Implementation of design rules for perception into a tool for 3D shape generation using a shape grammar and a parametric model

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ABSTRACT

The user experience of a product is recognized as of increasing importance in particular in consumer products. Current approaches to designing user experiences are not easily translated to languages that a computer can understand. This paper examines a particular aspect of user experience, namely perception of the aesthetics of a product, to formalize this to rules which are embedded into a tool to generate design. Investigating the perception of consumers is key for designing for their aesthetic preferences. Previous research has shown that consumers and designers often perceive the same products differently.

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This paper aims to embed rules on perception into a tool to support designers during design synthesis. Aesthetic design rules connecting perceptions with aesthetic features were integrated into a set grammar and a parametric modelling tool, and applied to the particular case of vases. The generated tool targeted the creation of vases with the perception of beautiful*,* elegant *and* exciting*. Results show that it is possible to generate* beautiful*,* elegant *and* exciting *vases following the three aesthetic design rules, i.e. tall, simple and curves. The main contribution of this paper is the method used to incorporate information on perception into the set grammar and the parametric model. The tool is additionally proposed for supporting designers during design synthesis of shapes. The results are valid for vases but the method can be applied to other perceptions and product categories.*

1. INTRODUCTION

Understanding consumer´s needs and preferences is key in today's consumer society. The wide range of solutions already existing in the market makes it increasingly difficult for consumers to differentiate and select amongst products with very similar functionalities. Consumer psychology explains how people purchase based on stimuli from products [1] and always choose the one that is more attractive between two of equal price and function [2,3]. The most attractive shape will stand out from the rest and will be chosen by consumers [4,5].The aesthetic response is one of the first response to a product and it is highly impacted by visual information [3]. The aesthetics of a product can additionally communicate information about the product, for example regarding its perceived quality [3]. Quality can be inferred through the shape of the product. That makes aesthetics a decision-making mechanism for purchase. Understanding the influence of aesthetics on product preference is relevant for concept generation whether computational or by designers.

The misalignment between consumer's and designer's perception of products [6,7] has led to research in understanding how the aesthetics of products influence consumer perception [8–12]. A number of aesthetic design rules were identified in the literature that relates aesthetic features to perception. These rules are key in generating new design concepts for specific perceptions. For research, this means that aesthetics can be used to understand perception from products and to develop tools that support design synthesis. Understanding how these aesthetic design rules for perception can be implemented into computational tools to support design synthesis is expected to increase the number of innovative solutions that can be generated while accounting for shape, function and perceptions.

Preference judgements of aesthetic attributes have been shown to vary depending on the choice of product representation (e.g. sketches, CAD models or prototypes) [13]. Simple representations, such as sketches of CAD models, focus the attention of the consumer on the aesthetic elements. More complex representation models, such as 3D prototypes, can lead the attention to functional aspects through the material and finish quality [13]. The choice of analysis method, either aesthetic and function evaluations independently or conjoin also influences the preference ratings [14] and should be considered in the analyses. For this study, vases were selected as the case study due to their high aesthetic appeal and simple functionality. Here, 3D CAD images were used to obtain information on perception through online surveys.

Previous research has investigated the influence that the background of consumers can have on product perception obtaining contradictory results. Some studies have found differences in perception of products among consumers of diverse backgrounds [15–19]. While other studies found similarities in the perception obtained from products [20]. Results from a study investigating the influence of background on perception for vases showed that the background factors of age, gender, country, style and design background do not influence perception of vases [21,22]. Since the case study in this paper is vases, the background influence was not considered.

In this paper, we introduce a methodology explaining how to implement aesthetic design rules for perception into generative designs systems. A set grammar and a parametric model are used for implementation. A tool has been generated (and evaluated) that generates designs targeting *beautiful*, *elegant* and *exciting* vases.

The structure of the paper is as follows: first a literature review of the relevant topics of the paper is presented. Second, the research aims for the study are described. Third, the methodology section explains the development of the tool for the case study on vases. Fourth, the results section shows the solutions generated by the tool and its evaluation. Finally, a discussion section and conclusions are presented.

2. LITERATURE REVIEW

For this research, three central topics are: 1) Aesthetics, 2) Emotional design and perceptions and 3) Generative design. Aesthetics have the ability to communicate to consumers and are one form of expressing perceptions through form, material and geometry. The aim of the emotional design research field is to understand the effect that design has on the emotions of consumers and to develop tools and methods that can support designers generate new solutions [23,24]. Literature in emotional design has confirmed the relevance of product aesthetics on perception and highlighted aesthetics as one of the first aspects of the product that people interact with. Identifying the relationship between aesthetics and perception is relevant to defining design rules for perception. Generative design is relevant to developing generative tools. Hence, these three topics are reviewed here.

2.1. Aesthetics

Aesthetics have a large impact on the perception of a product. Visually attractive products provide information about the quality of the product [3] and are usually preferred by consumers over competing products of similar price and functionalities since it makes them stand out [2–5]. In design research, aesthetics stand for the features of a product that create its appearance and have the ability to generate immediate responses when the product is experienced through the sensory system [25]. A number of design principles have been identified in the literature that gives some guidelines on important aesthetic features with high influence in product preference. An overview of these principles is shown in Perez Mata *et al.* [26]. In the paper, the principles have been grouped in 3 categories according to the level of detail of the design principles. These principles range from: 1) the very general principles, such as the Gestalt rules or laws of organization in perception that show how people interpret the world around them [27–32]; to 2) design principles that affect preference and evaluation [33–36], and 3) the more detailed design principles relating aesthetic features to perceptions [8–11,37]. Recent methods have been proposed that measure the Gestalt from 2 dimensional elements [38,39] or websites [40] and can guide the selection of the preferred design by consumers for the new generation of designs.

2.2. Emotional design and perceptions

The field of emotional design originated to understand how aesthetics can evoke feelings and to use this understanding to generate aesthetically pleasing products [41]. The interaction between people and products has been described in different ways. Jordan (2000) through the psychological pleasantness approach describes how people feel practical (perform a task), emotional (affect mood) or hedonic (sensory and aesthetic) pleasure from a product. Norman (2004b) through the neurobiological process-level approach describes three levels of information processing: visceral (first impressions through the senses), behavioral (perception of use) and reflective (rationalization of the product). Desmet [44] through the cognitive appraisal approach describes how through evaluation people can find products as being useful (supports / obstructs a goal), pleasant (provides pleasure or pain) and rightful (meets or exceeds expectations). The research presented here focused upon how people perceive the aesthetics of objects, which falls within the hedonic category from Jordan [42], the visceral level from Norman [43] and the pleasant category from Desmet [44]. These categories deal with the first impression of the product through its aesthetic elements.

Previous research has investigated the influence that the background of consumers can have on product perception obtaining contradictory results. Some studies have found differences in perception of products among consumers of diverse backgrounds [15–19]. While other studies found similarities in the perception obtained from products [20]. Results from a study investigating the influence of background on perception for vases showed that the background factors of age, gender, country, style and design background do not influence perception of vases [21,22]. Since the case study in this paper is vases, the background influence was not considered.

Connecting perceptions to the aesthetic elements of a product is an established approach in a number of fields, including consumer marketing [4,5] and engineering design [9,20,37,41,45–49]. Methodologies have been developed to understand consumer preference and perception and its link to product aesthetics (including shape, geometry, colour, material, etc.). The majority of these studies investigate only one product category at a time (e.g. Rocker switches [8], while others aim to find common properties across product categories (e.g. cars, sofas and kettles [9]. Other studies focus upon the influence of the background, culture and demographic information from consumers in perception to find common and / or independent relationships [15,17–21,27]. The general approach undertaken in the emotional design studies involves the selection of a number of perceptions to be investigated and then relating them to aesthetic features from a product through different settings, either using: statistics (to find quantitative relationships between the variables); experts (to define the products features related to perceptions based on their experience); users (to evolve the shape of a product to represent a perception); or combinations of these.

