, essentially market segmentation expectations, on various silhouettes of vehicles. Their direct association of affective responses to visual imagery was an important exploration that influenced much of the visual conjoint work in design thus far. Lugo et al. (2012) used purely visual representations of vehicle wheels to determine consumer aesthetic preference. Macomber and Yang (2011) reported on how the method of visual imagery can influence user response to conceptual designs. For a thorough background of how imagery is being used effectively in engineering design for eliciting consumer response, refer to Reid et al. (2013).

3 THE POWER OF CONTINUOUS VISUAL CONJOINT

In all conjoint analysis, the researcher must choose a set of attributes, or variables, and a set of levels for each of those attributes. These are then assembled into specific options through a design of experiments. The consumer, or user, response to each of these options is analysed statistically to generate an overall preference model for the attributes. Verbal conjoint presents these options, discrete levels of the attributes, with explicit written descriptions. It becomes quite obvious to the respondent which attributes are varying in which way and what potential combinations may be available. Continuous visual conjoint options are presented as just an image. The continuous variables are selected as attributes and their discrete levels are "hidden" behind visual imagery. Rather than viewing explicit written descriptions changing per option, the respondent sees only a changing image and likely does not comprehend which attributes are actually being modified.

The heart of continuous visual conjoint is its dependency upon gestalt perception and its relationship with atomistic perception (Durgee, 1988). Gestalt is the idea that objects are perceived as a whole. Atomistic perceptions are the opposite in that a form is broken down into its sub-elements. Continuous visual conjoint resides at the confluence of both these theories. It relies upon the assumption that consumers respond to visual imagery as a whole and are not inclined to separate it into its distinct sub-elements. Likewise, continuous visual conjoint leverages atomistic methods by choosing the sub-elements, continuous attributes at discrete levels, that most likely effect the gestalt perception of the image. It is this delicate balance that enables an effective continuous visual conjoint analysis.

Maybe more important than just the visual element is the effect it has on eliciting consumer preference feedback. A major limitation of verbal conjoint is that respondents tire quickly from having to continually read and respond to the various options. Visual imagery, explicitly in line with gestalt perception, enables respondents to quickly analyse a variety options and move through a complete study before fatigue begins to negatively affect them (Green and Srinivasan, 1978, Holbrook and Moore, 1981). This enables design researchers to collect more data in the same amount of time.

The primary benefit, and key differentiator between the use of visual conjoint in marketing and engineering design, is that discrete levels for a particular attribute do not necessarily represent discrete design potential. Unlike the original introduction of visual conjoint by Dahan and Srinivasan (2000) and the use of discrete visual conjoint by Michalek et al. (2005), continuous visual conjoint (Orsborn et al., 2009) leverages continuous variables and eventually enables the generation of consumer preferred design concepts that were never seen by respondents. The discrete levels in traditional visual conjoint limit the consumer response to prefer discrete options that have already been seen by the consumer. Continuous visual conjoint takes these discrete levels and interpolates between them through the consumer preference model to generate preferred design concepts that most likely were not options in the original design of experiments.

Within the context of design research, visual conjoint can provide even more value beyond its fundamental structure. First, it can provide insights into the existing marketplace when combined with market research variables like demographic data. Second, it can reduce iteration within the conceptual design phase by providing explicit, albeit broad, design constraints. This can help prevent designers from unnecessary iterations in which they are simply trying to find concepts that users will respond to positively. Third, because the root of the method is borrowed from marketing, it can provide designers with quantitative support for their qualitative decisions. Often designers run into a tension with marketing and production when they make informed decisions because other disciplines are not trained to recognize and pursue intuitive directions. Visual conjoint can provide designers with mathematical formula that support their design concepts and can give designers the leverage they need to enforce design decisions when marketing and production attempt to steer design concepts away from their original intent.

4 HOW IT WORKS

Throughout the published work, the fundamental method for using continuous visual conjoint is the same. We will now walk through this method in the context of a design problem: design a novel bicycle helmet. First, take a diverse sample of the variety of products within that space currently available in the market to determine what are some of the key design attributes that should be considered as the design moves forward towards conceptualization.

4.1 Defining Attributes

Generally, this stage requires an expert to pull out the key physical attributes that are foundational to this design space. For example, the shape of the footprint of a bicycle helmet is a key continuous attribute that needs to be considered as this design space is explored (Figure 5). All the important physical features should be chosen and the geometric data for these elements should be collected. This can be as simple as importing information from previous designs or tracing drawings or as complicated as 3D scanning.

