The consumers' response to product design

A narrative review

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Abstract:

This paper reviews the research ideas around consumer response to product design. From the product side, we discuss the most significant design features preferred by average consumers, such as aesthetics and utility. And from the consumer side, we investigate the human factors influencing consumer perceptions. We present the main approaches used to measure the consumer response to product design and summarize the multiple biases that occur during the evaluation. Finally, we present in detail the most commonly used methods to analyze consumer response data and their roles in the design evaluation context.

Keywords:

Product design, consumer design perception, product design response.

Practitioner Summary:

To answer the question: What causes differences in design response? We summarize the research findings related to product design features and human factors. We highlight the biases that can emerge from the measurement approach. And discuss the most common analysis methods used for product design response information.

1 Introduction:

Consumers have access to a large variety of products in almost every market segment. In such intense competition, design has become a primary added value. And besides the product's functional quality, modern companies must deliver designs that spark precise emotion from their customers. First, to communicate the quality of their products. And to fulfil their customer's affective needs such as the feeling of safety, comfort, and elegance. Such accurate design is challenging because, on the other side, not all consumers respond in the same manner to a particular product design [1].

Research suggested it may be profitable to design products that elicit "paradoxical emotions [2]." This argument is supported by the classic theory of human appreciation of aesthetics [3], as well as the recent aesthetic emotions studies [4–6]. Creating a precise product design that can spark such emotion while achieving the design goals, is a challenging task [7–10]. Because it requires a profound understanding of the target customer and the possible co-occurrence of several different emotions [11]. As well as consider the fact that we also react to product designs for their symbolic value [12]. Feng et al. [13] reviewed the latest research in data-driven product design and listed the first step, the analysis of customer design perception requirements.

Product design theory has reached an advanced understanding [14], as we found that we share basic aesthetic preferences [15], and developed consumer product design response theories that allowed further advancement [16]. And allowed researchers to create several methods that measure the consumer’s response to product design, and to connect design features to particular design response elements such as the perception of the robustness of elegance [17–19]. However, the design precision requires understanding the consumer response at the individual level.

Several investigations have been made on customer profile factors [20] and found that consumers from the same regions expressed similar perceptions of colour [21, 22]. But in the case of product design variations, no correlation has been found between consumer profile and their perceptions [23, 24]. In this review paper, we aim to summarize the latest understanding of the consumer's response to product design and discuss the most important factors influencing the product design response both from the product side and the consumer side. And our latest understanding is related to measuring consumer response. For the introduction of individual consumer response findings into precision consumer studies.

2 Search Method

2.1 The search terms

This review focuses on product design and the consumers' product design response (PDR). We consider the definition of product design as the combination of properties that define its shape, its haptic sensory characteristics, and the properties that define its functional capabilities [14]. The "consumer" is the person for whom the product is intended [25, 26], it is also referred to in research as the "customer" or the "user" [27, 28]. We focus on the consumer side and exclude PDR studies on the designer side.

PDR is defined in this study as the generated subconscious reaction to a product design [25, 29]. However, because this reaction is studied from various angles, it is referred to in research as "Emotion", "Affect", "Perception" and "Kansei". We considered the various terms to cover this topic properly. Nonetheless, we use the term "PDR" to englobe the different terms. The method of mixed studies review was employed when conducting the literature search.

The basic human emotion theories suggest that they emerge from the combination of basic emotions. However, from the product design perspective, this model creates a limitation because it contains only one pleasant emotion, Joy, Simplifying all the pleasant variations of product impressions into one variable [30]. However, product evaluation studies do not favour such an emotional model for that reason, as it does not fairly represent intuitive product emotions [31]. However, the term "Emotion" appear in product design research to describe product-related emotions, on a separate basis often referred to as "product emotion" [31–33].

The term "Affect" is defined as the subconscious interpretation of emotions based on personal experiences [34]. In product design studies, affect is considered the compound of the person's temperament, current mood, and current emotion. It is used in product design studies to describe the consumers' most abstract, positive or negative, responses to a product design [35].

The term "Kansei." It is a Japanese word that is close in meaning to "Affect," with an extra edge toward the interaction of a person with a product. Several attempts have been made to give it a definition, Levy [36] summarized these efforts. We mention two; the first came from an analysis of a set of definitions made by sixty researchers in Kansei engineering and resulted as "An internal process (a high function) of the brain, involved in the construction of intuitive reaction to external stimuli." The second is a definition proposed by Nagamachi [17] as "The individual's subjective impression from a certain artefact, context, or situation using all the senses of sight, hearing, feeling, smell, taste as well as recognition."

The term “Perception” is often used to refer to one particular aspect, such as luxury or novelty [37]. While the terms “Kansei” and “Affect” are used to describe the complete consumer PDR. They englobe multiple perceptions. Nonetheless, the term “Perception” is sometimes employed synonymously with “Affect” and “Kansei”. On the other hand, the term “Preference” is used clearly in PDR studies to indicate the notion of choice based on design variations.

2.2 Search screening

The search is designed to capture studies that focused on product design, and the consumers’ PDR. We allowed aesthetic design response because there has been extensive research and theories on human factors in aesthetics that are referenced in product design.

Table 1. lists the search strategy, and table 2. List the search exclusion criteria. Where the search numbers 7, 8 and 9 are refinery searches to further explore details learned from the first 6 searches. Particularly to investigate the human factors of personality and exposure, the measurement biases, and the process of Kansei engineering. We excluded studies that fit the search criteria but are not directly related to the consumer PDR (EX1, EX2). And the research that focuses on the designer’s PDR, also papers that focus on the design process (EX3).

Table 1. Search terms and search strategy.

Search Number	Search terms and combinations
1	“product design” “response” OR “perception” OR “affect” OR “emotion”
2	“aesthetic design” “response” OR “perception” OR “affect” OR “emotion”
3	“human factors in product design” OR “Human factors in aesthetics”
4	“product aesthetics” OR “product utility” OR “product ergonomics”
5	“individual” OR “personal” OR “cultural” + 1 + 2 + 3
6	1 + 2 + 3 + 4
7	“personality” OR “intelligence” OR “exposure” +1 + 2 + 3
8	“measurement” “bias” + 1 + 2 + 3 + 4
9	“kansei engineering” + 1 + 2 + 3 + 4

Table 2. Search exclusion criteria.

Exclusion code	Exclusion criteria
EX1	The research does not focus on product design, aesthetic design or human factors.
EX2	The research does not discuss human factors or design/aesthetic response.
EX3	The research focuses on the designer.
EX4	The research paper was not written in English or not peer-reviewed.
EX5	The article does not belong to Scopus, Web of Science, IEEE Explorer and ScienceDirect databases.

2.3 PDR terms overview

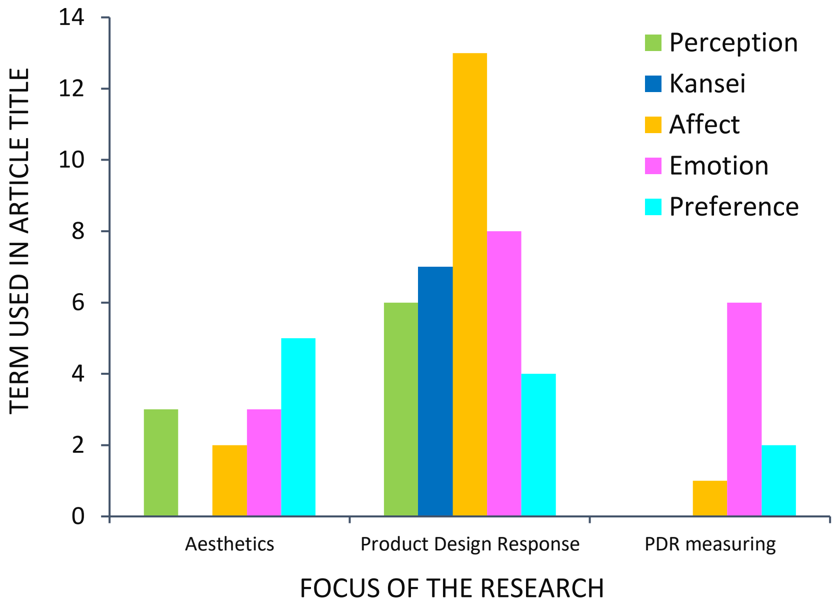

Figure 1. Terms to describe product design response in research article titles.