As stated earlier, differences have been reported between the intention of the designer and how consumers perceives the product [6,7,20,50], highlighting that despite designers designing products to convey a particular intention, consumers often perceive this differently. Hence, there is a need for support for designers to create product forms with intended perceptions. Until now, designers have relied on their intuition or experience to relate perceptions with shape and geometry.

2.3. Generative design

'Generative design systems are aimed at creating new design processes that produce spatially novel, yet efficient and buildable designs through exploitation of current computing and manufacturing capabilities' (Shea et al., 2005). There are three main computational design synthesis approaches or generative systems, these are: 1) Spatial grammars, 2) Evolutionary algorithms and 3) Generative Design Method. These are briefly described below.

2.3.1. Spatial grammars

Spatial grammars were originally developed to support design synthesis (i.e. generation of form) by encoding design style and knowledge about spatial and functional relations [51,52]. In terms of understanding aesthetics, efforts have been made in two directions: 1) explaining styles, primarily in architecture [53–55] and also in engineering design and consumer products [56–58]; and 2) developing methods that allow for the generation of hybrid or crossover designs from existing products [59] or implement shape grammars to automatically generate forms for designs following consumer aesthetic form preferences [60].

Recent research has begun to incorporate perceptions in the generation process, for example the shampoo bottle grammar [61] that generates *professional looking* bottles by embedding the professional looking bottle shapes identified in the market, and the vase grammar [62] that generates *beautiful* vases by implemented some of the identified aesthetic design rules for *beauty* in vases.

2.3.2. Evolutionary algorithms

Evolutionary algorithms were originally employed for functional optimization, machine learning and control [63]. The strategy originated to simulate evolution processes from nature to optimize engineering problems [64]. Traditionally, evolutionary algorithms have been used in design to evaluate the functionality of generated designs [64]. However, later research has included evolutionary algorithms in the generation of forms [65–67]. More recent research by Cluzel et al. [68] has proposed a method for 2D-closed-curve for meeting the desired style, in particular using car silhouettes. An Interactive Genetic Algorithms (IGA), characterized for having the designer evaluate the solution options, was used to explore car profiles by asking a number of students to interact with the system until they found the best example of a *sporty* and of a *friendly* car based on their own evaluation.

2.3.3. Generative Design Method

The Generative Design Method (GDM) (2011) is a designer driven design process to stimulate the creativity of designers aiming to generate new solutions. The GDM method supports subjective design activities by allowing the designer to choose the design direction through viable design spaces constrained by performance criteria. [69]. The GDM is an implementation of generative design 'on top of a history based parametric CAD system' [69]. It is a CAD based generative exploration method intended to be used at all stages of the product development process, that is, from conceptualization to detail design [69].

Parametric modelling is characterized for having parts of a design related to each other to allow for a coordinated change of all of them together [70]. GDM supports design synthesis by the use of a genetic model, which is 'the representation of a family of objects that share the same topological constraints but have different geometry' [71]. The GDM is not intended for engineering problems where the key performances can be computed or for design problems where the problem and solution space can be mapped [69]. The GDM shares with the GA some terminology: the generic model, performance space, mutation and selection criteria [69]. The GDM has been used for the generation of new design solutions , e.g for an MP3 player and coffee tables [69]. However, perceptions have not yet been included in this approach.

3. RESEARCH AIMS AND MOTIVATION

The paper has two aims. First, the paper aims to develop a method and a tool to support design synthesis for perception by implementing aesthetic design rules and principles which encode knowledge on perceptions into the design synthesis process. Second, the paper aims to evaluate the designs generated by the tool for the set grammar and the parametric model implementations to determine the success of generating the intended perception.

A more formal approach is needed to: 1) support designer´s in identifying users perceptions and embodying these into the aesthetics of a product, 2) reduce the time of the design process and the number of iterations needed with consumer panels or focus groups to assess the accuracy of the perceptions achieved through the shapes generated, and 3) explore the generation of forms excluding fixation issues reaching to potentially more innovative solutions.

From the above literature, a number two hypotheses were derived for this study that were used to evaluate the designs produced from the tool and these are described below together with the evaluation in Section 4.2.1.2. The next section describes the methodology used in this study, including tool development and evaluation of designs.

4. METHODOLOGY

The Methodology section is divided in two main areas: 1) the implementation of the aesthetic design rules for perception into a set grammar and a parametric model, and 2) the evaluation of the designs generated through the tools implemented.

4.1. Implementation method

The method to integrate aesthetic design rules for perceptions into tools to automate the generation of designs is described here. Two parallel approaches were considered, the grammar approach (see Figure 1) and the parametric model approach (see Figure 1). Figure 1 illustrates a flow diagram of the research adopted for this process and is explained below. The case study to which this was applied is using vases due to their high aesthetic appeal and simple functionality, hence are a suitable choice as it is easier to evaluate the perceptions separating any judgement on usability and functionality [6]. Although vases are selected as the case, the methodology is intended to be transferrable to other product categories and extendable to other perceptions. Previous research [11] collecting perception information from consumers on vases found that *beautiful*, *elegant* and *exciting* perceptions were highly correlated to the desire to own a product. Therefore, these perceptions have been considered for implementation.

[Insert Fig. 1 around here]

The aesthetic design rules for perception (or perception rules) linked single perceptions, for example *aggressive,* with aesthetic features, e.g. High Lines Curves Ratio (LCR) = more straight lines than curves. Perez Mata *et al*. [11] found that for the case of vases, *beautiful* was correlated to: 1) high number of curves, 2) simple and 3) tall; *elegant* correlated to: 1) tall, 2) simple and 3) high chroma (e.g. that the colour is pure and not mixed with black, white or grey); while *exciting* correlated to: 1) tall and 2) simple. Figure 2 shows some examples of the vases perceived as *beautiful*, *elegant* and *exciting*. Figure 3 shows the common aesthetic design rules that influence perception *beautiful*, *elegant* and *exciting*. The focus of the paper is solely upon shape, therefore, the third rule for *elegant* is not implemented (i.e. chroma) and it is not shown in Figure 3.

[Insert Fig. 2 around here]

[Insert Fig. 3 around here]

Beautiful, *elegant* and *exciting* vases share the tall and simple (i.e. few visually independent modules) rules. These aesthetic design rules influence the perception independently of each other. That is, a vase is perceived as *beautiful* if it has curves or is simple or is tall or has combinations of these three rules. Not all properties need to be present in the shape simultaneously. The curves only affect the perception of *beautiful* and therefore were only implemented for these. These aesthetic design rules were translated into a set grammar and a parametric model to demonstrate how the aesthetic design rules can be implemented in different approaches.

4.1.1. Method A: Set Grammar implementation

A set grammar is composed of a finite set of shapes (S), labels (L), rules (R) and an initial shape (I) [72]. The vocabulary of the grammar, expressed as $(S, L)^0$, comprises the set of all labelled shapes including the empty labelled shape [73]. The rules are defined from A → B, where A and B are shapes of the vocabulary. Rules have two sides, a left hand side (LHS) and a right hand side (RHS). If there is a shape or set of shapes in the current working shape (CWS), also called the working shape C, that matches the left hand side of a rule (part A of the rule) then the rule can be applied and the working shape C is changed. To find all possible matches of the LHS on the working shape, Euclidean transformations (t) are used. These include: translation, rotation, reflection or combinations of them. Once a match is found, the elements from the LHS of a rule are subtracted from the working shape C and the elements from the RHS are added. The result of applying the rule is a new working shape C' which can be expressed as: C'= C – t(A) + t(B) [73].