Figure 5. Parametric curve representing the footprint of a bicycle helmet with assumed symmetry

4.2 Determining Numerical Representations

Regardless of how it's captured, the shape, or other key design attributes, of the product can be represented mathematically. As explained earlier, this does not need to be just shape. It could be colour. Not all attributes need to be continuous, e.g. one attribute is the quantity of vents on the top which is represented by a discrete number. Anything that can be represented with a number can be used in continuous visual conjoint. Since discrete attributes are a subset of continuous attributes, they can be analysed within continuous visual conjoint. The challenge lies in determining which are the key design attributes. For simple design spaces, like the RGB colour space (Orsborn and Talecki, 2011), there are only 3 attributes that range from 0 to 255. These are too many levels to analyse quickly and so they must be split into evenly spaced product attribute levels that can then be used to create the design study. More complicated spaces, like the curves in vehicle headlights (Swamy et al., 2007), need to be distilled down to key shapes. It is best if experts determine which shape attributes are independent variables and which are dependent variables. There are likely even some constrained variables that are completely dependent upon engineering or manufacturing constraints (Orsborn et al., 2006, Sylcott et al., 2013b, Tseng et al., 2013).

4.3 Design of Experiments

Continuous visual conjoint relies upon design of experiments to determine which continuous attributes at which discrete levels should be combined into options (Kuhfeld, 1994). These options can then be presented to respondents differently depending on the type of data that the designers are seeking. Choice-based models have been used most often in that they seem to most closely represent the thought process that consumers go through when purchasing real products (Green and Srinivasan, 1978). Other methods, such as ranking and rating, can be even more effective at accurately determining consumer preference for the design space despite presenting the information to respondents in a seemingly unnatural way (Reid et al., 2010, Tseng et al., 2013). Complexity within the attribute space can be controlled through statistical-based reduction of a space such as with principle component analysis (Orsborn et al., 2009)

4.4 Collecting Responses and Analyzing Results

User response to design concepts can occur in a variety of scenarios from showing conceptual drawings within a consumer study to online surveys. Given the mathematical nature behind continuous visual conjoint, it is quite easy to create an online study where users can simply select a preferred design from a set of options (Figure 6), or rate or rank designs. This information is then translated back and used to inform conceptual exploration. The extra value in this stage of the process is that user feedback, when represented with mathematical models, can be leveraged by the designer to support their design decisions when production engineering and marketing try to force a design away from its original intent.

Most studies up to this point have presented respondents with an online or digital survey in which visual representations are presented (Michalek et al., 2005, Swamy et al., 2007, Orsborn et al., 2009, Reid et al., 2009, Petiot and Dagher, 2008, 2011, Orsborn and Talecki, 2011, Lugo et al., 2012). Visual conjoint is not limited to digital representations and can just as easily be presented using drawings on paper, physical prototypes (Sylcott et al., 2014), or virtual reality (Tovares and Cagan, 2014). Results from the respondents are analysed using statistical measures appropriate to the design of experiments such as logit, probit, or the Luce method. While some researchers have aggregated the data to look for a single design optimum, others have analysed the respondents individually, in response to Page and Rosenbaum (1987), and then used the individual's assessment to generate individualized concepts. Regardless of the technique used, all of the studies have relied upon utility functions to appropriately represent the consumer preference model (von Neumann and Morgenstern, 1944, Keeney and Raiffa, 1976, Thurston, 1991, Chen, Wiecek, and Zhang, 1999, Orsborn et al., 2009a).

