

## Research Article

# Applying Noise-Based Reverse Correlation to Relate Consumer Perception to Product Complex Form Features

Jose Antonio Diego-Mas <sup>1</sup>, Jorge Alcaide-Marzal <sup>1</sup> and Rocio Poveda-Bautista <sup>2</sup>

<sup>1</sup>Institute for Research and Innovation in Bioengineering (i3B), Universitat Politècnica de València, Camino de Vera s/n, Valencia 46022, Spain

<sup>2</sup>Institute of Innovation and Knowledge Management (INGENIO) (CSIC-UPV), Universitat Politècnica de València, Valencia 46022, Spain

Correspondence should be addressed to Jose Antonio Diego-Mas; [jodiemas@dpi.upv.es](mailto:jodiemas@dpi.upv.es)

Received 18 May 2022; Revised 27 June 2022; Accepted 9 July 2022; Published 16 August 2022

Academic Editor: Ning (Chris) Chen

Copyright © 2022 Jose Antonio Diego-Mas et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Consumer behavior knowledge is essential to designing successful products. However, measuring subjective perceptions affecting this behavior is a complex issue that depends on many factors. Identifying visual cues elicited by the product's appearance is key in many cases. Marketing research on this topic has produced different approaches to the question. This paper proposes the use of Noise-Based Reverse Correlation techniques in the identification of product form features carrying a particular semantic message. This technique has been successfully utilized in social sciences to obtain prototypical images of faces representing social stereotypes from different judgements. In this work, an exploratory study on subcompact cars is performed by applying Noise-Based Reverse Correlation to identify relevant form features conveying a sports car image. The results provide meaningful information about the car attributes involved in communicating this idea, thus validating the use of the technique in this particular case. More research is needed to generalize and adapt Noise-Based Reverse Correlation procedures to different product scenarios and semantic concepts.

## 1. Introduction

Knowledge about customer requirements is essential to developing successful products [1, 2]. Moreover, in marketing research, product aesthetics is considered a key factor to the affective response and purchase intention of consumers [3–8]. Scholars have studied for long the complex relationship between the visual appearance of an object and the elicited consumer response. As a result, a variety of models have been proposed to explain the consumer affective response (CAR) to product design, either generic ones, such as the Unified Model of Aesthetics [9], or directly actionable such as Kansei Engineering [10, 11]. The modeling of this consumer behavior is a complex problem due to two main reasons. The first one is the difficulty of measuring subjective judgements [1]. The second one is that products need to be parameterized, it is, described in terms of shape

characteristics (product form features, PFF), to find relationships between them and the consumer response. These parameterized models must reflect the complexity of the product visual representation using a limited number of variables to make their use feasible. Therefore, from a marketing perspective, it is essential to detect the most relevant product features to evaluate their influence on consumer perception [12].

The problem of parameterization is also present in some psychological and social sciences experiments; for example, those focused on studying prototypical images of social stereotypes. In these cases, indirect approaches such as Reverse Correlation (RC) are used to overcome the problem. RC operates by presenting random variations of stimuli of the object under study (pictures of faces, in most cases) with no prior assumptions, leaving the participants the task of making the most meaningful attributes emerge through their

responses to a given judgement [13]. RC studies produce a Classification Image (CI), which is considered to represent a mental image of the prototypical object the participants were asked about.

In this study, we propose applying the same approach to the case of product perception. In particular, we analyze the application of a RC technique, the Noise-based Reverse Correlation (NBRC), to the identification of the aesthetic features of a product that contribute to convey a desired affective concept, through the determination of the CI for that product-concept pair. To assess the viability of this approach, we performed an exploratory experiment using sports cars as the object of study.

*1.1. The Relevance of the Aesthetic Factor in Marketing Research.* The visual appearance of consumer products plays a crucial role as a marketing differentiation factor, especially in highly saturated consumer markets [3–7]. The image is the first information channel in the consumer-product interaction [14], and consequently, aesthetics becomes a key factor in the product judgement by consumers [15–17]. It has been shown, for instance, that products with higher hedonic qualities are more appealing [18]. An in-depth analysis of these complex aspects of user-product interaction is carried out in [19].

Due to this reason, the influence of the visual appearance of products has been studied for long [8, 20–22], even in terms of purchase experience design [23]. However, knowledge about how users perceive a given product cannot be implemented through design without knowing why it is perceived this way. Thus, much research has focused on the relationship between this consumer perceptual response and the design parameters of the product, as they are the objective features that the designer can control [24, 25].

For instance, Kansei Engineering [10, 12] and Conjoint Analysis [26, 27] constitute two effective tools to find relationships between consumer response and product visual features. However, several factors are difficult in their use in a more general approach. For example, it is necessary to preestablish the formal characteristics of the product in order to use these tools. Product parameterization is needed in advance to obtain results. Then, the utility of these results depends on the ability of researchers to select product features relevant to the consumer affective response [12]. Moreover, these features are often broadly described to simplify the product description, thus limiting the ability of these techniques to capture the influence of specific design details [28]. Techniques such as eye-tracking [29] have been used to overcome these limitations.

This paper proposes an alternative approach to overcome the problem of detecting product features meaningful to consumer perception. It consists of using the RC technique, described in the next section, to obtain a “prototypical image,” an image containing the visual features of an object that convey a specific message. This image may provide the designer with information useful to communicate this concept through the product’s appearance. This information is especially interesting as typicality is a relevant factor in consumer’ judgement. It has been shown that typicality

influences the consumer response to a product [30]. The identification of “prototypical features,” product form features highly contributing to the whole perception of the prototypical product, would allow designing with sound criteria to control to which extent the image of the product is conveying typicality in the desired concept.

RC methods have an extensive application in psychosocial studies, but no research has been found to be applied to product design. We explore in this work the feasibility of using RC techniques to obtain the prototypical image of a product representing an aesthetic/affective concept. The next section is devoted to explaining this technique thoroughly.

*1.2. The Reverse Correlation Methods.* People generally agree in their judgements of the aesthetic of consumer products. Therefore, there must be a relationship between the stimulus (the product) and the response (the perception). Several methods have been used to model this complex relationship. Direct approaches use sets of stimuli built by varying the values of the attributes which define the product (product form features, PFF) to produce different responses. These responses are then correlated to the stimuli to determine the relationship model. However, using this approach will produce larger experiment designs as the number of defining attributes and their possible values increase. This is the case of most consumer products, which need many attributes to get their form fully defined. In these situations, it might be preferable to use a different approach, such as RC [31, 32], to develop this type of stimulus-response model.