Previous work by the authors include the development of a set grammar to incorporate aesthetic design rules for perception [62]. Four types of grammar rules were developed for the vase grammar that implemented the aesthetic design rules. In general, the first group of grammar rules generated the first primitive. The second group of grammar rules added the second primitive on top of the first one. The third group of grammar rules added the third primitive and the fourth group of grammar rules stopped the addition of new primitives. The addition of primitives and the end of the generation process is controlled by state labels that change name or are removed from the Current Working Shape (CWS). The grammar is able to generate vase designs with one, two or three primitives. Figure 4 shows the four types of grammar rules developed [62].

[Insert Fig. 4 around here]

Spapper [74], a 3D shape grammar interpreter implemented within FreeCAD [75] was used for the set grammar implementation [62]. FreeCAD is an open source parametric 3D CAD system [75]. Spapper is a Python module that has been integrated into FreeCAD and adds a new workbench and two toolbars for the development and application of spatial grammar rules to the existing CAD system [72].

The first two perception rules for developing *beautiful* vases, i.e. tall and simple, were implemented. This implies that perceptions *elegant* and *exciting* were also implemented in the grammar as they share the tall and simple rules. The last rule for curves was not implemented due to software restrictions regarding the shapes and operations available for generation. The simplicity rule was implemented by limiting the number of parametric primitives (i.e. box, cylinder and cone) that could be applied per shape to a maximum of three. The tall was implemented by making sure that the final design (composed of up to three primitives) was always taller than wider.

4.1.2. Method B: Parametric Model implementation

For the parametric modelling implementation, the Grasshopper [76] plug-in within the Rhinoceros [77] environment was used. This was selected as it allows a wide range of operations that can include curves (e.g. profile revolution and loft with curved transitions). Rhinoceros is a commercial 3-D modeler (CAD system) software [77] and Grasshopper "is a graphical algorithm editor tightly integrated with Rhino's 3-D modeling tools" [76]. Grasshopper is used primarily to build generative algorithms and it utilizes visual coding algorithms which perform actions in Rhino.

The perception rules for developing *beautiful*, *elegant* and *exciting* vases, namely: tall, simple and with curves [11] were considered for implementation. The first aesthetic design rule, i.e. tall, limited the generation of shapes only to those that are taller than wider. The second aesthetic design rule, i.e. simple, was related to the number of visually independent modules. In Grasshopper, this was controlled with the number of operations that can be applied to generate the vase, which at all times is only one, in this case a profile revolution and a loft between profiles. These operations were used as they were found in the vases perceived as *beautiful, elegant* and *exciting (see* Figure 2*);* namely those under study. The profile revolution operation consisted of four points connected with at polyline (see Figure 5), while the loft operation consisted of three profiles (i.e. circle, ellipse and polygons between 3 and 10 edges) (see Figure 5). Curves were inserted to the design in Grasshopper by adding a second degree to the NURBS curve that linked the points in the revolution operation, and by having a soft transition between profiles in the loft operation. For each of the operations (i.e. revolution and loft) a generic form for a vase (in this case a cylinder) was used as the parametric shape definition from which all designs would evolve. Unlike grammars, in a parametric model it is necessary to start with a pre-defined common shape to which parametric changes can be applied.

[Insert Fig. 5 around here]

4.2. Evaluation method

This subsection describes the evaluation of vase designs generated by the set grammar and the parametric model in order to assess the success of generating the intended perception. The study, including data collection and analysis methods are described below.

4.2.1. Data collection

The vases designed to be *beautiful*, *elegant*, *exciting* were compared to the control vases (i.e. the vase designs generated not to be *beautiful*, *elegant* and *exciting)* to prove that the tools and method proposed in this research are able to support design synthesis for perceptions. Significant differences in perception between the vase designs and the control vases would indicate that the implementation method was successful in generating vase designs for specific perceptions.

4.2.1.1. *<u>The vases</u>*

A total of 90 solutions were generated from the set grammar and parametric model implementation to see the potential of the tool in generating a variety of designs. Six vase designs were selected from the set grammar and another six from the parametric model; where four for each were representing perceptions *beautiful*, *elegant* and *exciting*; and two were control vases. The set grammar and the parametric model are programed to generate tall, simple and curvy products. The control vases were selected among the solutions generated from the implementations and manually modified to follow the opposite perception rules. That is, they were modified to be short, complex and with many straight lines. The selected vases for the study are illustrated in Figure 6 and a summary of how they are generated is provided in Table 1.

[Insert Fig. 6 around here]

[Insert Table 1 around here]

4.2.1.2. *<u>Hypotheses</u>*

Hypothesis 1: The vases generated with the perception rules to be *beautiful, elegant* and *exciting* respectively were expected to be perceived as more *beautiful, elegant* and *exciting* respectively than the control vases. The control vases are designs generated not to be *beautiful*, *elegant* and *exciting* . This is expected to be true for all the vases independent of whether they are generated through a set grammars or a parametric model approach. This hypothesis is divided into three sub-hypotheses, one for each perception:

- Hypothesis 1a: vase designs generated to be *beautiful* are expected to be perceived as more *beautiful* than the control vases.
- Hypothesis 1b: vase designs generated to be *elegant* are expected to be perceived as more *elegant* than the control vases.
- Hypothesis 1c: vase designs generated to be *exciting* are expected to be perceived as more *exciting* than the control vases.

Measurement: Wilcoxon signed-rank tests (the equivalent of a paired t-test but for non-normally distributed ordinal data) will be used to compare the solutions generated by the tool that score highest for *beautiful*, *elegant* and *exciting* against the vases that score lowest for each perception. A z-value below 0,05 is considered significant.

Hypothesis 2: Vase designs generated with more curves than straight lines are expected to be perceived as more *beautiful* than those with less curves. This is expected to be true for all the vases independent of whether they are generated through a shape grammars or a parametric model approach. Even though *beauty* is influenced by tall, simple and curves [11], previous research on a set grammar implementation [62] has shown that simple and tall are not enough to generate *beautiful* vases. It is therefore expected that vases with more curves will score higher on *beauty* than those vases without many curves.

Measurement: Wilcoxon signed-rank tests (the equivalent of a paired t-test but for non-normally distributed ordinal data) will be used to compare the vases generated by the tool that score higher and lower for the *beautiful* perception. A z-value below 0,05 is considered significant.

4.2.1.3. *The participants*

A total of 86 participants undertook the survey. However, only 66 participants answered all questions and only these are analysed here. For the preliminary evaluation of the solutions from the proposed tools, the 66 participants of the survey were considered sufficient. The 66 participants of the study included researchers and graduate students with a management, design or mechanical engineering background. The participants were recruited by the authors of the paper by email and did not receive any monetary compensation. No question to gage attention was used due to the short length of the survey (5 minutes) and the nature of the participants (volunteers).The participants were from four universities in three locations to obtain data across cultural backgrounds. The universities are those where the authors are employed and have easy access to students and staff. These universities were: Technical University of Denmark

(Denmark), ETH Zurich (Switzerland), Imperial College London and Royal College of Art (United Kingdom).