The research resulted in papers that are focused on Aesthetics, PDR or the PDR measurement. We identified five terms used to describe the consumer PDR in the research papers titles, namely, Emotion, Affect, Preference, Kansei, and perception. For the term “Kansei” we considered the cases where it was expressed as Customer Kansei, User Kansei, individual Kansei or Kansei preference, and excluded it when it was mentioned to describe the process of Kansei engineering. Figure 1. Presents a histogram describing the count terms used to describe PDR in the article titles, relative to the focus of the research.

Figure 1. shows that researchers used all these terms to describe PDR, although the term “Emotion” is more dominant in PDR measurement studied, namely in Physiological-signs-based research. It is worth noting that the term “Kansei” (Customer Kansei, User Kansei, individual Kansei) is the most exclusive term for describing product design response research in its article title. And the term “Affect” is the most used.

2.4 Review structure

This review intends to provide a clear understanding of the factors related to consumer interaction with product design and the methods employed to measure and analyze their response. We formulate the narrative to discuss the questions shown in Table 3.

Table 3. Questions discussed in the review.

Question	Section
What are the design aspects influencing the product design response?	3
What are the consumer factors influencing the differences in PDR?	4
How we should measure the consumers' response to product design?	5-6
What are the methods used to analyze PDR?	7

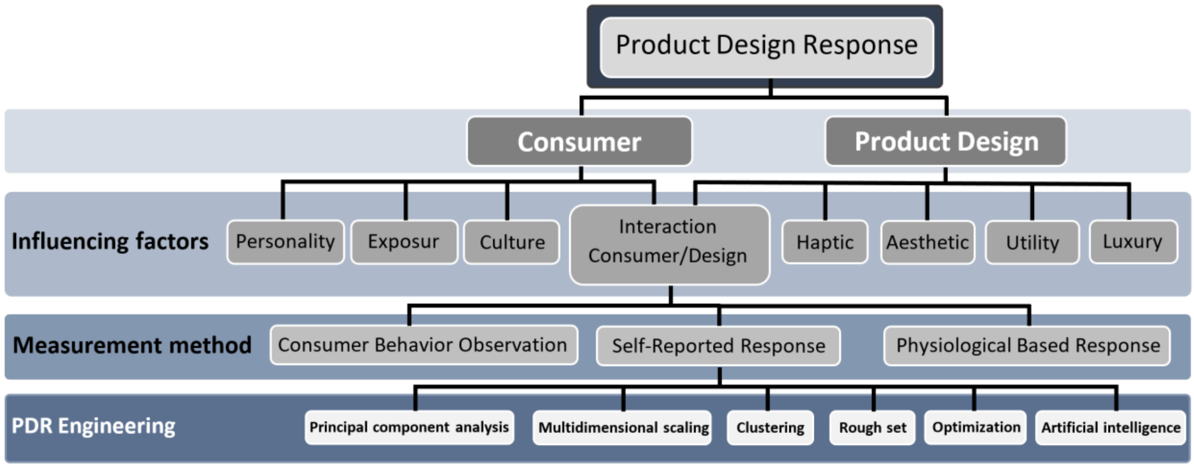

Figure 2. The hierarchical structure of reviewed studies.

Besides the product form, there exist multiple aspects of product design. In the third section, we discuss the design features found to receive common consumer responses, particularly, in the design aspect of aesthetics, product perceived utility, haptic design, and the aspect of luxury of the product.

Although there is a good overall agreement in product design responses, the margin of responses is wide due to individual differences. There has been a large effort in investigating the consumer's characteristics causing these differences. In sections 4 and 5, we discuss these studies and present the human factors found to have the strongest association with product design response such as the factors of individual exposure and openness in personality, and the group factor of culture.

Product design evaluation is challenging because the consumer response is not a value that we can measure directly. It requires an effort from the consumer to present their response in a language form, and we can only extract basic emotion from the brain signal. The semantic methods are found to be the most efficient because they can help us estimate the consumer's true affect by choosing from multiple adjectives.

However, researchers still have to consider the existence of many cognitive and consumer mood biases that can impact the quality of their experiments. In section 5 we discuss these potential biases, and in section 6 we present the common methods employed for measuring the PDR and highlight the difference between self-reported and physiological-based emotions studies. The 7th section presents the most commonly used methods to analyze the PDR data, and discuss the advantages of each method. Figure 2. Describes the hierarchical structure of reviewed studies.

3 Design factors influencing PDR

3.1 Product aesthetic and haptic design

It is well established that emotional satisfaction leads to consumer loyalty and advertisement through word of mouth [38, 39]. In order to win that free publicity, businesses must first understand the objective aesthetic aspects of their product. Berlyne [40] theorized that we share common affective processes in aesthetic valuation [41]. Since then, scientists have dedicated several studies to understanding our aesthetic appreciation [42, 43]. For instance, we found that humans favour symmetry [44, 45], complexity [46, 47], curvatures [48, 49], and balance [50, 51]. Figure 3 presents four iconic Nokia designs with noticeable innate aesthetic preferences and features.

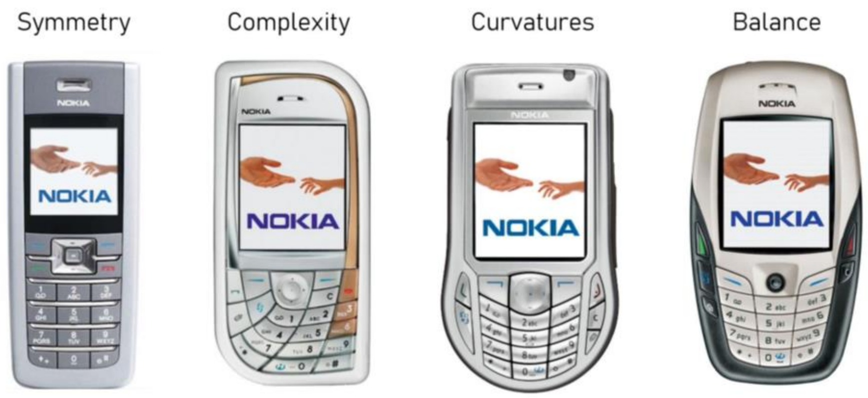

Figure 3. Examples of mobile phone designs with innate aesthetic preferences: Nokia models from left to right: 6235, 7610, 6630, and 6600.

Evidence shows that hard-wired visual system mechanisms detect these aesthetic features automatically. [52, 53]. Van Geert and Wagemans [54] wrote a detailed review of the research findings related to the relationship between aesthetic appreciation and a) complexity, b) order and c) balance between order and complexity. And concluded that "it is important to study their relation to aesthetic appreciation together, not separately". In product design, Bloch proposed one of the earliest models for product design [25]. In this model, he discussed innate human preferences for product design, like order and unity, and suggested that too much unity can be unappreciated [55]. This idea is supported by human emotion-aesthetics theories [31, 54]. And it is confirmed by recent studies [15, 53].

The research showed that haptic design properties play a considerable role in the consumer's design response. James et al. [56] showed that haptic exploration of novel three-dimensional objects evokes activation in brain areas associated with visual processing. In consumer-product interaction, Vrána and Mokrý [57] wrote a review on studies that observed the effect of product haptic qualities on brain activity. They concluded that the haptic aspect of product design might be underestimated.

Ranaweera et al. [58] conducted an experimental study on the influence of weight and texture on consumer haptic sensing and perception. Considering three products; a photo frame, a remote controller and a water bottle. Their results suggest that smooth textures with heavier weights provoke excitement, and show favourable responses toward exciting brands. While smooth textures with lighter weights provoke the perception of sophistication.

3.2 Product utility

Bagozzi et al. [59] theorized that people simultaneously evaluate products according to two classes. On the utility side, i.e. the product is beneficial to what degree? And on the hedonic side, i.e. how pleasant are the feelings associated with using this product? The overall evaluation of the product is, in differing degrees, the combination of assessment in both dimensions [60]. Van Rompay et al. [61] presented a modern equivalent based on the embodied cognition framework [62].

Research showed that a misalignment between the utilitarian and hedonic aspects of the product is more likely to cause strong negative emotions [63, 64]. The utility aspects relate to functionality and reliability, while the hedonic element refers to the product's ergonomics, Kansei, and aesthetics [65, 66]. That means a product with high functional quality but low enjoyability can cause negative emotions relative to a product with equivalent hedonic and utilitarian attributes [63, 67].