In direct methods, the relevant attributes of the stimulus are fixed, and their values are systematically manipulated and correlated to the responses. In RC methods, it is the opposite. The relevant attributes of the stimulus are not fixed, while the response variable is. Each stimulus is randomly generated, and the obtained responses are used to classify each input regarding the judgement. Due to this, these techniques are called “reverse,” as the information about the influence of the attributes on the judgement is obtained by correlating the presented stimuli with the given responses. RC is a data-driven technique that does not need priory suppositions about the relevant attributes of the stimulus and permits the participant to use the criteria they want to judge the stimuli [32, 33].

## 2. Materials and Methods

The procedure for conduct a RC experiment is based on the use of a base stimulus, which is randomly modified, generating many samples for a survey. Participants are asked to judge them, and the CI is derived from their answers. There are different variations of this basic approach [34]. One of them is NBRC, often used to obtain mental representations [33]. In recent years, NBRC procedures have been mainly used in face perception research [32, 33, 35–40]. When we see a face for the first time, we infer the personality traits of that person by matching the visual input to our mental prototypes of faces with different attributes. From the result of this match, we infer the personality traits of the owner of

the face [38], making attributions such as trustworthiness or dominance [41–46]. NBRC methods produce relevant CIs displaying the image that the participants use as a referent to evaluate the required judgement, referred to as “prototypical image” [33]. Following the same approach in this work, the NBRC method was used to obtain the prototypical image of a consumer product. As far as we know, this work is the first study applying this approach to product design.

The NBRC technique uses a starting base face to generate many variations by applying random noise layers over it. Usually, this base image is not an actual one but a composition of different greyscale images in which the face contour is made coincident and subsequently blurred. The base face features (gender, age, expression) are selected according to the requirements of the study. Once the base face is obtained, variations are generated applying different types of noise over it. The most usual ones are sinusoidal noise, white noise, or Gabor noise [32, 40, 47].

A survey is then prepared using these images. It consists of around 300/1000 tasks per participant, and in each one, a pair of pictures is shown. One of them is the base image with a noise pattern applied. The other one uses the same base image, but the noise pattern is inverted. The participants must select one of them for each task. The CI is created by averaging all noise patterns of the chosen pictures. When this average pattern is applied over the base face, the resulting image displays the traits that induced the judgement under study. In other words, this image represents a face conveying this particular social judgement (prototypical face). According to [32], the image obtained by applying the average pattern from nonselected pictures in the survey (the anti-CI) would display the inverse of the prototypical face.

Our intention in this work was to check if the NBRC could be used to visualize mental representations of products that fit some target judgement in the same way that it does for faces. Perceiving faces is a critical task for humans, and, to meet this need, after millions of years of evolution, our brain developed complex specialized neural networks intended to perceive faces [48]. For this reason, faces are perceived in a different way from other kinds of objects [49–51]. Human observers perceive faces in some objects that resemble the shape of a human face, such as a clock or the front of a car. Facial perception research has studied this effect extensively, known as pareidolia.

Several works found similarities between the neural activity of observers during the perception of faces and those registered when an object that resembles the shape of a face is perceived [52–55]. The front end of a car is one of the best examples of anthropomorphization in the perception of consumer products [56]. Cars can be classified using many criteria. One of the most common and well-known taxonomies is the sports car versus the family car, and the difference between these kinds of cars can be clearly seen on the front end of the cars. Therefore, in this first attempt to obtain the prototypical image of a consumer product using NBRC, we selected the frontal view of a car as the product and the appearance of a sports car as the fitting judgement.

### 3. Case Study

Sports cars were used as a case study to test the applicability of NBRC to relate consumer perception to complex product form features. We perform the task following the procedure depicted in Figure 1, which consists of 5 steps detailed in the following sections.

*3.1. Stimuli and Participants.* Randomly varied images of cars were created, overlaying different random noise patterns over a base image (Figure 1 (A)). The base image is obtained by averaging grayscale images of the object analyzed (typically a face), which leads to base images with blurry contours. To create our base image of a front end of a car, frontal images of six subcompact cars (B-segment) were selected. The images were converted to grayscale, cropped, and centered to get the area of the cars to span as a large part of the image as possible. The six images were overlaid using different transparency values, finally obtaining the base car image (Figure 2).

In this work, we used sinusoidal noise [32, 40] to generate the stimuli because it generated more meaningful variations of the base car than other commonly used types of noise such as white [57, 58] or Gabor noise [47]. To use sinusoidal noise in this task, the image height and width must be equal and have a power of 2. Therefore, the resulting image was resized to  $512 \times 512$  pixels. The *rcicr* R package [59] was used to generate the stimuli. Firstly, 300 sinusoidal noise patterns were created by combining five layers of sinusoidal patches. The five images differ in the spatial frequency of the sinusoids (2, 4, 8, 16, and 32 cycles per image). In the same way, each one of these images was obtained by averaging twelve sinusoidal patches that differ in orientation and phase (6 different orientations and two phases) and in the contrast of the image, that was randomly assigned. Lastly, a final pool of 600 paired images was obtained by inverting each noise pattern. This complete noise generation process is shown in [32]. Finally, each noise pattern pair was superimposed on the base car image, obtaining 300 slightly different pairs of stimuli. Figure 2 shows the base car image and one stimuli pair obtained following this process.

25 Spanish young adults (65% men and 35% women) between 24 and 35 years old ( $M = 27.40$ ,  $SD = 3.67$ ) participated in the experiment [60], which was approved by the ethics committee at the Universitat Politècnica de València (P15\_10\_01\_20). Individual consent forms were also gathered.

*3.2. Survey Procedure.* The survey consisted of two blocks of 150 tasks. Each one presented a pair of pictures (direct and inverse noise layers) side-by-side (Figure 3). The participants were asked to quickly choose in each task the car they reckoned as having a sports car appearance at first impression, insisting on this point despite the understandable difficulty of the task.