4.2.1.4. The survey

An online survey was employed for data collection, facilitating data from the various location, the survey took 5 minutes to complete. Participants were asked to provide information about their background, namely: the country that they were from, age, gender and if they had a design background knowledge or experience. The participants were then asked to rate the 12 vase designs from Figure 6 for three selected pairs of opposite perceptions: 1) *Boring - Exciting*, 2) *Clumsy – Elegant* and 3) *Ugly – Beautiful*. The perceptions were selected based on prior work by one of the authors [6,78]. The 12 vase designs were evaluated one at a time in a randomized order, i.e. each participant rated them in a different order, to account for the possible effect of the ordering of the vases on perception. The survey was trialled with three participants (not included in the data analysis) to check for clarity of images and the rating scales and, also identify any IT issues.

Semantic Differential scales (SD scales) [79] with seven levels were used to capture perception from participants. SD scales were used, as the validity of the scales is accepted within the research field and they are widely used in similar studies. The internal reliability of the three perception pairs was calculated using Cronbach's alpha [80]. The Cronbach's alpha for *Boring - Exciting* was 0,7272; for *Clumsy – Elegant* was 0,6887 and for *Ugly – Beautiful* was 0,6868. These values are either above 0,70 or very close to it. According to Nunnally and Bernstein (1994), values above 0,70 show modest reliability. Therefore, the reliability of our perceptions is considered acceptable.

4.2.2. Data analysis

4.2.2.1. Predicted perception value from vase designs

In order to aesthetically evaluate the designs produced, a measure was needed to assess how well each design is predicted to achieve its perception. In Perez Mata et al. [11], three aesthetic feature ratios significantly influenced the perceptions of *beautiful*, *elegant* and *exciting*. These are CLR (Curve Line Ratio), the SL (Simplicity Level) and the HWR (Height Width Ratio) [11] (see Table 2). These ratios were used as a characterization of the aesthetic properties after the survey evaluation with participants. Averaging the values of the ratios influencing each perception can provide a value for the expected evaluation of the vase based exclusively on the aesthetic elements. A similar approach is employed to calculate or predict aesthetic pleasure from products [82,83]. However, other approaches have shown that the assumption that all ratios have the same influence is incorrect [39,59] and this should be considered if the perceptions are not accurate.

[Insert Table 2 around here]

Two Predicted Perception Values (PPV) were derived: one for *exciting* and *elegant* as they share the same aesthetic design rules, and one for *beautiful* (see Table 3). The average of the ratios is chosen as a suitable strategy as it limits the range of values from 0% to 100% (like the ratios themselves). For example, for vase 1 for *exciting*, SL = 100% and HWR = 53,31%. Therefore, the PPVex is the average of those two ratios, i.e. PPVex =1 00+53,31 = 76,65%. It is acknowledged that this approach assumes that all ratios have the same influence on the perception. However, it is considered a suitable starting point that can later on be adapted with weightings.

[Insert Table 3 around here]

4.2.2.2. *Comparison of predicted and real perception values*

The data from the online survey was tested for normality through the skewness/kurtosis test [84,85] and the Shaphiro-Wilk test [85,86]. The test showed that most of the variables were not normally distributed. The Wilcoxon signed-rank test (the non-parametric test equivalent to the dependent t-test [87–89]) was performed for the vases with the highest score on the Prediction Perception Value (PPV) against those vases that scored lowest, e.g. vase 10, 1 and 7 against vase 5, 11 and 6 for perception *exciting* (see scores in Table 5). *A significant difference between the lowest and highest scoring vases for each perception would prove that the design rules implemented for generating* beautiful, elegant *and* exciting *vases were sufficient to evoke those perceptions. This would mean that the high scoring vases were perceived as significantly different from the lower scoring ones.* Effectively the lowest scoring designs were the control vases.

5. FINDINGS

This section consists of two parts. The first describes the vase designs generated through the set grammar and parametric model implementation tool. The second part describes the results from the survey evaluating the perception of the vase designs generated with the implementation tools.

5.1. Generated vase designs

The vase designs for the grammar method were generated by randomly applying the grammar rules iteratively in Spapper [74]. The grammar rules specify the ranges within which the parametric aesthetic features can obtain a value. All dimension ranges, such as the height for the cone or the radius for the cylinder, are defined in the rules. A maximum of four rules can be applied to generate the new solutions. A total of 30 vase designs were created that include one, two and three primitives (see Figure 7).

The vase designs for the parametric model method were generated with the Genoform [90] plug-in by randomly assigning values to the aesthetic features of the generic model of the vase (see Figure 7 with dashed lines). The generic model specifies the ranges within which the parametric aesthetic features can obtain a value. All the dimension ranges for each aesthetic feature, such as the distance in *x* for a point or the radius for a circle, are defined within the generic model in Grasshopper. A total of 30 solutions were generated for each of the parametric models, i.e. revolution and loft operations. The solutions were generated with and without curves (see Figure 7).

[Insert Fig. 7 around here]

Post-processing operations such as solid fillets and solid shell were applied to the solutions to produce more refined vases. This was done to generate comparable vases for the survey in terms of visualization, i.e. same colour, background and lighting. All vases have fillets of 3 mm radius (radius 1 if 3 could not apply) and a shell of 1 mm thickness. Although color and material are properties that the 3D programs offer and can easily apply to the model, as the focus of this research is purely on shape, these were not used.

5.2. Support tool evaluation

This section presents the results from the online survey performed on the perception of 12 vase designs generated through the two different approaches: the shape grammar and the parametric model. A total of 66 complete participant responses were analysed. Participants were from 25 countries, with Germany (13,64%), Denmark (12,12%) and United Kingdom (10,61%) as the countries with highest representation. A total of 92,42% of participants were aged between 20 -39 years old, 59% were males and 71,21% had design background.

5.2.1. Predicted perception from vase designs

Table 4 presents the values of the vase designs for: 1) the different aesthetic ratios (i.e. Curves Lines Ratio (CLR), Simplicity Level (SL) and Height Width Ratio (HWR)); 2) the Predicted Perception Value (PPV) following the equations in Table 3 (i.e. score predicting the vase design perception for a given perception) for *exciting* (PPVExc), *elegant* (PPVEl) and *beautiful* (PPVBe); and 3) the average values of the real perceptions obtained from the participants of the online survey (i.e. how the vases were really perceived) for *exciting* (AveExc)*, elegant* (AveEl) and *beautiful* (AveBe).

[Insert Table 4 around here]

The data was ordered from higher to lower PPV for each perception (see Table 5). In Table 5 the scales of the PPV have been changed from % to the scale of the perceptions (with values 1 to 7) for better comparison. It was expected that vases generated with the perception rules to be *beautiful*, *elegant* and *exciting* respectively would be perceived as more *beautiful*, *elegant* and *exciting* than the control vases (i.e. vase 5, 6, 11 and 12) (Hypothesis 1). The predicted perception value (PPV) found that this expectation was true for vase 5, 6 and 11 for the predicted perception *exciting* and *elegant;* and for vase 6 and 11 for predicted perception *beautiful* as they were predicted to be rated the lowest through the PPV (see bottom of Table 5 column PPV). However, vase 12 was rated higher than expected for all three perceptions. Vase 5 was also rated higher for the *beautiful* perception than predicted. These results indicate that the prediction of a perception from the aesthetics of a product might be influenced by something other than those ratios used to calculate the perception. Additionally, the perception rules could perhaps not be accurate enough and need further investigation to add any missing influencing aesthetic element which could explain the perception of vase 12.