Norman [68] theorized that we expect better-designed products to function better. Sundar confirmed this principle in their study [69]. Hoegg et al. experimented on different products, examining the effect of appearance on the expected performance against the product description [70]. They concluded that higher aesthetics is more favourable in many cases where conflicting cues exist. Radford et al. studied the perception of newness and its effect on consumers' judgment [71]. They concluded that the evaluation of the aesthetics tends to occur before the consumer can consider the product's functional aspects. And suggested that people may not focus on a product that does not evoke sufficient aesthetic interest. Adeyeye et al. [72] examined the perceived user experience of eco-friendly showerheads. Participants expressed their preference for designs different from regular showerheads, even though the design changes do not necessarily correspond to better performance [73].

Han et al. [74] examined creativity in product design and its relationship with functionality and aesthetics. Their case study suggested no tangible relations between creativity, utility, and aesthetics [66]. Haug [75] studied the complexity of aesthetics in product success and offered a framework for understanding the aesthetic experience of products. Considering the following stages of aesthetic emotions: Objective emotion, Personal context, External context and Reflection, the stage where the consumer justifies their emotion or argues against it.

3.3 Product luxury and brand

Besides the aesthetic and the utility values, research showed that we also consider products for symbolic value [12, 14, 76]. Luxury products, in particular, hold high social signals value and are often accompanied by a brand image [77]. In addition, luxury products are often identified by distinctiveness, exclusivity, and craftsmanship [78]. Also by timelessness, sensuality and beauty [79]. Tynan et al. [80] discussed in their review that symbolic values are essential in luxury products because it communicates the signal of consumer status to others.

Hemonnet-Goujot and Valette-Florence [81] studied the PDR regarding the aspect of luxury and brand love and their social drivers (Informational influence, Utilitarian influence and Value-expressive influence) and individual drivers (Self-consistency, Self-enhancement and Self-differentiation). Considering PDR as the Aesthetic, Functional and Symbolic values. The experiment studied luxury in two commonly used products, a pen (Mont Blanc Meisterstuck pen) and a wristwatch (Rolex Oyster Perpetual watch). The study collected design evaluation data from a multinational pool of participants through an online survey, resulting in 276 evaluations for the watch and 249 evaluations for the pen. Besides design evaluation, the participants were asked to answer questions related to the product brand, and describe the important drivers for buying a watch or a pen.

The study results supported the known antecedents of product design value perception, namely the “importance of the need for status” [82] and the “self-expression” [76], and showed that the social drivers for watch products are significantly higher than for the pen. And that the individual drivers are higher for the pen product. Which suggests distinguishing between socially consumed products and privately consumed products. Their results also showed that brand identification has a mediating role and design that triggers affective experience has a symbolic value. Both of these drivers act as catalysts for brand love. Adding to the antecedents R&D and advertising intensity, found by Nguyen and Feng [83].

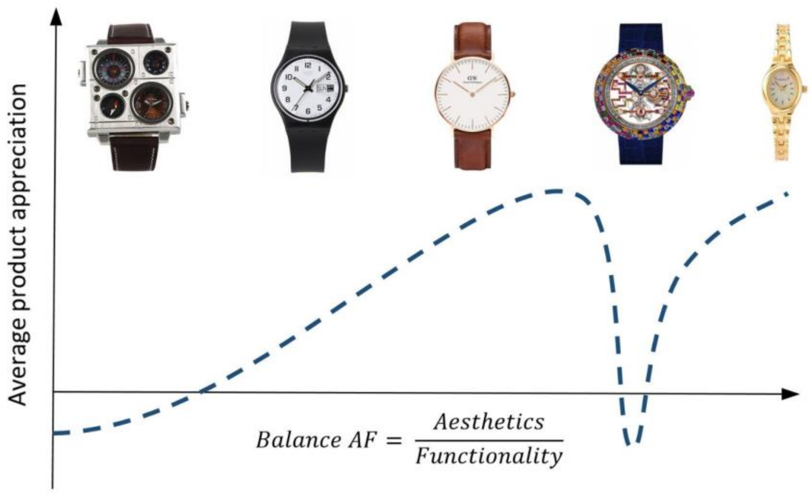

Figure 4. Aesthetic/functionality product evaluation (watches from left to right: a fake Oulm, a Swatch, a Daniel Wellington, a Jacob & Co, a Sekonda).

Hagtvedt et al. [84] investigated products with extravagant aesthetic features. In their experiment, participants associated excessive levels of styling to lower levels of functionality. However, the results also suggested that products in the Beauty category can be valued based solely on their design, regardless of their perceived functionality. Greenberg et al. [85] Suggested the use of design extravagance as a new luxury product design element.

Tynan et al. [80] also classified hedonic appeal as self-directed because it refers to messages of allow the consumer to satisfy their individual stylistic identity. Amatulli et al. [86] studied the effect of hedonic versus utilitarian messages on consumers' perceptions, and attitudes toward luxury products. And found that the hedonic message is more important than the utilitarian message in product perceived luxuriousness when the promoted product carries lowly prominent logos.

We present a visual summary in Figure 4. Focusing on the notion of balance between aesthetics and functionality, referred to as "Balance AF". This figure describes the two extremes. On one side, products with multiple functionalities but low aesthetics and on the opposite side, the products with high aesthetics but little functionalities. The graph describes that the latter is appreciated much more than the former on average. And outperformed by the products that have little functionalities but higher aesthetics, as they score higher is the Balance AF, to our best knowledge this balance is not a countable value, we suggest it illustrate our understanding of research findings. This graph would have been a straight line if we simply appreciated higher aesthetics. But, on average, we do not highly value the overdesigned products that belong to the utility category. The graph shows this as the valley that separates the luxury category.

3.4 Summary of product factors

Product design evaluation is based on aesthetics, utility and symbolic values, Researchers developed a good understanding of the design aesthetic features and showed that we share significant common preferences in terms of product shape and haptic sensory characteristics. In the dimension of product utility, research showed that the most important factor is the alignment of the aesthetic and the functional aspects of the product design. and the utility on its own is not responsible for positive consumer response. As opposed to the product with high aesthetic characteristics, it can be appreciated without or with very little utility. Research shows that we appreciate the latter product for its symbolic value.

4 Consumer factors influencing PDR

4.1 Consumer culture

Diverse cultures have distinctive aesthetics [87]. In product designs, product design that is motivated or inspired by a local culture is referred to as "Cultural Design" [88]. It is the design that is associated with an identity and holds the signs of the social context in which it was created, signs that can be functional or aesthetic aspects of the cultural product and mark the distinction between the people of different cultures [89]. Several studies discussed the distinct differences in traditional aesthetic features [90–93]. Gul Gilal et al. [94] suggest that dissimilar cultures have different common interests in terms of symbolic or aesthetic values in a product design.

The “Cross-cultural Design” On the other hand, is the design that identifies with multiple groups across national and cultural boundaries and seeks to receive consumer acceptance globally, regardless of their cultural background. Ikeda discussed the history of Japanese product design [95] its origin, and inspirations from European and American product design. And Adelabu et al. investigated the product design inspired by the African culture [96], suggesting a cultural product evaluation approach based on the Kansei method. Due to global culture dominating local cultures, and most technological products do not adopt local cultural designs, people from different backgrounds tend to have a joint position in product design perception [97, 98].

Chai et al. [99] showed in their study that the consumer tends to prefer products with cultural meanings compared to superficial design and that they may prefer cultural products with a modern design element to traditional cultural elements. Qin et al. [100] Executed quantitative research to understand consumer attitudes toward culturally innovative design and sustainability. Focusing on how young consumers perception of cultural products. And showed that the perceived novelty of culturally innovative products is important for the consumers’ purchasing intentions and their consumption attitudes. Qin later suggested a framework for designing new products based on cultural inspiration [101]. And Zhou suggested an approach for cross-cultural design based on Deep learning [102].

We summarize with a visual illustration of cultural design in figure 5. This framework shows that most people perceive product design similarly. The most significant part of the population worldwide uses the same products in their daily lives, for example, technological products, formal clothing and transportation. Within this category of global products, slight design variations are made in local regions, mainly motivated by competition and marketing as well as functional features. Such design variations are primarily present in locally made products, like home furniture, packaging and beauty-related products. Furthermore, aesthetics for these products are more likely to be perceived similarly by neighbouring cultures and, to different degrees, less similarly by farther cultures.