The participants were shown both the stimuli pairs and the position of direct and inverse pictures randomly. They had to select one of the stimuli by clicking the corresponding

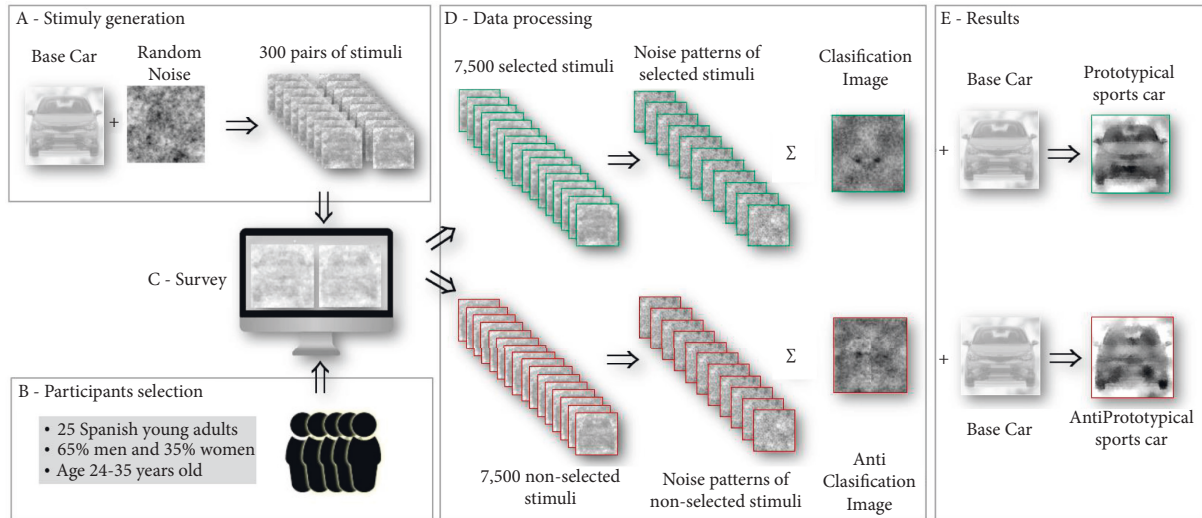


FIGURE 1: Five steps of the NBRC task to obtain the prototypical and antiprototypical images of a sports car.

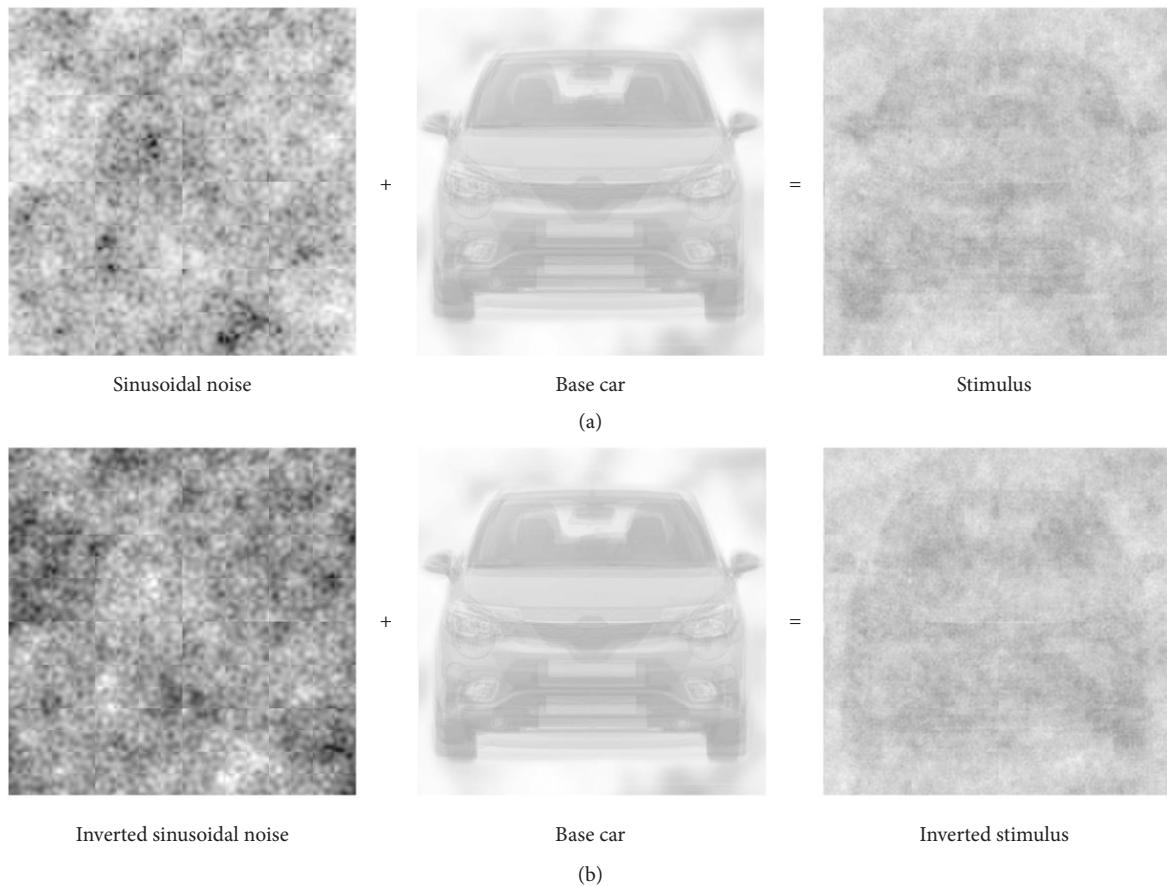


FIGURE 2: Sinusoidal noise is applied to the base image to obtain a stimulus (a). The inverted stimulus is obtained by applying the inverted noise to the base image (b).

button under the stimuli (see Figure 3) or by pressing the left/right arrow key.