[Insert Table 5 around here]

Wilcoxon signed-rank tests were performed on the survey data on vases that scored above 70% on the Predicted Perception Value for *exciting* (PPVExc), *elegant* (PPVEl) and *beautiful* (PPVBe) against those vases that scored the lowest in the same table. The purpose was to find significant differences that would confirm that vases that score high on the PPV scale are perceived different from the ones that score low and additionally there is agreement between the prediction and the real perception of the vase. The results from the test are shown in Table 6. The column labelled High in Table 6 indicates the vase design that was expected to be rated highest for each of the perceptions. The column labelled Low indicates the vase design that was expected to be rated the lowest for each particular perception. The results show that all signed-rank tests were significant except the one marked in italics between vase 10 and 5 for perception *exciting*. Those two vase designs are not perceived as significantly different. All positive values of z prove that the vase that was predicted to rate higher for each perception was significantly different from the vase that was expected to rate lower and the prediction was correct. The negative values of the Z column indicate, however, that the vase that was predicted to rate higher was in reality rating lower than the vase predicted to rate low and the prediction was incorrect.

For perception *elegant* and *beautiful* it was found that vases that were designed to achieve that perception did in fact achieve it and were significantly different from the vases that were predicted to be *clumsy* and *ugly*. This implies that the support tool was successful at generating vase designs to be perceived as *elegant* and *beautiful* by consumers. This means that perception *elegant* can be obtained without the chroma rule. For perception *exciting*, results were mainly the opposite of what was expected, except for vase 7. For example, vase 6, 11 and 5 were expected to rate lower than vase 10 and 1, but this was not confirmed with the data collected from the survey. This implies that the support tool for generating *exciting* vases is not accurate and further research needs to be undertaken to determine the influence of the perception rules. Some perception rules could be missing in this approach or the proportion of their influence might not equal as suggested by the work of [39,59]. Exciting is a perception belonging to the historical category [91]. This could have an influence on that perception.

[Insert Table 6 around here]

5.2.2. *Influence of curves on perception*

The vase designs generated with curves were expected to be perceived as more *beautiful* than those without curves (Hypothesis 2). Vase 7 and 10 were predicted to score high on the *beautiful* perception according to the prediction with the PPV due to the presence of curves in addition to being simple and tall. Results from the survey have shown that those vase designs were among the ones that consumers in the survey find most *beautiful*. These results agree with the statement in hypothesis 2 and imply that curves positively influence the perception of *beautiful*.

However, vase 12 was not expected to be *beautiful* because it is short and has more straight lines than curves, i.e. it was generated to act as a control. However, inspecting the shape of vase 12, curves were found to take up a lot of the visual space in the shape in comparison to the short straight lines. This result points towards investigating not only the presence of more curves than straight lines, but also how much of the total vase those curves occupy. A possible explanation could be that *beautiful* does not have equal weighting between the three rules (see objective assessment PPV) and curves have a greater influence.

6. DISCUSSION

The current paper describes the implementation of perception rules into a tool to generate product shapes. This has been implemented into two models: a shape grammar model and a parametric model. The solutions generated by the two models show a wide range of vases following the aesthetic design rues specified (i.e. curves, tall and simple). The advantages of shape grammars include the detection, addition, substitution and removal of geometry belonging to the shape in progress. Additionally, the randomness option generates new solutions every time the grammar is used. The limitation is the reduced number of operations and the shapes available for generation, i.e. primitives (in this case, box, cylinder and cone). More free forms are needed in Spapper to increase the range of solutions that can be generated.

The advantage of parametric modelling includes the wide variety of operations and shapes that can be used, especially including curves. However, it is limited to the topology defined for the generic models. To obtain new solutions the initial shape has to change. Genoform was used to generate random solutions from the parametric generic models and includes functionality to select the preferred designs and therefore, which properties should be kept for the next iterations, but this was not used here. Similarly, the combinations of properties which are not preferred by the person controlling the generation process can be removed from the system so they no longer appear as well as similar versions in future generations. These properties of the tool could be used to investigate preference of shapes at the individual level. Nevertheless, it is an interesting tool for analyzing the design space and has the potential to generate vases outside the designer's solution space.

The implementation of aesthetic design rules into the tool developed can guide and support designers in generating shapes for specific perceptions or combinations of perceptions. The method presented has proven to successfully generate vases targeting perceptions, although further research is necessary to improve the prediction of how vases will be perceived. The method used to generate the tools can be extended for additional perceptions or for different product categories. The proposed method can be integrated in the design process as a tool for idea generation once the perception to be evoked with the shape is clarified. It can provide a multitude of different solutions in a short period of time and even help overcome fixation issues.

As future work, include improving the design rules to include more information on the range between which an aesthetic feature moves in and produces the desired result, i.e. the *tipping point* of a perception. For example, if *beauty* is related to more curves than straight lines, perhaps having too many curves is also perceived as *ugly*. Therefore, the tipping point or the range in which curves has a positive influence on *beauty* can be established. Additionally, research could look into allowing customers to interact with this tool to generate their own designs, i.e. expanding the support tool to include non-designers.

7. CONCLUSION

This paper describes the implementation of perception rules into a set grammar and a parametric model for the generation of 3D forms for target perceptions. The research used the case study of a vase to support the generation of *beautiful*, *elegant* and *exciting* vases. The research presented has shown that the computational generated vases that were predicted to be *beautiful* and *elegant* were indeed perceived as more *beautiful* and *elegant* than the control vases that followed the opposite rules. For *exciting*, the design rules proved not to be enough to generate *exciting* looking vases and additional research should be undertaken. Results have also shown that vases generated with more curves are more *beautiful* than those without, indicating that this aesthetic feature has a larger influence on perception of *beauty* than other factors and a vase maybe perceived as *beautiful* despite none of the other perception rules are met.

The research contributes to quantifying perceptions through a focus on aesthetic features. Current approaches to designing for perceptions are not easily translated to languages that a computer can understand. The research additionally contributes with the method and the tools to implement aesthetic design rules for perception with a focus on shape solely, excluding color and material, into both a set grammar and a parametric model for three perceptions. The potential of the tool in generating designs outside of the designers’ solution space is expected to result in innovative designs.

Additionally, this tool should speed the process of shape generation by supporting the designer to achieve the final shape targeting a specific perception.

The tool developed is expected to generate *beautiful and elegant* vases only. However, the method proposed can be applied to other perceptions and product categories as demonstrated by the model presented.