Based on our understanding, we theorize that the perception of traditional aesthetics receives agreement from people of the same culture of origin. But, they do not evoke similar emotions in people from other cultures. Therefore they are the most isolated in terms of perception agreement. The best examples of such aesthetics can still be found in items related to traditional ceremonies. The above remarks support the idea that: human perception of aesthetics is dependent on exposure, and its emotional meaning is shaped by society.

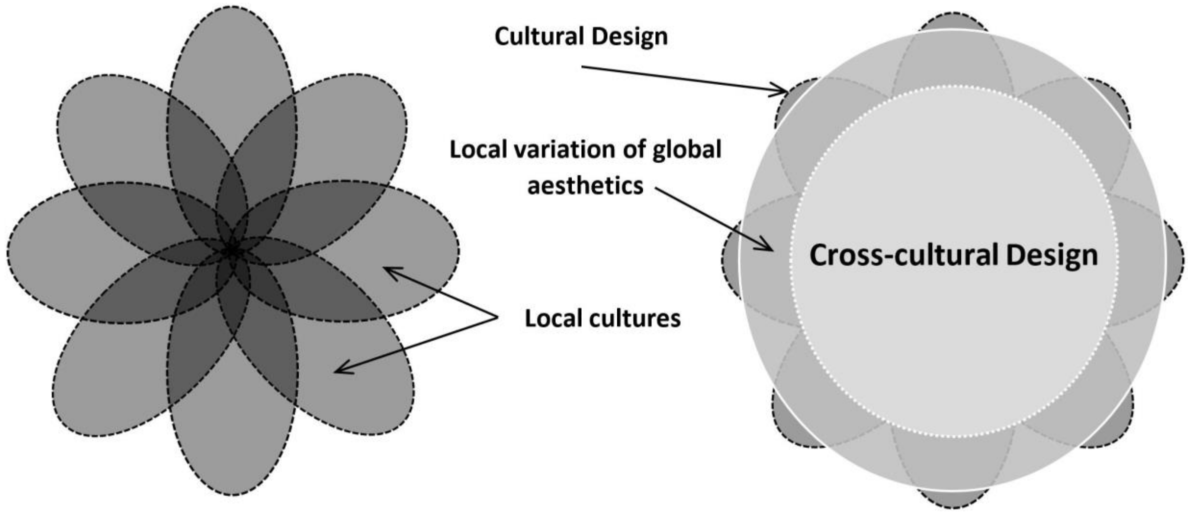

Figure 5. Cultural and Cross-Cultural design.

4.2 Consumer exposure

In personal aesthetic perception, it is evident that each person is different. Corradi et al. [103] studied the individual aesthetic sensitivity of previously mentioned human aesthetic preferences, i.e., complexity, order, curvatures and balance. They found that people agree on these aesthetic preferences, but to different degrees. As a conclusion of their experimental study, they suggested that "Variations in aesthetic sensitivity should not be treated as noise". Highlighting the importance of the individual. This idea is supported by other theoretical and experimental studies [104–106].

Aesthetic sensitivity is a concept that explains a person's ability to recognize and appreciate aesthetic quality [107], previously thought of as a unique trait present in some people more than others [108]. Because specific shapes, proportions, and characteristics were considered inherently attractive [109]. Since then, our understanding of aesthetics has evolved toward relativity, as more and more research showed that aesthetic appreciation is dynamic and depends on other personal and learnable characteristics [103, 104].Several research projects aimed to understand the relationship between general intelligence and aesthetic sensitivity and found conflicting results, from negative to positive correlations [110, 111]. Myszkowski et al. [112] analyzed data from 23 previous studies and found a weak positive correlation (0.3 with a 95% confidence interval). These results raise more questions than answers regarding what constitutes aesthetic appreciation.

Summerfeldt et al. [113] conducted an experiment on the correlation of aesthetic interests, experience, and knowledge with basic human aesthetic preferences (order, complexity, balance). They measured the art-related expertise of the participants through questions. Then asked them to rate the aesthetics of computer-generated elementary shapes. The objective aesthetic characteristics of these shapes were calculated based on their geometry and used to evaluate the participant's answers. Results showed that people with higher experience correspond to higher objective aesthetic appreciation.

Weichselbaum et al. [105] studied the aesthetic valuation relative to consumer expertise. They subjected the participants to an art-related exam and ranked them based on their scores. Then later asked them to rate patterns according to their perceived beauty. The results showed that the average participant rated symmetrical patterns significantly higher than asymmetrical ones. And that participants that have higher expertise valued the asymmetrical patterns higher. This experiment suggests a natural tendency to appreciate symmetry, but people with significant aesthetic exposure were able to challenge that natural tendency.

Similar results were found by Silvia and Barona [114], where the experiment suggested that, in the case of simple shapes, people typically prefer angular shapes. However, as expertise increased, the effect of angularity decreased. Their experiment, however, presented the contrary regarding complex design shapes because experts prefer angular shapes more than participants who are less experienced. We think this might be related to the idea that experts have a more tolerant perspective on weighing the tradeoff between complexity and simplicity.

Bloch et al. [115] suggested measuring the importance of aesthetics of a product for a particular consumer through the concept of Centrality of Visual Product Aesthetics (CVPA). It differentiates between consumers who evaluate products with low regard for aesthetics and consumers whose product valuation is dominated by how it appears aesthetically. At the individual level, the CVPA was found to be dependent on the ability to understand and evaluate product designs. Studying the effect of exposure on design appreciation [116], Carbon asked the participants to evaluate car designs in terms of liking, curvature, complexity, quality, innovativeness and safety. before exposing them to highly innovative designs of concept cars. The results showed changes in the overall evaluation of past car designs as people saw them later as less creative. The paper refers to this concept as “Zeitgeist” [117].

Design novelty is an essential aspect of design, and from the subjective perspective, it is related to exposure. Raymond Loewy [118] highlighted the importance of balancing the comfort of familiarity with the uncertainty of the unknown, characterized by the acronym MAYA (Most advanced yet acceptable). Vazquez and Yamanaka [119] studied the impact of novelty on consumer evaluation using actual commercial products, considering the participant's prior experience with such products. The results showed slightly higher pleasure levels for the familiar designs and that visual stimulation before the first interaction has arousal enhancing effect relative to the novelty aspect. Researchers developed several mathematical models to simulate the effect of novelty [120–123].

Van Geert and Wagemans [54] reported evidence of considerable individual variation when it comes to aesthetic appreciation of order and complexity. The research projects suggested that expertise, and personality traits, might be the most significant drivers for such variation.

4.3 Consumer personality

The link between personality and aesthetic experience has been researched from different angles [124–126]. De Young wrote an in-depth review of evidence associating Openness and aesthetic appreciation in general [127]. And the results found by Antinori et al. [128] indicated that open people are characterized by higher engagement with aesthetic information.

Myszkowski and Storme [129] conducted a correlation study between the Big Five model of personality traits and the quality of product aesthetics (Conscientiousness, Agreeableness, Neuroticism, Openness and Extraversion) [125]. They measured the Centrality of Visual Product Aesthetics (CVPA [115]) of 158 participants, mostly female students. The test is an 11-item self-report questionnaire that has three subscales. Namely: Value, how significant is the design for the consumer? The Acumen is how capable the consumer is in recognizing design details is? And The Response is how crucial the customer’s need to buy products that have appealing designs is. The results suggested that people with low Openness tended to prefer higher quality designed products. And agreeableness is found to correlate with Value.

In later research, Myszkowski et al. [111] conducted the Visual Aesthetic Sensitivity Test (VAST [130]) on a similar subject pool constituted of 129 participants, mostly female students. This test is also a self-report questionnaire considering the following six subscales: Openness to aesthetics, Openness to fantasy, Openness to feelings, Openness to ideas, sensation-seeking tendency and tendency to seek order. But in this study, the results showed a correlation between Openness and aesthetic sensitivity. However, the author recognizes the limitations of self-reporting. Participants have to use their imagination when answering the questions, which is not ideal because they may not have the same view of what makes a highly designed product. Furthermore, there are many variables to a product design; therefore, the design perception can impact their judgment in an actual product evaluation exercise.