**3.3. Data Processing.** After the survey, a CI per participant was obtained by averaging the noise patterns of the chosen pictures and, similarly, an anti-CI was produced using the

noise patterns of the unselected ones. A total of 7,500 answers were processed, with the average response time by trial across all participants being 3.67 seconds. The *rcicr* R package (v. 0.3.4.1) was used for this task [59]. According to [32], the CI and anti-CI represent the extreme images in the individual judgement scale (an image displaying the visual

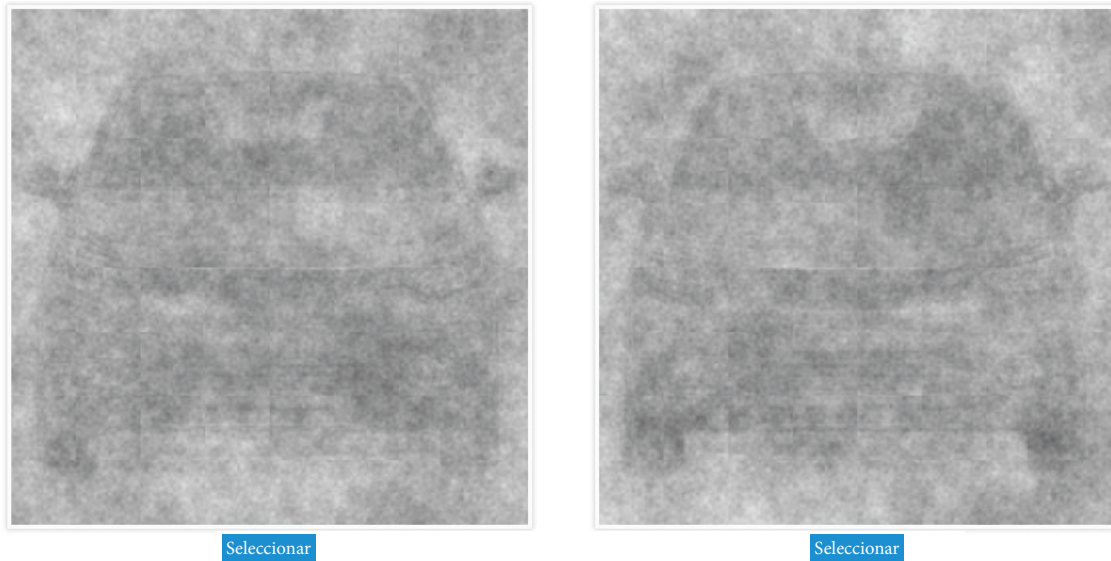


FIGURE 3: Stimuli pair presented to participants in one trial.

features of a sports car and another one showing what is not considered a sports car). Finally, the average CI and anti-CI for all participants were generated by averaging the noise pattern of the individual CIs and anti-CIs (Figure 1 (D)).

#### 4. Results

The individual CIs and anti-CIs of each participant were overlaid on the base image (Figure 1 (E)). S1 Table in the Supplementary Material of this paper shows all the 50 images. As an example, Figure 4(a) shows the images obtained for participant 3. To increase the visibility of the results, a selective Gaussian Blur filter (radius = 30; max delta = 10) and a shadow/highlight compensation filter were applied, resulting in the images in Figure 4(b). The global CI and anti-CI images in Figure 5 were obtained by overlaying the average CI and anti-CI for all the participants on the base car, while Figure 5(b) shows the filtered version of the global CIs.

To show which parts of the image were most relevant to convey the sports/nonsports appearance, we used *rcicr* to prepare a z-map (Figure 6) using a Gaussian filter of radius 5, a background mask and applying a z-transform over the luminance of the CIs noise pixels [32]. Green zones in this representation correspond to areas of the image that directly convey the sports car look, while the red and white zones provoke the inverse response (nonsports car).

#### 5. Discussion

In this work, we have proposed the use of RC, a technique used in social research, to the identification of product visual features relevant to eliciting a particular consumer response. To explore the viability of this approach, a case study has been conducted.

Due to the exploratory nature of this work, cars were selected as the object of study to facilitate the generation of a

distinguishable CI. Cars are products of very widespread use and they display easily interpretable visual attributes. NBCR has proved to be a successful tool in the face perception field [61] and the front end of a car resembles the shape of a face, being one of the best examples of anthropomorphizing in the perception of consumer products [56]. In addition, sports cars are generally recognizable by many people, and their stereotype features are easy to forecast. Therefore, we could contrast if the resulting CI depicted some of the main characteristics typical of this kind of product.

According to this, the results of the experiment are satisfactory and the image obtained can be related to that of a sports car in several of its visual features. It is true that, as expected, individual CIs (Figure 4) are difficult to interpret. However, the addition of the information contained in the noise of all individual CIs leads to a clearer pattern, and some features typically related to a sports car can be identified in the global CI (Figure 5(a)) while they are not present in the global anti-CI (Figure 5(b)). In this regard, it should be noted that the base image used in an NBCR task significantly influences and limits the space of attainable results. The information sampled in the noise patterns of the CIs cannot deeply change the base image. We created our base image using frontal images of six subcompact cars out of the typical sports car segment. Therefore, slight changes in the form and details increasing the sportiness perception of the base car were expected, rather than major changes to the main dimensions or basic shapes that would transform a subcompact car into a typical sports car. Despite this, interestingly, a modification of the ratio height-width can be perceived in the CI.

Moreover, comparing the global CI image with the global anti-CI and the base image, some differences can be noticed (Figure 5). The vehicle in the global CI seems lower and presents a slight increase in the width of the front from the anti-CI. There are differences in the headlights area, giving a more aggressive impression on the global CI due to

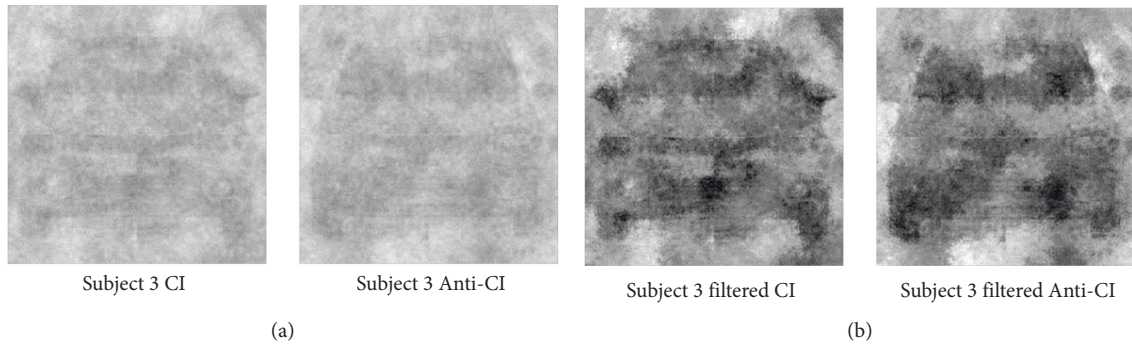


FIGURE 4: (a) Individual CI and anti-CI of subject 3 and (b) individual CI and anti-CI of subject 3 after the blur and shadow/highlight compensation filters were applied.