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Figure Captions List

Table Caption List

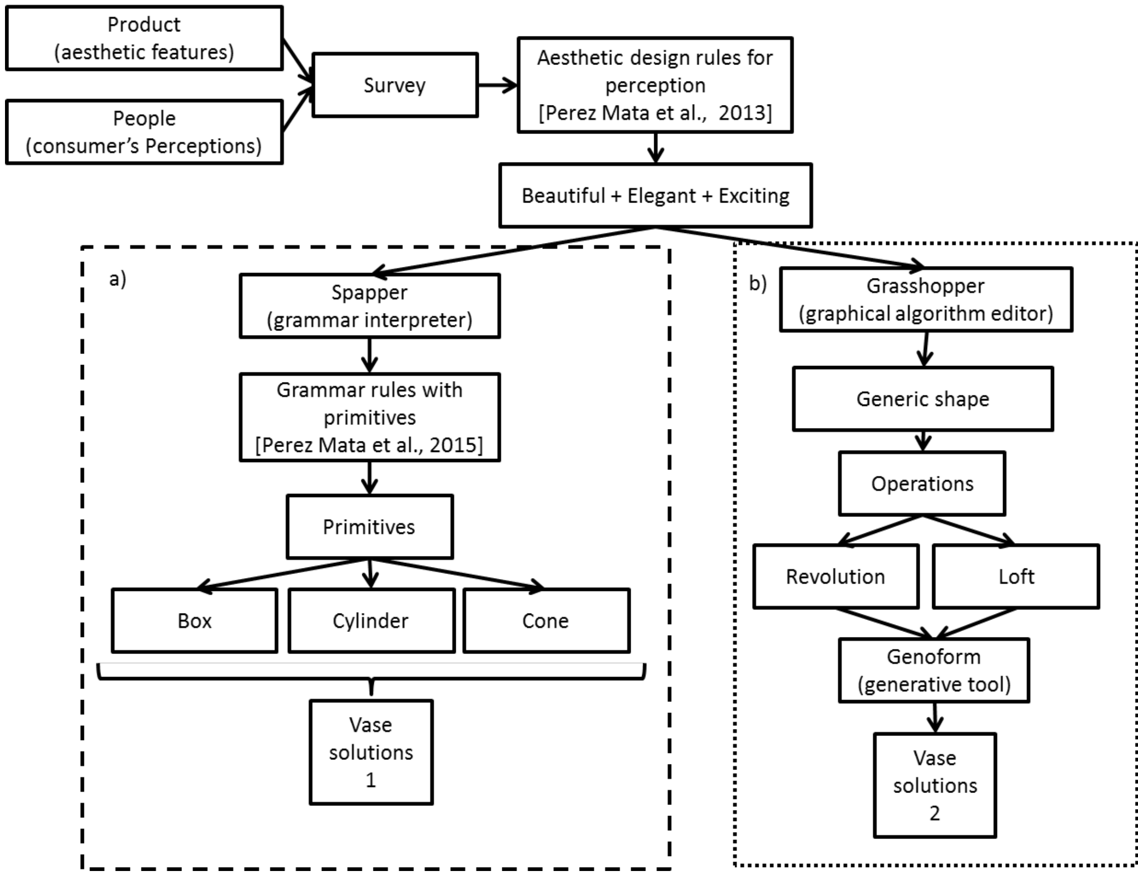

Figure 1 Flow diagram describing the research process to implement perception rules. The dashed rectangle on the left indicates the steps followed by the set grammar implementation (see section 4.1.1.). The dotted rectangle on the right indicates the steps followed by the parametric model implementation (see section 4.1.2.).

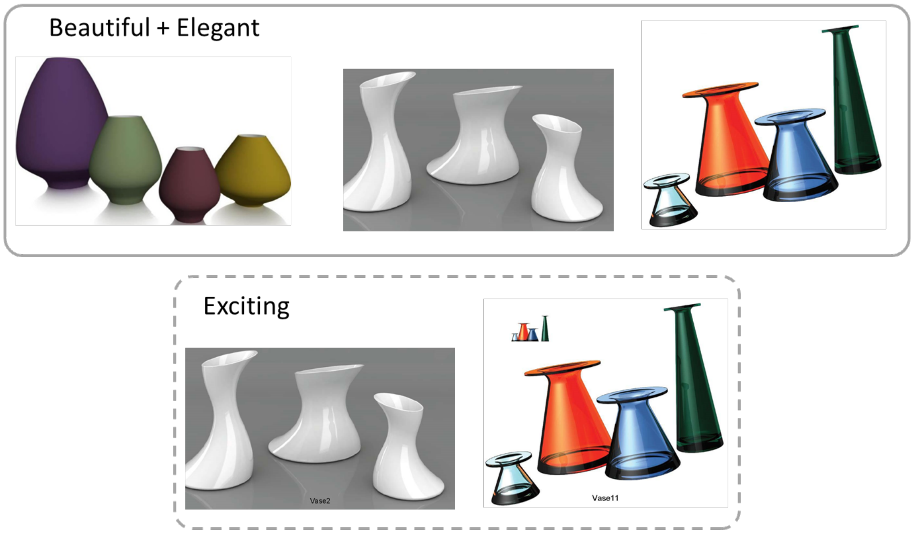

Figure 2 Beautiful, elegant and exciting looking vases (Perez Mata et al., 2013)

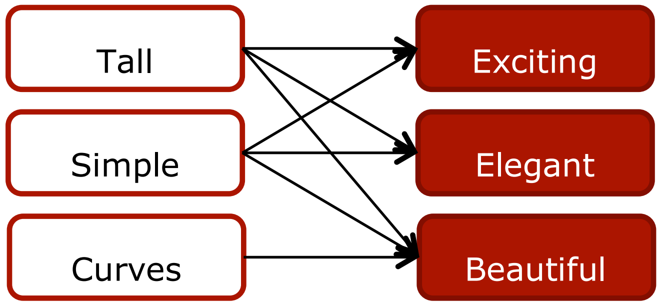

Figure 3 Common aesthetic design rules (left) that influence each of the three perceptions under study (right)

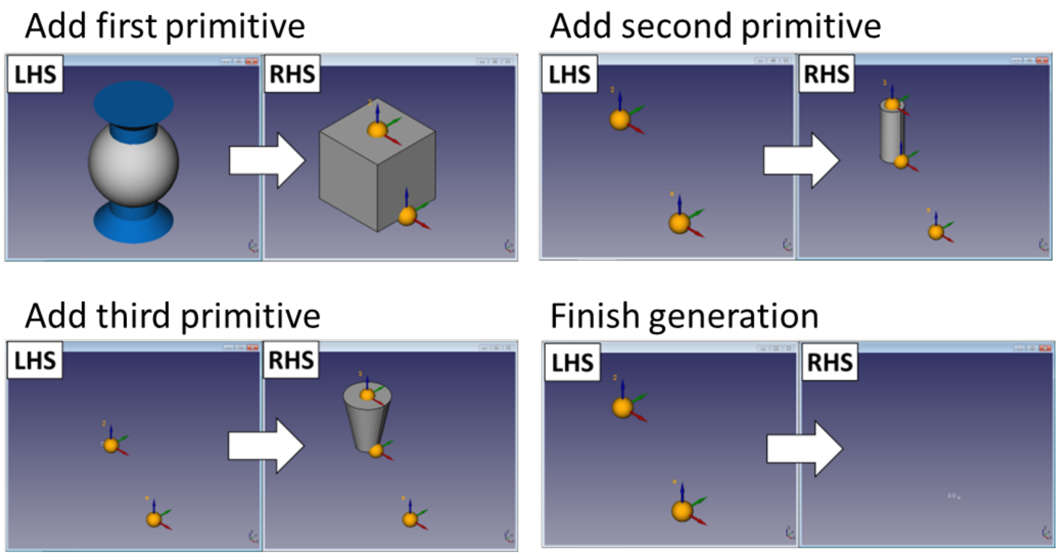

Figure 4 Four types of grammar rules developed for the vase grammar [62]

a)

b)