De Bont et al. [131] made one of the earliest consumer personality studies in product design. They identified the consumer in terms of two cognitive styles; Tolerance of Ambiguity (ToA [132]) and Categorization Width (CW [133]). A person with a high ToA is equivalent to what we consider open to experiences. And a consumer with low CW is a person that gives high importance to product details. And may, for example, recognize the difference between trainers, running shoes and sneakers. Nonetheless, this study asked 76 participants to rank 15 expresso machine designs according to what they consider an ordinary design. They set the standard ranking, on the other hand, using the answers of five experts. They found men to have higher categorization width than women, and older participants had a lower tolerance for ambiguity. The results showed that people with high ToA, and high CW, tend to accept deviating (according to the judges' standards) product designs.

Han and Ma [134] studied the relationship between consumer personality and jewellery item perception. Their experiment studied the personalities of 60 highly familiar female customers and classified them into 4 clusters. Namely “Casual and free”, “Introvert and sensitive”, “Rational and calm”, and “Extrovert and optimist”. They asked each to rate 278 items from a well-known brand to conduct a study based on 100 words. The results suggested that personality has an impact on the participant's perception. And that there is a correlation between the personality cluster members. Chen et al. [135] studied the effect of personality type on the design perception of elderly products. They classified the 30 elderly participants into four types. Namely, “Dominance”, “Influence”, “Steadiness”, and “Compliance”, and collected their impressions on a shoe product with eight design variables, including the shape, material texture and colour. Similarly to the above study, they found that personality groups have different preferences in shoe material and colours.

Other studies showed that some personality traits are essential in preferring luxury design. For instance, Kang et al. [136] discussed that narcissistic orientations encourage people to prefer luxury products. In their studies of actual brands and consumers, Fujiwara and Nagasawa [137, 138] showed that Openness to Experience is a significant trait among consumers of luxury items. In another field study, Greenberg et al. [85] established a link between extravagance and preferences for luxury product design as a motive for the “need for status.

4.4 Summary of consumer factors

The consumer response to product design can be influenced by culture, however, this is mostly true in a limited set of products inside the local regions. The cultural factor is not very significant in most mass consumption of modern products. From the individual characteristics of the consumer, two factors were the most responsible for PDR differences, namely the consumer experience, and the consumer personality element of Openness to experiences.

5 Design Evaluation context factors

5.1 Product-Consumer Interaction

The product design response is not a reflection of the nature of the product alone, but also on the characteristics of the evaluator and their experience [76, 139]. Locher et al. [29] created a detailed framework combining product-driven and cognitively driven processes underlying the consumer's experience with product design. Based on the models for aesthetic appreciation and judgments [140] and the model describing the affective product interactions [141]. Tavares et al. [142] presented a systematic literature review in the field of cognitive-affective needs in product design. There exist many factors that can impact the consumer response, starting from personal elements like the mood, at the moment of evaluation, to more complex influences that can emerge from consumer-product interaction.

We present a visual summary illustration in figure 6; to describe the influencing factors in product design evaluation, on one side, there is the consumer, including the cultural background, former experience with aesthetics, consumer personality and consumer mood at the moment of interaction with the product. And on the other side, the product, which consists of product characteristics and context:

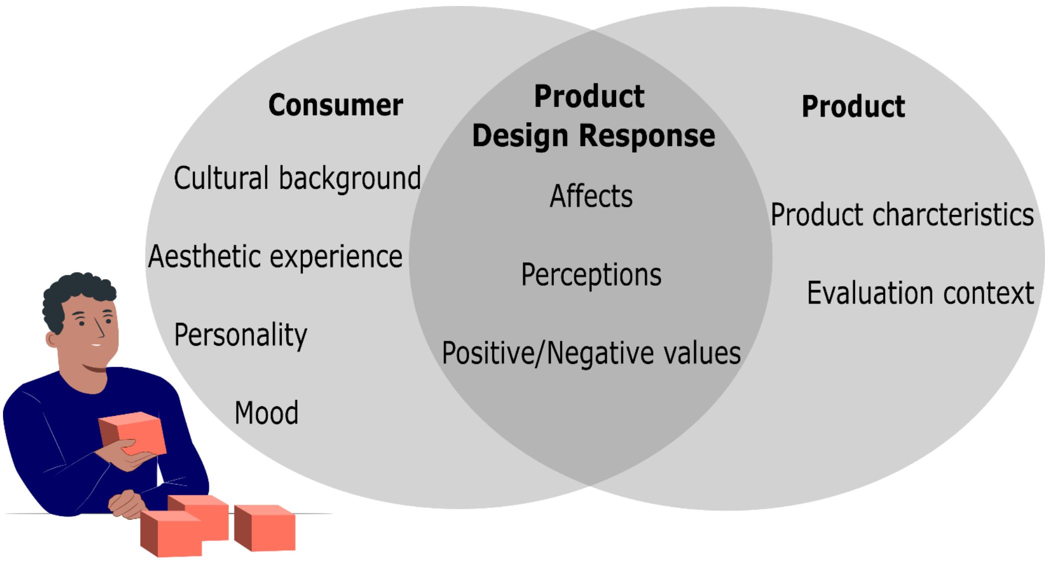

Figure 6. The subjective product design response, a suggested illustration of Locher et al. [29] framework.

5.2 PDR measurement biases at the moment of evaluation

The evaluation context has a significant effect on the overall consumer response [143]. Logkizidou et al. [144] showed in their study that products presented in a museological manner (inside a glass cube for instance) are perceived to be more luxurious, less risky and thus more purchasable. The order of product display can cause other cognitive biases that may affect the product design evaluation, like the "Anchoring bias", which occurs when a reference design, intentionally or unintentionally, is considered the reference point for evaluating all other designs. The "Recency bias" says that people would remember the first and last designs more accurately when assessing a series of product designs than those in the middle. And lastly, the "Framing bias" occurs when the evaluation context positively or negatively influences the design evaluation [145].

The product's prior connection with the consumer can encourage some consumer decision biases, such as the “Endowment effect”, which is the tendency for people to value a product they own more than people who do not [146]. Furthermore, Bushong et al. [147] showed in an experimental study that people value products higher when they see them in real than in pictures. And Peck and Shu [148] demonstrated that touching a product increased the affective reaction toward that product, similarly to the endowment effect.

Another effect, called the “I Designed It Myself” effect, also known as the Effort bias, says that people are attached to objects they created or helped create. And value them higher than other objects. In their paper, Franke et al. [149] discussed the different aspects of this effect. They suggested its incorporation in the online design customization tools, for its substantial impact on the willingness to buy. Yanagisawa [150] discussed the “expectation effect” and proposed mathematical modeling of this effect in product design.

Another consumer bias factor is the mood at the moment of evaluation. It is shown to be an important variable that can affect product design evaluation. Locher et al. [151] conducted an experimental study that looked at the problem of design evaluation from the consumer's mood angle. Half of the participants in this experiment were trained design students, and the other half were untrained students from other departments. The task is to rate the visual appeal of a set of six digital cameras by thinking out loud about the design features using camera prototypes. To introduce a positive mood, half of all participants, trained and untrained, were presented with a nice bag of candies and explained that it was an appreciation for participating in the experiment. This idea was inspired by Estrada et al. [152], who showed that it influenced doctors to demonstrate more efficiency and openness to information. The design evaluation results showed that; participants that were gifted the candy gave, on average, a significantly more appealing rating than the rating of individuals who were not given candy.

Furthermore, the untrained participants who received candy provided the fewest reactions overall, and design students who received candy generated more reactions than design students who did not. This suggests that the effect of positive mood is similar, but depending on the consumer's perspective, the means can be different. It is worth mentioning the following research results that showed a strong effect of consumer mood on perception. Djamasbi and Strong [153] demonstrated in an experimental study that people are more willing to accept new technology when in a good mood, even in high levels of uncertainty. Their results were examined further in recent experiments regarding consumer personality and the duration of the positive/negative mood effect [154].

More results were found in the service evaluation study by Sirakaya et al. [155]. That surveyed a cruise vacation and found that a positive mood is significant enough to be considered a bias and recommended a neutral mood for more accurate service evaluation surveys. In a more detailed experimental study, Kocabulut and Albayrak [156] surveyed hotel customers on the quality of service. On the other hand, they measured their personalities and mood before taking the survey. They found that “good mood” has a stronger correlation, with high-quality evaluation, than personality. And surprisingly, results showed that, in a good mood, people with aggressive/competitive characters perceive higher quality service than people with easygoing/happy personalities.