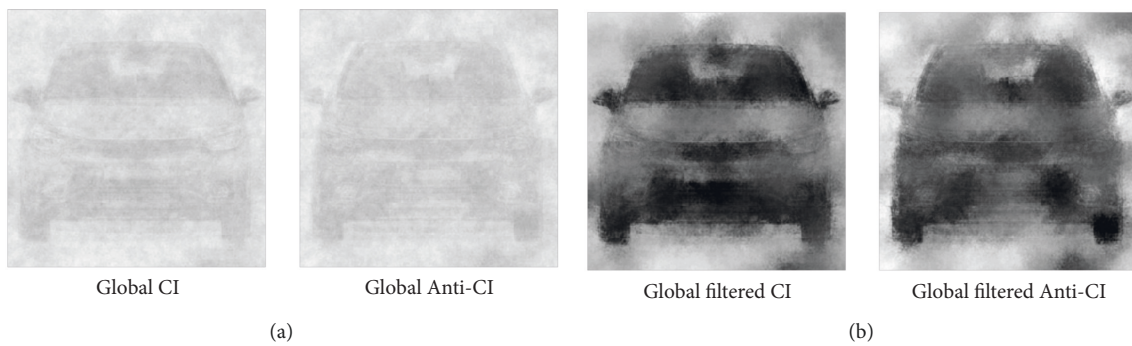


FIGURE 5: (a) Global CI and anti-CI and (b) global CI and anti-CI after the blur and shadow/highlight compensation filters were applied.

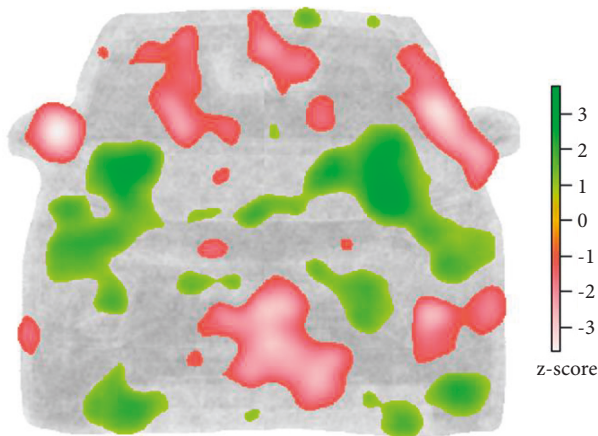


FIGURE 6: Z-map of the CI. Areas eliciting sports car perception are displayed in green, while those conveying the inverse perception are displayed in red and white.

its bigger size and curvature. The front bonnet looks different on both cars. The bonnet appears dark in the center and clearer on the sides in the CI, while the anti-CI presents the opposite pattern. This conveys the impression of the presence of elevated feature lines near the bonnet boundary in the CI. In the anti-CI, the bonnet seems to be a rounded continuous metal sheet, as in the CI, it looks like a more complex concave/convex surface. Finally, the CI has the appearance of having longer side-view mirrors and shorter

ground clearance. All these individual features are common characteristics of sports vehicles and, in general, the car in the CI conveys the impression of a sports car to a greater extent than the car in the anti-CI. Therefore, we could conclude that the technique has performed successfully in this particular case.

These subjective impressions are compatible with the results of the cluster test performed on the noise data of the CIs (Figure 6). The resulting z-map shows the parts of the car that significantly influence the stimuli classification (green, red, and white zones). It can be seen how, in general, the elements of the car mentioned above fall into these areas. The luminance of the pixels in the bonnet and headlight areas of the car shows that these parts have a great influence on the sportiness perception, while those in the lateral rear mirror area do the same but correlate inversely. The features related to structural changes (for example, changes in the apparent height, width, or ground clearance of the car) are more difficult to detect in the z-map. However, the green zone between the car underbody and the ground can be related to the shorter ground clearance appearance of the car in the CI than that in the anti-CI.

As aforementioned, assessing consumer perception is a complex process. However, the results of this study have been satisfactory and the NBRC can be considered a promising marketing tool in the field of product design. The obtained global CI reflects, at different grades, several of the features expected. Some of these features are easily noticeable, such as the bonnet line, the headlights, or the lateral

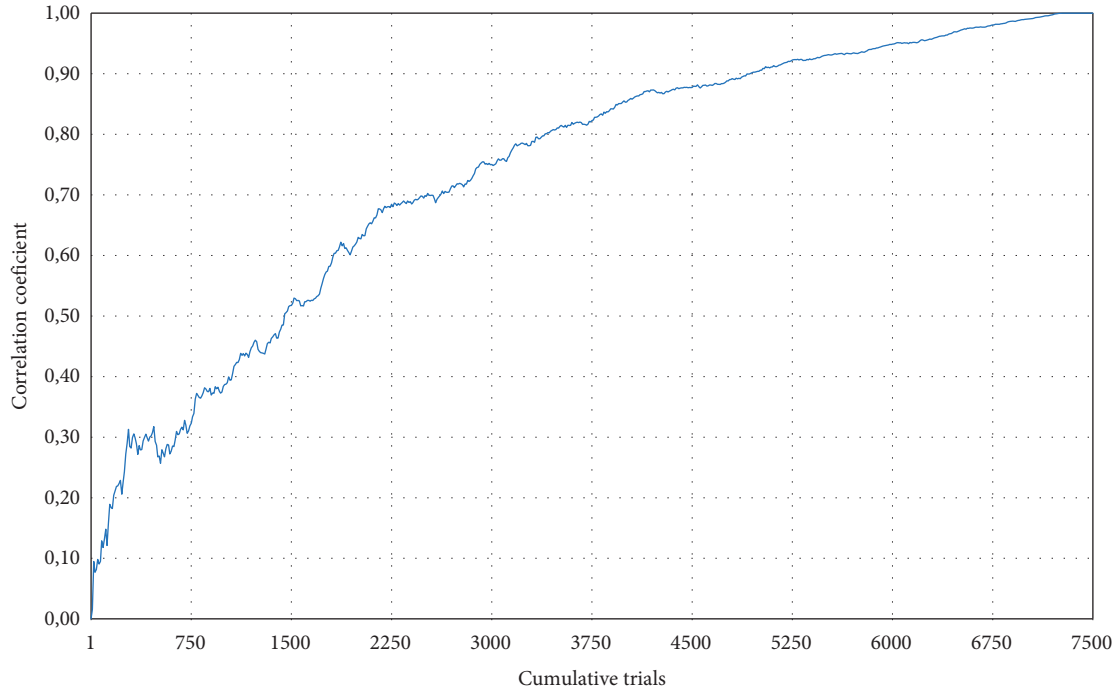


FIGURE 7: Correlation between cumulative CI and final CI.