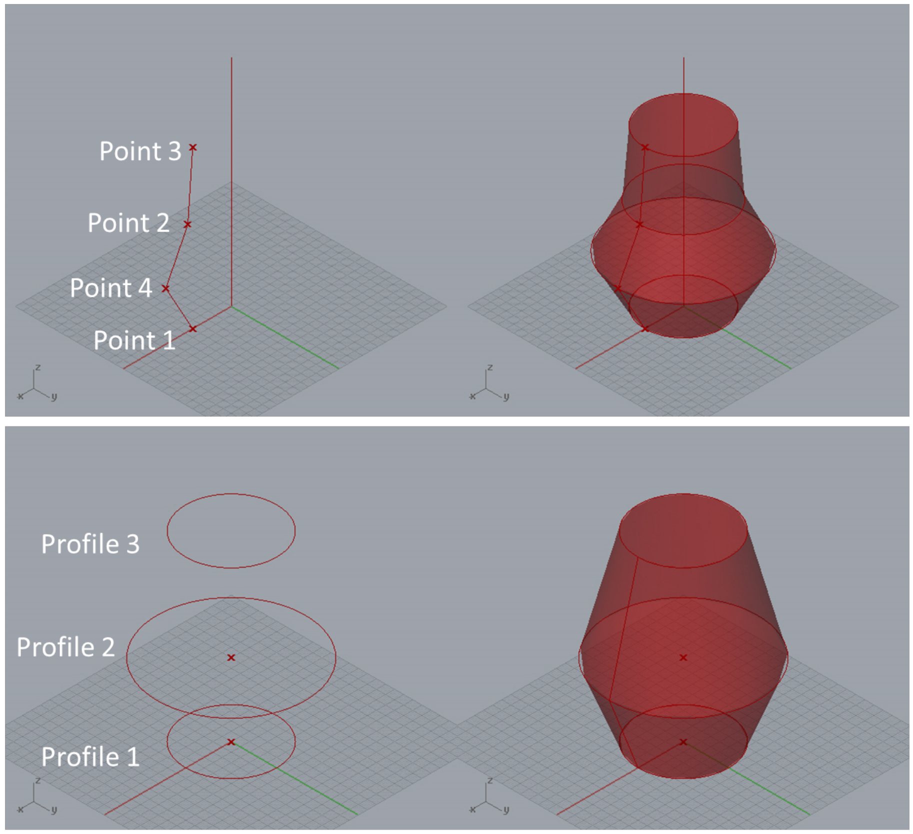

Figure 5 Generic parametric model for the revolution of the profile

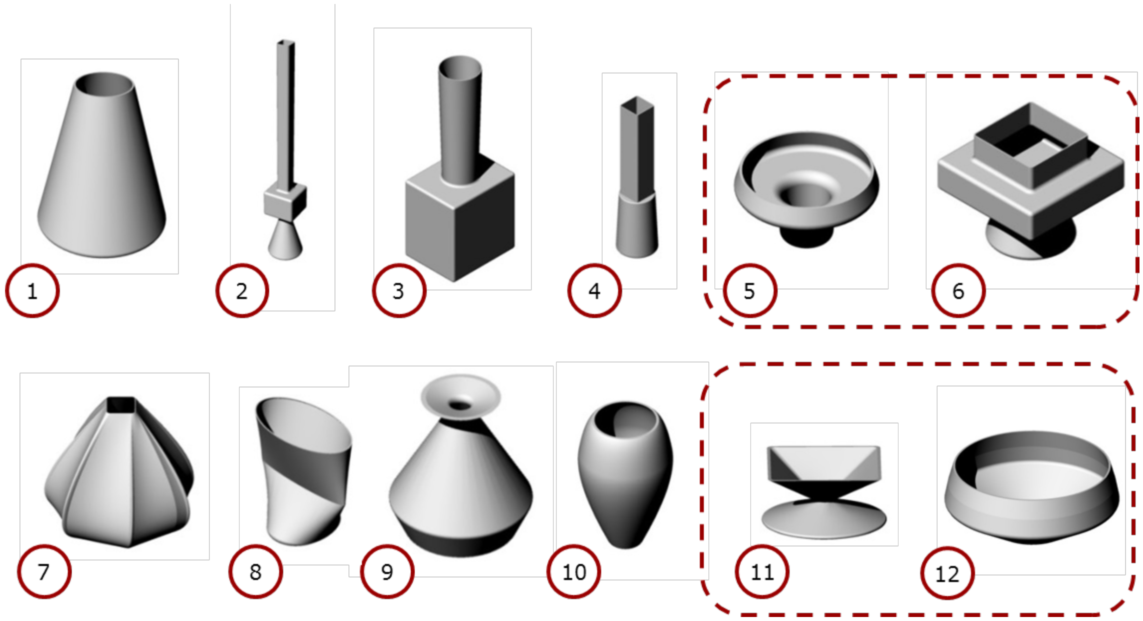

Figure 6 Images of the 12 vases designs. The dotted line indicates those vases that were control vases. Vases 1 to 6 are generated with the set grammar. Vases 7 to 12 are generated with a parametric model

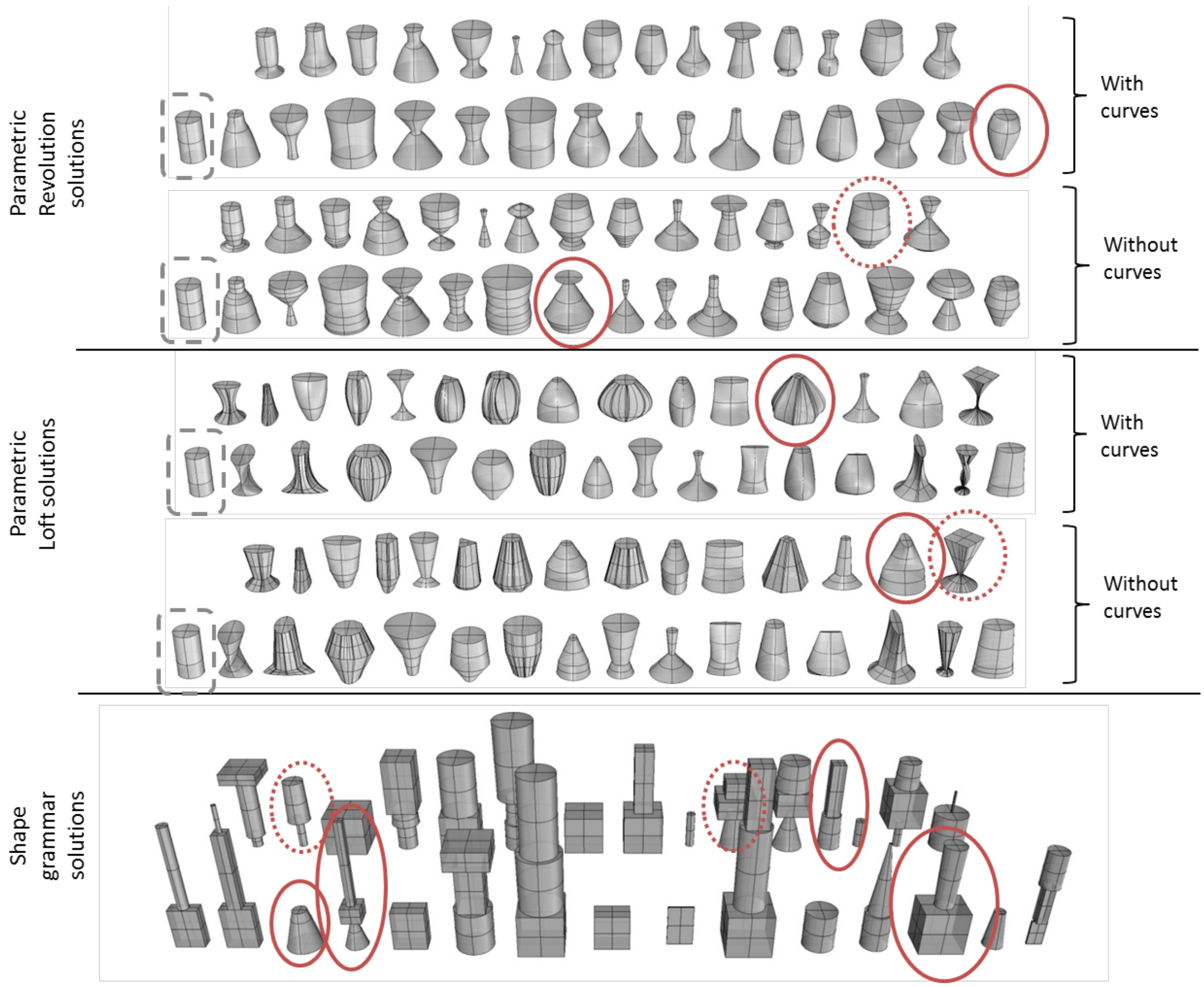

Figure 7 Vase designs from the set grammar and the parametric model implementation. The dashed line indicates the starting shape of the parametric model. The ellipse indicates the vases selected for the survey. Solid ellipse for the *beautiful*, *elegant* and *exciting* vases. Dotted ellipse for the vases transformed into control vases.