6 Measurement methods of product design response

6.1 Physiological-based measurement

An emotional experience can reflect on various physiological signs such as pupil size, heart rate [157], skin conductance [158] and brain activity [159]. Yu and Qi [160] reported the recent advancement in emotional recognition based on Electroencephalogram (EEG) recordings and proposed guidance points on EEG-based user-experience-focused product design. Cela-Conde et al. [161] presented one of the earliest investigations in visual aesthetics. Under Magnetoencephalography (MEG), participants were shown different artworks and natural photographs and asked to decide whether each picture was beautiful or not using a finger sign. The brain activation tracings showed a significant difference between beautiful and not beautiful conditions. In a similar study, Yang et al. [162] found that EEG plus eye-tracking can indicate one's affective responses toward picture aesthetics. And Chew et al. [163] expanded the quest toward 3D shapes.

In research related to product design, One of the early attempts to understand PDR, using physiological-based exploration, was made by Tomico et al.[164]. They studied the comfort levels of six stylus designs during and after the interaction. Lin et al. [165] sequentially exposed Eighteen participants to table-chair pairs and asked them to make design-match judgments while connected to the EEG machine. Thirty-two chairs from four categories and eight tables. The Event-Related Potential (ERP) brain activity showed that, depending on the styles, the reaction time for match/mismatch is different.

Deng and Wang [166] presented a paper where they conducted an emotional scale survey in reaction to pictures of cultural symbols of the "Shu culture" on the one hand. They recorded the brain activity of the 20 participants using an EEG. On the other hand, understanding the brain signal patterns that reflect the relationship between product experience, user emotion, and the degree of pleasure is independent of cultural bias. Guo et al. [167] found that it is possible to indicate the consumers' product design preferences through EGG data. In another study, the authors used EEG to identify accurate adjectives to assess product design features.

Chen et al. [168] studied product colour attractiveness and the perception of product affordance based on its colour. They connected the 20 participants to an EEG machine and measured their ERP in reaction to seeing pictures of coloured sofas, then target words (affordance or attractive). The brain signal results showed that colour affordance is involved in the cognitive process before colour attractiveness. Wang et al. [169] investigated the ability to predict design choice decisions using eye movement and EEG response. Using Thirty-five participants and four designs of a construction truck, they found that the fusion of data from brain signals and eye movement can help predict product design decisions.

Liu and Sourina [170] developed an algorithm for human emotion recognition based on real-time EEG readings. In recent work, Liu et al. [171] used it in a study to detect the design preferences of humanoid robots. To understand the design traits that correspond to higher perceptions of likeability, smartness and friendliness, perceptions of 12 robot designs based on the evaluations of 20 inexperienced participants, along with eye-tracking and EEG data. The results suggest that the emotion predictions are equivalent to the likeability responses. And on average, the first impression does not change. On the other hand, eye-tracking suggests that facial features are the most important aspect in humanoid robot design.

These studies of product design emotion mainly focus on understanding the brain's priorities when interacting with a design. And how the decision to like or dislike is made. They do not identify a distinct emotion or what caused it. Instead, they find brain signal heuristics corresponding to a positive or negative emotion. For designers, such an approach cannot serve as part of the design process. But they can extract general ideas about how the consumer decides to like/buy the product [172].

6.2 Self-reported measurement

Psychological questionnaires are used to identify emotional states. But are not adopted in product design because they mainly focus on disorders. On the other hand, simply asking consumers how they feel about a product design does not help identify its real affect. Because people might restrict their answers to what they think is socially acceptable, they can also be easily motivated to provide an answer that pleases the researcher [173]. Schoen and Crilly [174] showed in their experiment that multiple questions, such as the "willingness to pay", "wanting," and "prior ownership", increase the possibility of identifying the consumer's response compared to the simple one question for attractiveness.

Even though the verbal expression is vulnerable to social biases [175], the verbal protocol method intends to overcome these drawbacks [176] by encouraging the participants to reflect on their mental processes. Nonetheless, the verbal self-report has the advantage of quick implementation. The participants are not required to learn about the specific answering process. They simply express what they feel about the product design or give quick answers to specific questions. The freedom of answer allows the participants to provide a variety of expressions, which is a good advantage for catching the complexity of the design emotions [177].

Other frameworks have been developed to capture both the complexity of the affect and the simplicity of implementation [178]. Desmet suggested the Product Emotion (PrEmo1) technique [179]. It allows the consumers to express their feeling about a product design through a cartoon character with 14 different pleasant and unpleasant facial and body expressions. This technique was thoroughly tested in different cultures and improved to PrEmo2 by Laurans and Desmet [180].

However, the most widely used techniques for measuring product design affect employ the semantic ideas introduced in psychology by Osgood et al. through the semantic differential method [181, 182]. In product design, semantics refers to its psychological message expressed through its design features, i.e. shape, form, colour, texture, etc... its early applications focused on the understandability of product function and easy use [183]. In product design, semantic studies first focused on creating brand personality through design [184, 185]. Then expanded to predicting consumer perceptions [186–188].

Researchers created several strategies to cover the different design priorities of a research experiment. For instance, the design evaluators select from a limited list of "adjectives", known as "semantic attributes" or "Kansei words." And the goal is to establish the relationship between the design attributes and basic affect. The design attributes are also fixed in an existing list [10, 189]. It is common to ask the design evaluator to choose a position in the Likert Scale between two polar attributes [190, 191]. Other approaches ask the experiment participants to rate a design, ranging from "not" to "very", on a selected set of attributes [192]. Table 4. presents a collection of shared attribute pairs used in product design research.

Compared to the previously mentioned physiological-based emotion studies, the self-reported approach is more suitable for product design and is the most widely used by designers and researchers. Not only because of its cost-effectiveness, but it also provides a deep understanding of specific perceptions of the design.

Online e-commerce sites provide a massive amount of information about consumers' affect. And with the maturation of machine learning tools, product design researchers took the opportunity to exploit this consumer-generated data [213].

Table 4. Common attributes pair in the domain of product design.

[K, Y, U, S] Adult-Childish	[H, U, J, G] Old-Young	[C, I] Mature-Youthful	[A] [193], [B] [194], [C] [195], [D][191], [E] [196], [J] [197], [H] [198], [I] [199], [G] [92], [K][190], [L] [200], [M] [106], [N] [201], [O] [202], [P] [203], [Q] [204], [R] [205], [S] [206], [U] [207], [V] [208], [W] [209], [X] [210], [Y] [211], [Z] [212].
[H, K, Y] Popular-Unique	[D, J, V, X] Ordinary-Special	[M, Y] Alternative-Usual	
[I, W ,N ,D ,S] Traditional-Modern	[Y] Progressive-Conservative	[M, X] Conservative-Innovative	
[S, O, I] Elegant-Not elegant	[P, J, N, H, G, U] Beautiful-Ugly	[Z] Horrible-Pretty	
[X] Strong-Soft	[H] Soft-Wild	[J, A, P, N, B, C, J, H, G] Hard-Soft	
[E, J, H] Relaxed-Stiff	[Y] Relaxed-Intense	[B, O, R, Z] Comfortable-Uncomfortable	
[K, D] Luxurious-Cheap	[H] Expensive-Cheap	[R] Expensive-Inexpensive	
[U, K, I, S] Stylish-Styless	[C] Classy-Trendy	[R] Fashionable-Unfashionable	
[K] Attractive-Not attractive	[P] Pleasant-Unpleasant	[R, U] Attractive-Repulsive	
[P] Calm-Strident	[J] Calm-Exciting	[N, E, X, R] Exciting-Boring	
[D, V] Simple-Gorgeous	[Y] Gorgeous-Pure	[W] Gorgeous-Plain	
[H, K, N] Exciting-Quiet	[D, N, R, V, X] Dull-Lively	[M] Dull-Cheerful	
[C] Aggressive-Passive	[J, Q, H, X] Passive-Active	[G, B] Active-Inactive	
[K] Intellectual-Wild	[R] Smart-Stupid	[L] Stupid-Intelligent	
[S, I] Bold- Plain	[N, H] Delicate-bold	[Q] Plain-Gaudy	
[K] Revolutionary-Retro	[I] Classic-Not classic	[R] Unconventional-Conventional	
[R] Cold-Hot	[E, H] Warm-Cool	[N, A, G, O, Y, A, B, C, Q, Z] Warm-Cold	
[M] Amateur-Professional	[J, H] Professional-Unprofessional		
[M, N] Dangerous-Safe	[R] Safe-Unsafe		
[R, L] Rational-Emotional	[W] Emotional-Intellectual		
[C, X] Humorous-Serious	[Y] Funny-Serious		
[J, H, R, B, L] Strong-Weak			
[L, O, W, G, J, I, Q, S] Masculine-Feminine			

For a detailed understanding of the recent works in this field, we refer the reader to these two surveys: First, Quan et al. [214] wrote a detailed layout of the new methods used for extracting valuable consumer preferences through text, image, voice and video data. Second, Jin et al. [215] wrote a comprehensive survey on extracting consumer needs from online reviews. From data acquisition to opinion recognition and sentiment analysis. [216] suggested a method for extracting consumer' design responses from online product reviews based on natural language processing.