rear mirrors. It is worth noting that the arising of these features is strongly restricted by the original car typology. RC studies have by their very nature this kind of limitation and the resulting CI is heavily dependent on the stimuli utilized [33]. Thus, the obtained prototypical image should be considered that of a subcompact sports car. This is something to consider when dealing with specific marketing goals (for example, when assessing sustainable or socially responsible product features).

We must also consider that RC works very efficiently with subtleties affecting facial features, but major changes in product structure are presumably harder to show up. As said above, in the present experiment, some of these structural variations were partially observed, such as changes in the appearance of the whole car proportions, which is very promising. An interesting future research field aims at studying if other kinds of products are less variable in shape but not in surface details (shoes, helmets, packaging). This factor is not so relevant and RC proves more powerful.

However, some limitations in this study must be pointed out. Every participant performed 300 trials in the NBRC task. The selection of this number was based on the face perception research literature using NBRC [62]. While increasing the number of trials by respondent would lead to more detailed CIs, the demotivation of the participants would also increase, raising the probability of random responding. Regarding the number of respondents, 25 participants took part in the NBRC task. Previous works in face perception research obtained well-defined CIs using between 20 and 30 participants [32, 39, 63].

Therefore, although 300 trials and 25 participants seem to be optimal in face perception, more research is needed to establish these values in the application of NBRC in the field

of marketing. Generally, product research intends to gather meaningful information about at least market segment sizes, so the CI should account for a significant number of individuals. Moreover, focusing on more specific products and judgements would require appropriately dimensioning the sample from a demographic point of view.

On the contrary, fewer trials may suffice if the shape of the analyzed product is simple, without small features, and with limited relevant details. The global CI obtained in this work is the result of the analysis of 7500 trials. Figure 7 shows how the number of trials affects the information gathered by the noise pattern of the final global CI. This graph represents the Pearson correlation coefficient between the luminance of the pixels of the final global CI and those in CIs obtained using fewer trials. To get these data, we varied the number of trials used to generate CI from 10 to 7500 (step-size = 10). As can be seen in Figure 7, the correlation between the cumulative CI and the final CI reaches 0.82 when half part of the available trials are used.

In any case, it is not possible to generalize the results obtained until more research is performed. As aforementioned, the product chosen is widespread and the prototypical image should supposedly be solid. In this sense, it is necessary to conduct more studies with different kinds of products to study the suitability of this technique with less familiar examples. Given the small number of existing studies using this approach outside face perception research, there is still a lack of information on how the base image used during the survey can influence its outcome. More experiments with different types of products would be required to contrast the validity of the method and to build a solid methodology. It is assumed that objects with a less generic shape or with a wider visual variability will require

specific graphic treatment of the base images used. On the other hand, we have already pointed out that there is some similarity between the way in which our brain processes facial information and that in which we perceive objects that resemble faces [52–55]. More studies are needed using less anthropomorphic products to check if the NBRC performs equally when the pareidolia effect does not occur.

Our future work will address these issues and explore other possibilities. It might be interesting to contrast the results obtained through NBRC with those from other user-product interaction assessment techniques such as Kansei Engineering or to contrast the z-maps obtained by NBRC with those produced using eye-tracking for the same product/judgement pair.

## 6. Conclusions

This work presents a proposal of the use of Noise-Based Reverse Correlation for product perception assessment. This is, to our knowledge, the first application of this technique to product analysis. The results obtained are satisfactory and promising: The CI produced in the exploratory study portrays some of the expected features of a sports car, thus validating this particular case.

However, as we have described, the product was chosen to meet certain requirements in order to intuitively facilitate the application of RC. Therefore, despite the favorable results of this study, similar experiments in other different cases are needed to be able to generalize the suitability of the application of this technique in marketing research.

## Data Availability

The image data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

## Supplementary Materials

Individual Classification and Anti-Classification Images by experimental subject are shown in Table S1 in the Supplementary Materials file of this paper. (*Supplementary Materials*)