Table 1 Overview of vase designs for survey

Vase design	Generation method	Comments
1	Set grammar	
2	Set grammar	
3	Set grammar	
4	Set grammar	
5	Set grammar	Control
6	Set grammar	Control
7	Parametric model	Loft operation with curves
8	Parametric model	Loft operation
9	Parametric model	Revolution operation
10	Parametric model	Revolution operation with curves
11	Parametric model	Control. Loft operation
12	Parametric model	Control. Revolution operation

Table 2 Aesthetic feature ratios from vases. Adapted from [11]

Curves Lines Ratio (CLR)	**Simplicity level (SL)**	**Height Width Ratio (HWR)**
(1) $CLR = \frac{NC}{NC + NL}100$ NC = no. of curves NL = no. of lines	(2) $SL = (1 - \frac{\mathrm{NM} - 1}{MNM - 1})100$ NM = number of modules MNM = maximum number of modules (3)	(3) $HWR = \frac{H}{H + W}100$ H = height of vase W = width of vase

Table 3 Predicted Perception Value (PPV) for perception *exciting (PPVex)*, *elegant (PPVel)* and *beautiful (PPVbe)*. For *exciting* and *elegant* the equation is the same.

PPV Exciting / PPV Elegant	**PPV Beautiful**
(4) $PPVel = \frac{SL + HWR}{2}$ SL= Simplicity Level HWR = Height Width Ratio	(5) $PPVbe = \frac{CLR + SL + HWR}{3}$ CLR = Curves Lines ratio SL= Simplicity Level HWR = Height Width Ratio

Table 4 Data on Aesthetic ratios, Prediction Perception Value and Average of perception from survey. Exc = Exciting, El = Elegant and Be = Beautiful. High PPV above 70%. Low PPV below 30%.

	Aesthetic ratios			Predicted Perception Value (PPV) (Values from 0 – 100%)			Average (Ave) of perception from survey (Values from 1 – 7 in SD scale)			Standard Deviation of perception from survey		
Vase no.	**CLR (%)**	**SL (%)**	**HWR (%)**	**PPV Exc (%)**	**PPV El (%)**	**PPV Be (%)**	**Ave Exc**	**Ave El**	**Ave Be**	**SD AveExc**	**SD AveEl**	**SD AveBe**
v1	50.00	100	53.31	76.65	76.65	67.77	3.14	4.42	4.39	1.38	1.30	1.05
v2	7.14	0	86.27	43.13	43.13	31.14	4.27	3.02	2.56	1.61	1.54	1.36
v3	12.50	50	71.76	60.88	60.88	44.75	2.97	2.3	2.48	1.59	1.24	1.53
v4	12.50	50	80.36	65.18	65.18	47.62	3.09	3.11	2.56	1.41	1.43	1.30
v5	75.00	50	35.74	42.87	42.87	53.58	3.82	3.48	3.52	1.46	1.50	1.44
v6	7.14	0	47.78	23.89	23.89	18.31	4.41	2.64	2.65	1.55	1.41	1.45
v7	83.33	100	46.64	73.32	73.32	76.66	5.15	4.48	4.26	1.32	1.64	1.76
v8	42.86	50	50.34	50.17	50.17	47.73	5.15	4	4.09	1.32	1.52	1.61
v9	50.00	50	52.16	51.08	51.08	50.72	3.83	3.74	3.55	1.35	1.45	1.33
v10	100.00	100	60.62	80.31	80.31	86.87	3.44	5.05	4.83	1.54	1.34	1.31
v11	16.67	50	32.48	41.24	41.24	33.05	4.42	2.98	2.83	1.55	1.40	1.44
v12	40.00	100	28.76	64.38	64.38	56.25	4.02	4.35	4.59	1.55	1.54	1.37

Table 5 Vases ordered according to the Predicted Perception Value (PPV). Scales from 1 to 7 for the PPV and the Average of the perceptions. The vases compared are marked in grey.

Exciting			Elegant			Beautiful		
Vase No.	PPV Exciting	AveExc	Vase No.	PPV elegant	AveEl	Vase No.	PPV Beautiful	AveBe
10	5.82	3.44	10	5.82	5.05	10	6.21	4.83
1	5.60	3.14	1	5.60	4.42	7	5.60	4.26
7	5.40	5.15	7	5.40	4.48	1	5.07	4.39
4	4.91	3.09	4	4.91	3.11	12	4.38	4.59
12	4.86	4.02	12	4.86	4.35	5	4.21	3.52
3	4.65	2.97	3	4.65	2.3	9	4.04	3.55
9	4.06	3.83	9	4.06	3.74	8	3.86	4.09
8	4.01	5.15	8	4.01	4	4	3.86	2.56
2	3.59	4.27	2	3.59	3.02	3	3.69	2.48
5	3.57	3.82	5	3.57	3.48	11	2.98	2.83
11	3.47	4.42	11	3.47	2.98	2	2.87	2.56
6	2.43	4.41	6	2.43	2.64	6	2.10	2.65

Table 6 Wilcoxon signed-rank test results for perceptions *exciting*, *elegant* and *beautiful*. Non-significant results marked in italics

Exciting				Elegant				Beautiful			
Predicted perception rating		Z	P value	Predicted perception rating		Z	P value	Predicted perception rating		Z	P value
High	Low			High	Low			High	Low		
10	6	-3.679	0.0002	10	6	6.538	0.0000	10	6	6.233	0.0000
10	11	-3.174	0.0015	10	11	6.302	0.0000	10	2	6.370	0.0000
10	*5*	*-1.181*	*0.2375*	10	5	5.412	0.0000	7	6	5.651	0.0000
1	6	-4.408	0.0000	1	6	6.003	0.0000	7	2	5.398	0.0000
1	11	-4.208	0.0000	1	11	5.188	0.0000				
1	5	-4.408	0.0000	1	5	4.018	0.0010				
7	6	2.830	0.0046	7	6	6.061	0.0000				
7	11	3.568	0.0004	7	11	5.466	0.0000				
7	5	5.170	0.0000	7	5	3.672	0.0002				

APPENDIX: Survey screenshot

Perception of shape from vases

Vase 1

*** 6. Rate this vase from Boring to Exciting**

Very boring	Quite boring	Slightly boring	Neutral	Slightly exciting	Quite exciting	Very exciting
○	○	○	○	○	○	○

*** 7. Rate this vase from Clumsy to Elegant**

Very clumsy	Quite clumsy	Slightly clumsy	Neutral	Slightly elegant	Quite elegant	Very elegant
○	○	○	○	○	○	○

*** 8. Rate this vase from Ugly to Beautiful**

Very ugly	Quite ugly	Slightly ugly	Neutral	Slightly beautiful	Quite beautiful	Very beautiful
○	○	○	○	○	○	○

*** 9. Rate this vase from Simple to Complex**

Very simple	Quite simple	Slightly simple	Neutral	Slightly complex	Quite complex	Very complex
○	○	○	○	○	○	○

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