6.3 Consumer observation-based measurement

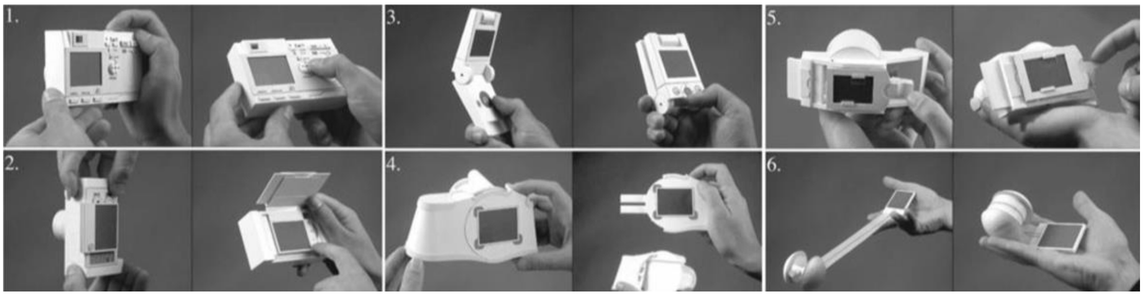

Figure 7. Camera prototypes in the Locher et al. [151] experiment.

Observation-based measurement is a popular technique in ergonomic design studies, it consists of real-time assessment of a user, directly or through Video records [217, 218]. Compared to the self-reported measurement approach, it requires extensive technical knowledge and experience to interpret the observed reactions [219]. In product design, this approach is mainly used to investigate the utility aspect of the design [220–222].

In aesthetic design assessment, Locher et al. [151] measured the product design response by consumer observation, the experiment participant evaluated six camera prototype designs. Each camera was modelled out of white foam with all functional parts. Two views of each camera are shown in Figure 7 The experimental session lasted approximately 25 minutes. They manipulated the prototypes manually, expressed their reaction verbally, and gave a rating of their appeal. A videotape of the participant's interaction with the design prototypes was created for examination. Besides observing the reaction of the evaluators, this method presents additional information on processing time. Their results showed that the trained design students spent more time evaluating the prototypes, however, no significant connection was found between the processing time and the evaluation outcome.

This method is not widely adopted in product design evaluation as it requires a specific experimental approach for different products. It is time-consuming in the evaluation step and, necessitates expert interpretation of the results. Which makes it relatively expensive compared to the self-reported measurement approach.

6.4 Summary of PDR measuring methods

Researchers were able to predict human emotion, based on Physiological signs, such as brain waves. PDR used such emotion to predict the emotion about particular aesthetic or design features and showed that it is possible to measure preferences. The method of consumer observation, on the other hand, offers much more data on the consumer's response, but it requires large efforts both from the consumer and the experimenter, and requires expert interpretation. Sematic-based approaches remain the most efficient method for extracting the deep consumer affect. However, experimenters need to pay attention to biases that can occur due to incorrect measuring approaches.

7 PDR Engineering methods

7.1 Kansei Engineering

Kansei Engineering (KE) is the process of capturing human affect/Kansei associated with a product design [19]. Not only the product form but also patterns, textures, sounds, and smells. It represents a method to study the users' interaction with a design by analyzing their product design response. Academic and industrial researchers use this methodology for various design investigations [9, 223–225]. López et al. [226] wrote a systematic literature study of KE product design, analyzing research papers from 1995 to 2020. They presented the most commonly used KE methods and showed that technology and furniture/home products make up approximately 60% of all research subjects. KE focuses on obtaining the Affect/Kansei related to a product design through semantics.

The early KE applications focus on identifying the users' affective and ergonomic needs. Such as the work made by Ishihara et al. [9] where they found that forklift drivers preferred standing in a risky position because they perceived it to be more comfortable. KE helped investigators understand the need for a better suspension system, which eventually allowed the drivers to work safely [227]. Razza and Paschoarelli [228] investigated the consumers' affective needs for the product of disposable razors using KE. Forty razor designs were evaluated in a virtual system by 321 adult men. Their factor analysis study presented no dominant correlations between the design features and the evaluator's affective response. The authors suggested that such data complexity is more suitable to analyze using more powerful modelling techniques.

Yanagisawa et al. [229, 230] presented a multi-sensory Kansei modelling methodology to extract users' product experience and study the cross-modal effect. A further study [231] investigated the impact of the product's visual appearance on the perception of sound made by that product. Kobayashi and Takeda [232] developed a product recommendation system based on KE. The new approach estimates the personal favourite design style based on past choices and suggests other products with similar design features. Hashimoto et al. [233] suggested a method for extracting Kansei product evaluation from online reviews. Its results were compared to a subjective evaluation of a selected collection of wristwatches and proved effective, supporting the ideas suggested in Figure 4. The Kansei Engineering process is summarized as follows:

1. Definition of the domain; Includes the product features, the target consumer, and the evaluation context.
2. Selection of the affect adjectives; through elimination (qualitative, quantitative), produce a list of low-level adjectives used for the evaluation.
3. Creation of the design matrix; containing all possible product properties with the most significant potential to impact the consumer's Kansei.
4. Collection of the design response data; by conducting the design evaluation and storing the survey responses in a database.
5. Analyzing the data using statistical tools and mapping the results.
6. Validation and drawing conclusions.

This procedure, however, is not the only approach to obtaining consumer product design response. We use the term "Kansei engineering" here to describe the studies focusing on the reaction of consumers to a product design [234], and the approaches that employ the consumer's PDR to serve further purposes, such as design features optimization [235], customer grouping based on product design features [190], PDR modelling [236] and design recommender systems [232]. In what follows, we describe the major analytical and computational methods used for building such systems.

7.2 Principle Component Analysis

The Principle Component Analysis (PCA) [237] is commonly used to find a lower-dimensional representation of the original dataset while retaining as much information as possible [238]. It is also used to find correlations and simplify data visualization. Aydoğan et al. [234] used PCA to determine the consumers' general preferences. Tang et al. [238] produced data visualizations based on PCA to study the cultural differences in product design and consumer evaluation. And in [239], Yang et al. used PCA to decompose online product evaluation reviews. It is generally defined by the following process:

1. Calculate the covariance matrix C for the original dataset matrix D as follows:

$$C = \mathrm{cov}(D) \tag{1}$$

   the size of D is $n \times p$, with n being the number of data vectors and p the number of parameters.

2. Extract the Eigenvectors U of the covariance matrix through the PCA operation:

$$C = U \, \Lambda \, U^T \tag{2}$$

3. Reduce the model size by selecting a subset of the eigenvectors U' with size $l \times p, with\ l < n$.
4. Reconstruct the reduced data matrix D' using the U'.

Similar factor analysis methods are used in design research to simplify complex sets of design evaluation data [240]. The goal is to find the underlying variables, by searching for interdependencies between design evaluation variables [166].

7.3 Multidimensional scaling

The multidimensional scaling (MDS) method helps us study the similarity between designs in terms of their inter-perception distances [241]. By creating the multidimensional semantic map presenting similar items in the same proximities. This method is used in various data analytics fields [242], as well as in various product design studies, such as material aesthetics [243] and shape design [244].