## References

- [1] J. Arenas-Gaitán and B. Sanz-Altamira, “Complexity of understanding consumer behavior from the marketing perspective,” *Complexity*, vol. 2019, Article ID 2837938, 3 pages, 2019.
- [2] Y. Zhang, A. Wang, and W. Hu, “Deep learning-based consumer behavior analysis and application research,” *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2837938, 7 pages, 2022.
- [3] M. Moshagen and M. T. Thielsch, “Facets of visual aesthetics,” *International Journal of Human-Computer Studies*, vol. 68, no. 10, pp. 689–709, 2010.
- [4] N. Crilly, J. Moultrie, and P. J. Clarkson, “Seeing things: consumer response to the visual domain in product design,” *Design Studies*, vol. 25, no. 6, pp. 547–577, 2004.
- [5] N. Crilly, J. Moultrie, and P. J. Clarkson, “Shaping things: intended consumer response and the other determinants of product form,” *Design Studies*, vol. 30, no. 3, pp. 224–254, 2009.
- [6] P. H. Bloch, “Seeking the ideal form: product design and consumer response,” *Journal of Marketing*, vol. 59, no. 3, p. 16, 1995.
- [7] M. Berkowitz, “Product shape as a design innovation strategy,” *Journal of Product Innovation Management*, vol. 4, no. 4, pp. 274–283, 1987.
- [8] P. Hekkert, “Design aesthetics: principles of pleasure in design,” *Psychological Science*, vol. 48, pp. 157–172, 2006.
- [9] M. Berghman and P. Hekkert, “Towards a unified model of aesthetic pleasure in design,” *New Ideas in Psychology*, vol. 47, pp. 136–144, 2017.
- [10] M. Nagamachi, “Kansei Engineering: a new ergonomic consumer-oriented technology for product development,” *International Journal of Industrial Ergonomics*, vol. 15, no. 1, pp. 3–11, 1995.
- [11] E. Akgül, M. Özmen, C. Sinanoğlu, and E. Kizilkaya, “Rough Kansei mining model for market-oriented product design,” *Mathematical Problems in Engineering*, vol. 2020, Article ID 6267031, 11 pages, 2020.
- [12] C.-C. Yang, “A classification-based Kansei engineering system for modeling consumers’ affective responses and analyzing product form features,” *Expert Systems with Applications*, vol. 38, no. 9, pp. 11382–11393, 2011.
- [13] M. Wagner, A. Curteza, Y. Hong, Y. Chen, S. Thomassey, and X. Zeng, “A design analysis for eco-fashion style using sensory evaluation tools: consumer perceptions of product appearance,” *Journal of Retailing and Consumer Services*, vol. 51, pp. 253–262, 2019.
- [14] S.-W. Hsiao, F.-Y. Chiu, and C. S. Chen, “Applying aesthetics measurement to product design,” *International Journal of Industrial Ergonomics*, vol. 38, no. 11–12, pp. 910–920, 2008.
- [15] M. Yamamoto and D. R. Lambert, “The impact of product aesthetics on the evaluation of industrial products,” *Journal of Product Innovation Management*, vol. 11, no. 4, pp. 309–324, 1994.
- [16] U. Bhandari, K. Chang, and T. Neben, “Understanding the impact of perceived visual aesthetics on user evaluations: an emotional perspective,” *Information & Management*, vol. 56, no. 1, pp. 85–93, 2019.
- [17] J. Hoegg, J. W. Alba, and D. W. Dahl, “The good, the bad, and the ugly: influence of aesthetics on product feature judgments,” *Journal of Consumer Psychology*, vol. 20, no. 4, pp. 419–430, 2010.
- [18] M. Hassenzahl, “The effect of perceived hedonic quality on product appealingness,” *International Journal of Human-Computer Interaction*, vol. 13, no. 4, pp. 481–499, 2001.
- [19] H. N. J. Schifferstein and P. Hekkert, *Product Experience. Product Experience*, Elsevier, Amsterdam, Netherlands, 2008.
- [20] A. H. Goldman, *Aesthetic Value*, Westview Press, Boulder, CO, USA, 1995.
- [21] Y. Reich, “A model of aesthetic judgment in design,” *Artificial Intelligence in Engineering*, vol. 8, no. 2, pp. 141–153, 1993.
- [22] J. Blijlevens, C. Thurgood, P. Hekkert, L.-L. Chen, H. Leder, and T. W. A. Whitfield, “The Aesthetic Pleasure in Design Scale: the development of a scale to measure aesthetic pleasure for designed artifacts,” *Psychology of Aesthetics, Creativity, and the Arts*, vol. 11, no. 1, pp. 86–98, 2017.