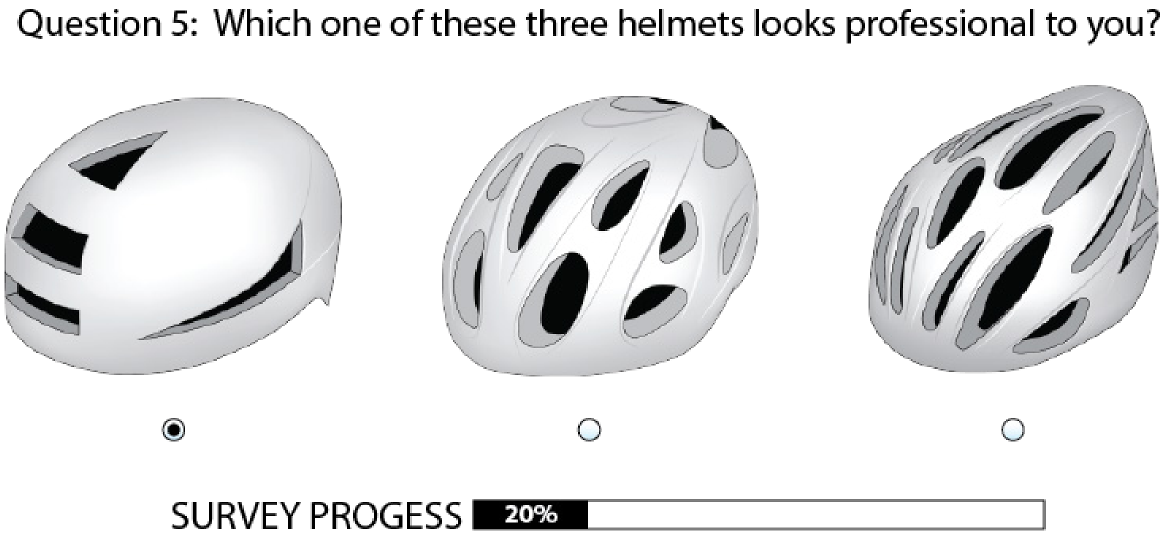

Figure 6. Example continuous visual conjoint survey question

4.5 Generating New Concepts

Continuous visual conjoint is simply a means to an end. The goal of the designer is to find what the consumer or user most likely appreciates. The purpose of the utility function is to mathematically represent the consumer's, or consumers', preference for the continuous visual design attributes that were analysed through the continuous visual conjoint. Once a utility function is created, then new design concepts are generated based upon that utility function. These design concepts can be created by an individual expert or can be automatically generated by an appropriate system (Orsborn and

Cagan, 2009). Once concepts have been created, these are then further explored in more detail, with or without the involvement of the user.

5 METHODOLOGICAL CHALLENGES

Most of the challenges with continuous visual conjoint are simply amplified version of the challenges already within verbal conjoint. But, the strengths may well outweigh the limitations. It is up to the designer to determine whether continuous visual conjoint is the best method for the task.

5.1 Strengths

As stated earlier, the primary strength of continuous visual conjoint is that much of the analytical information is implicit and the respondent primarily interacts with a visual representation that is cognitively easy to process. This, combined with the experimental design behind continuous visual conjoint, can provide trustworthy numerical data which in turn can be used to confidently create design concepts with significant potential for impact. Likewise, the analytical nature of the output of continuous visual conjoint as a utility function can provide designers with extra leverage when defending specific aesthetic features as designs move through production and marketing.

Additionally, visual conjoint takes continuous data and breaks it into discrete levels to create a discrete set of visual options that are assessed. The preference models for this discrete data, often a utility function, can then be mapped back to the continuous preference space resulting in concept designs that have never been seen but are more likely to match user or consumer preferences.

One possible, yet untested, strength is that respondents evaluate product attributes in a way that may not make varied attributes unduly salient. For example, by design, verbal-based conjoint exercises emphasize the tested attributes and respondents may possibly focus on these more than they would when making actual marketplace decisions. Similarly, if respondents are asked to focus on colour, they will likely overweight colour in their choices. Conversely, if respondents are presented with studies and simply asked to evaluate aesthetic options holistically, respondents are not likely to overweight particular product attributes if all are presented equally.

5.2 Limitations

One of the most difficult challenges with conjoint in general is the impact of interaction effects (Sylcott et al., 2013b). This can be fairly easy to manage when the attributes are all distinct and easily isolated. But, in visual representations the attributes and their relationships are often not so clearly understood. While this can cause immense challenges in creating and assessing visual information, it also reveals an enormous amount of potential for continuous visual conjoint. The other significant limitation is due to the mathematical nature of the design of experiments. While it is possible to choose a very large number of attributes, this can then proceed to an unwieldy study that no human could possibly respond to without fatigue. Visual representations, if not chosen wisely, can exacerbate this problem. For example, if designers choose to simply translate every continuous geometric variable into a continuous visual conjoint attribute, even a simple shape could easily end up in a study with well over 100 options, far too many for a respondent. As stated previously, continuous visual conjoint is still at the point where design space experts are needed to determine which are the best attributes to include in a particular study. Some promise has been shown in leveraging multi-dimensional scaling methods to understand dependencies between the various continuous visual attributes to reduce the complexity of the design space (Orsborn et al., 2008).

6 CONCLUSIONS

Over the past 15 years visual conjoint has evolved from simple, static imagery within verbal, or written, discrete conjoint analysis to purely visual imagery in choice-based consumer studies. Continuous visual conjoint provides design researchers with a technique for quickly gathering user responses to visual information about product concepts, be it shape, colour, or experience. This preference information can then be modelled with a utility function and used to generate emergent design concepts that should be preferred by the targeted users.

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