- [23] J. He, F. Li, Z. Li, and H. Liu, "The effect of mobile marketing design on consumer mobile shopping," *Complexity*, vol. 2021, p. 10, 2021.
- [24] S. H. Han and S. W. Hong, "A systematic approach for coupling user satisfaction with product design," *Ergonomics*, vol. 46, no. 13-14, pp. 1441-1461, 2003.
- [25] O. Demirbilek and B. Sener, "Product design, semantics and emotional response," *Ergonomics*, vol. 46, no. 13-14, pp. 1346-1360, 2003.
- [26] P. E. Green and V. R. Rao, "Conjoint measurement for quantifying judgmental data," *Journal of Marketing Research*, vol. 8, no. 3, p. 355, 1971.
- [27] R. D. Luce and J. W. Tukey, "Simultaneous conjoint measurement: a new type of fundamental measurement," *Journal of Mathematical Psychology*, vol. 1, no. 1, pp. 1-27, 1964.
- [28] H. Y. Chen and Y. M. Chang, "Extraction of product form features critical to determining consumers' perceptions of product image using a numerical definition-based systematic approach," *International Journal of Industrial Ergonomics*, vol. 39, no. 1, pp. 133-145, 2009.
- [29] M. Wedel and R. Pieters, "Eye tracking for visual marketing," *Foundations and Trends® in Microeconomics*, vol. 1, no. 4, pp. 231-320, 2006.
- [30] R. Veryzer, Jr. Veryzer Jr and J. W. Hutchinson, "The influence of unity and prototypicality on aesthetic responses to new product designs," *Journal of Consumer Research*, vol. 24, no. 4, pp. 374-385, 1998.
- [31] A. Todorov, "Evaluating faces on social dimensions," *Social Neuroscience: Toward Understanding the Underpinnings of the Social Mind*, pp. 54-76, Oxford University Press, Oxford, UK, 2011.
- [32] R. Dotsch and A. Todorov, "Reverse correlating social face perception," *Social Psychological and Personality Science*, vol. 3, no. 5, pp. 562-571, 2012.
- [33] L. Brinkman, A. Todorov, and R. Dotsch, "Visualising mental representations: a primer on noise-based reverse correlation in social psychology," *European Review of Social Psychology*, vol. 28, no. 1, pp. 333-361, 2017.
- [34] H. Dai and C. Micheyl, "Psychophysical reverse correlation with multiple response alternatives," *Journal of Experimental Psychology: Human Perception and Performance*, vol. 36, no. 4, pp. 976-993, 2010.
- [35] J. C. Jackson, N. Hester, and K. Gray, "The faces of god in America: revealing religious diversity across people and politics," *PLoS One*, vol. 13, no. 6, Article ID e0198745, 2018.
- [36] R. Dotsch and D. H. J. Wigboldus, "Virtual prejudice," *Journal of Experimental Social Psychology*, vol. 44, no. 4, pp. 1194-1198, 2008.
- [37] E. Hehman, J. K. Flake, and J. B. Freeman, "Static and dynamic facial cues differentially affect the consistency of social evaluations," *Personality and Social Psychology Bulletin*, vol. 41, no. 8, pp. 1123-1134, 2015.
- [38] R. Imhoff, J. Woelki, S. Hanke, and R. Dotsch, "Warmth and competence in your face! Visual encoding of stereotype content," *Frontiers in Psychology*, vol. 4, p. 386, 2013.
- [39] J. R. Kunst, J. F. Dovidio, and R. Dotsch, "White look-alikes: mainstream culture adoption makes immigrants "look" phenotypically white," *Personality and Social Psychology Bulletin*, vol. 44, no. 2, pp. 265-282, 2018.
- [40] M. C. Mangini and I. Biederman, "Making the ineffable explicit: estimating the information employed for face classifications," *Cognitive Science*, vol. 28, no. 2, pp. 209-226, 2004.
- [41] V. Bruce and A. Young, *Face Perception*, Psychology Press, New York, NY, 2012.
- [42] R. Poveda-Bautista, J. A. Diego-Mas, and J. Alcaide-Marzal, "Analysis of the visual perception of the competences of project managers," *Sustainability*, vol. 13, no. 9, p. 4984, 2021.
- [43] J. A. Diego-Mas, F. Fuentes-Hurtado, V. Naranjo, and M. Alcañiza, "Effect Size of the Appearance of Each Facial Feature on How We Perceive and Interpret Human Faces," in *Proceedings of the 24th International Congress on Project Management and Engineering*, pp. 84-91, Alcoi, Spain, July 2020.
- [44] J.-A. Diego-Mas, F. Fuentes-Hurtado, V. Naranjo, and M. Alcañiz, "The influence of each facial feature on how we perceive and interpret human faces," *I-Perception*, vol. 11, no. 5, Article ID 204166952096112, 2020.
- [45] F. Fuentes-Hurtado, J. A. Diego-Mas, V. Naranjo, and M. Alcañiz, "Automatic classification of human facial features based on their appearance," *PLoS One*, S. Mirjalili, Ed., vol. 14, no. 1, Article ID e0211314, 2019.
- [46] F. Fuentes-Hurtado, J. A. Diego-Mas, V. Naranjo, and M. Alcañiz, "Evolutionary computation for modelling social traits in realistic looking synthetic faces," *Complexity*, vol. 2018, pp. 1-16, 2018.
- [47] N. van Rijsbergen, K. Jaworska, G. A. Rousselet, and P. G. Schyns, "With age comes representational wisdom in social signals," *Current Biology*, vol. 24, no. 23, pp. 2792-2796, 2014.
- [48] N. Kanwisher, J. McDermott, and M. M. Chun, "The fusiform face area: a module in human e cortex specialized for face perception," *Journal of Neuroscience*, vol. 17, no. 11, pp. 4302-4311, Article ID 9151747, 1997.
- [49] D. W. Piepers and R. A. Robbins, "A review and clarification of the terms "holistic," "configural," and "relational" in the face perception literature," *Frontiers in Psychology*, vol. 3, p. 559, 2012.
- [50] J. W. Tanaka and M. J. Farah, "Parts and wholes in face recognition," *The Quarterly Journal of Experimental Psychology Section A*, vol. 46, no. 2, pp. 225-245, 1993.
- [51] A. W. Young, D. Hellawell, and D. C. Hay, "Configurational information in face perception," *Perception*, vol. 16, no. 6, pp. 747-759, 1987.
- [52] J. L. Voss, K. D. Federmeier, and K. A. Paller, "The potato chip really does look like elvis! Neural hallmarks of conceptual processing associated with finding novel shapes subjectively meaningful," *Cerebral Cortex*, vol. 22, no. 10, pp. 2354-2364, 2012.
- [53] S. Bentin, N. Sagiv, A. Mecklinger, A. Friederici, and Y. D. von Cramon, "Priming visual face-processing mechanisms: electrophysiological evidence," *Psychological Science*, vol. 13, no. 2, pp. 190-193, 2002.
- [54] S. Bentin, T. Allison, A. Puce, E. Perez, and G. McCarthy, "Electrophysiological studies of face perception in humans," *Journal of Cognitive Neuroscience*, vol. 8, no. 6, pp. 551-565, 1996.
- [55] S. Kühn, T. R. Brick, B. C. N. Müller, and J. Gallinat, "Is this car looking at you? How anthropomorphism predicts fusiform face area activation when seeing cars," *PLoS One*, vol. 9, no. 12, Article ID e113885, 2014.
- [56] P. Aggarwal and A. L. McGill, "Is that car smiling at me? Schema congruity as a basis for evaluating anthropomorphized products," *Journal of Consumer Research*, vol. 34, no. 4, pp. 468-479, 2007.
- [57] R. E. Jack, R. Caldara, and P. G. Schyns, "Internal representations reveal cultural diversity in expectations of facial expressions of emotion," *Journal of Experimental Psychology: General*, vol. 141, no. 1, pp. 19-25, 2012.

- [58] F. Gosselin, B. A. Bacon, and P. Mamassian, "Internal surface representations approximated by reverse correlation," *Vision Research*, vol. 44, no. 21, pp. 2515–2520, 2004.
- [59] R. Dotsch, "Rcicr: Reverse-Correlation Image-Classification Toolbox," 2016, <https://cran.r-project.org/web/packages/rcicr/index.html>.
- [60] B. Piqueras-fiszman, G. Ares, J. Alcaide-marzal, and J. A. Diego-Más, "Comparing older and younger users' perceptions of mobile phones and watches using c questions and preference mapping on the design characteristics," *Journal of Sensory Studies*, vol. 26, no. 1, pp. 1–12, 2011.
- [61] A. Todorov, R. Dotsch, D. H. J. Wigboldus, and C. P. Said, "Data-driven methods for modeling social perception," *Social and Personality Psychology Compass*, vol. 5, no. 10, pp. 775–791, 2011.
- [62] L. Brinkman, S. Goffin, R. van de Schoot, N. E. M. van Haren, R. Dotsch, and H. Aarts, "Quantifying the informational value of classification images," *Behavior Research Methods*, vol. 51, no. 5, pp. 2059–2073, 2019.
- [63] R. Imhoff and R. Dotsch, "Do we look like me or like us? Visual projection as self- or ingroup-projection," *Social Cognition*, vol. 31, no. 6, pp. 806–816, 2013.