Metric MDS calculate the Euclidean distance between the elements of the design variables, while other distances can be considered. It is generally defined by the following process [245]:

1. Create the $n \times p$ matrix of coordinates X representing the position of each element n in their parameter dimensions p.
2. Calculate the distances between all elements of the same dimension. And create the $n \times n$ distances matrix Δ, which is symmetrical, non-negative and hollow (equation 4).

$$\delta_{ij} = \sqrt{\sum_1^p (x_i - x_j)^2} \tag{3}$$

$$\Delta = \begin{bmatrix} 0 & \cdots & \delta_{1p} \\ \vdots & 0 & \vdots \\ \delta_{p1} & \cdots & 0 \end{bmatrix} \tag{4}$$

3. Minimize the stress function using optimization. The tress function can be calculated in various ways, Equation 5. Present the most commonly used equation.

$$S(X) = \sqrt{\frac{\sum_{i \neq j=1..n}^{p} (\delta_{ij} - \|x_i - x_j\|)^2}{\sum_{i \neq j=1..n}^{p} (\delta_{ij})^2}} \tag{5}$$

The Metric MDS assumes that distances present a perfect representation of the similarity. To accept the complexity of the data, Non-Metric MDS avoid the linearity assumption and use the ranking of the distances between points instead of the actual distances. By using a monotonic transformation function $f(x)$ that represents the scaled proximities. Generally, a monotonic transformation function help transform a set of numbers into another set while preserving the order of the original set [246].

$$S(X) = \sqrt{\frac{\sum_{i \neq j=1..n}^{p} (\delta_{ij} - f(x))^2}{\sum_{i \neq j=1..n}^{p} (\delta_{ij})^2}} \tag{6}$$

7.4 Clustering methods

There exist multiple clustering algorithms [247]. They are commonly used in scientific research and data analysis. And their task is to:

a) Identify elements that belong to the same category/cluster in studies where the amount of categories is known.
b) Find the number of underlying categories in a dataset in studies where the number of categories is unknown.

Hierarchical clustering algorithms are based on the idea that elements in the same proximity belong to the same group. So it finds the maximum distance between cluster members. And consider members outside this range as members of another cluster. However, the hierarchical algorithms do not split the dataset but instead create hierarchal clusters based on found distances. Variables of this algorithm consist of the method of computing the distances and the linkage criteria. The algorithm can start clustering from the top by considering that the dataset is one cluster, and dividing it into smaller clusters based on the algorithm parameters. Or start from the bottom by considering every element unique [248].

Statistical distribution clustering is based on the idea that cluster members are most likely in the same statistical distribution, such as the Gaussian distribution [249]. On the other hand, density-based clustering methods use the idea that high-density areas separated by less dense areas most likely constitute a cluster of the same group members. Their technique is to find the borders of an area by ignoring isolated data points or by moving them to the nearest dance area [250]. This idea is developed further by grid-based clustering algorithms, where they divide the data space into even cells and incrementally compare the densities of each cell to its neighbour. This method starts with small clusters and merges them based on their densities [251].

K-means clustering methods focus on the idea that cluster members are distributed around the cluster centre. And its goal is to find the position of the centres for which the square distance to cluster members is minimum [252]. The K-means algorithm is an optimization problem; therefore, it requires running multiple times with different starting points. Their biggest drawback is that they assume the number of clusters is known [253]. However, in product design studies based structured method of response, the number of clusters is the number of study parameters.

Qiao et al. [245] suggested a method based on MDS and clustering for modular product design and compared the performance of the different clustering algorithms. Shieh and Yeh [254] used cluster analysis to choose the right sets of attributes in the study of shoe design. Kuroda et al. [255] proposed a method for clustering customers based on their product impression resemblance. Yamamoto et al. [256] proposed a clustering technique for grouping customers based on the similarity in product design evaluation. Kobayashi and Niwa [190] employed hierarchical clustering to group customers based on their decision rules similarities. The decision rules in this study derive from customer evaluations of existing products using the Rough Set method.

7.5 Rough set Analysis

The Rough set (RS) methodology is a mathematical tool for extracting hidden patterns from a data set [257]. With the ability to handle nonlinear patterns and the advantage of not requiring information besides the dataset. It considers the system $S = (U, A, V, f)$, with U being the finite non-empty set representing the data set. A is a collection of attributes. V stores the attributes values. And f is the function that links the attributes and the dataset. A is defined by the following expression:

$$A = C \cup D, C \cap D = \emptyset \tag{7}$$

Where C contains the conditional attributes, D contains the decision attributes. The process of rough set requires calculating the following approximations, $\underline{B}(X)$ and the $\overline{B}(X)$, respectively, the upper approximation set and the lower approximation set. The positive domain $POS_C(D)$. And the core attributes $Core(C)$. The dependencies $\gamma_C(D)$, and the importance degree $\sigma_{(C,D)}(a)$. Expressed as follows:

$$\underline{B}(X) = \{x | x \in U, B(x) \subseteq X\} \tag{8}$$

$$\bar{B}(X) \ = \{x|x \in U, B(x) \cap X \neq \emptyset\} \tag{9}$$

$$POS_c(D) = POS_{C-C_q}(D) \tag{10}$$

$$Core(C) = \cap\ Red(C) \tag{11}$$

The lower approximation $\bar{B}(X)$ combines elements contained in the set. While the upper approximation $\underline{B}(X)$ combines all the elements that are in the non-intersection. The positive region $POS_c(D)$ contains all the elements of the block U/D with q being a condition attribute. The $Core(C)$ is the set of attributes shared by all Reduction sets $Red(C)$. The Reduction $Red(C)$ contains the degrees of dependence between the condition attribute C and decision attribute D.

The goal is to find the subsets containing minimum attributes, with the $Core$ being the intersection of all subsets of minimum attributes. We calculate the indispensability of a condition attribute a by comparing the dependencies γ_C with and without it. $\sigma_{(C,D)}(a)$ calculates the importance of this attribute [258].

$$\gamma_C(D) = \frac{|POS_c(D)|}{|U|} \tag{12}$$

$$\sigma_{(C,D)}(a) = \frac{\gamma_C(D) - \gamma_{C-\{a\}}(D)}{\gamma_C(D)} \tag{13}$$

RS is useful for feature extraction, dimensionality reduction and decision rule generation. Ito et al. [259] employed the Rough Set method to analyze mascot design impression and its influence on design evaluation. Kang [260] used the RS method to determine the core aesthetic qualities of a product design and their importance degrees. The new synthetic designs respect each group's decision rule. In the method suggested by Shieh et al. [261], RS is used to study the relationship between product shape design, its colour and the effect on consumer perception. Regression and soft computing-based modelling

7.6 Regression and Soft computing-based modelling

Multiple linear regression methods are widely used in design research, particularly Kansei Engineering (KE) research. They help model the relationship between the design features and the consumer Kansei through the following equation:

$$\mathrm{y} = \alpha + \beta_1 \mathrm{x}_1 + \cdots + \beta_n \mathrm{x}_n + \varepsilon \tag{14}$$

y is the response, x_1, …,x_n are the predictor variables, and α, β_1, …,β_n are regression coefficients, generally estimated by the least square method, with ε being the error [262].

Nonlinear regression methods can solve complex design studies. The Support Vector Regression approach (SVR) [263] is an extension of the popular Support Vector Machine (SVM) approach [264]. SVR constructs a linear model $f(\mathrm{x}, \omega)$ in the high dimensional features space, representing the variable distribution mapped with the help of a kernel function, like the Radial Basis Functions or Sigmoid functions.

$$f(\mathrm{x}, \omega) = \sum_{j=1}^{p} \omega_j \mathrm{g}_j(\mathrm{x}) + b \tag{15}$$

ω_j, b are the coefficients of the non-linear transformations $\mathrm{g(x), j} = 1, \ldots, \mathrm{p}$. SVR performs linear regression in the features space using ε-insensitive loss while minimizing $||\omega||^2$ (reducing the model complexity). The loss function is expressed by:

$$L_\varepsilon\big(\mathrm{y}, f(\mathrm{x}, \omega)\big) = \begin{cases} 0 \text{ if } |y - f(\mathrm{x}, \omega)| \ \le \varepsilon \\ |y - f(\mathrm{x}, \omega)| - \varepsilon \ \ other\ wise \end{cases} \tag{16}$$

SVR use the principle of structural risk minimization, where the empirical risk is expressed as follows:

$$R(\omega) = \frac{1}{n}\sum_{j=1}^{n} L_\varepsilon\big(\mathrm{y}, f(\mathrm{x}, \omega)\big) \tag{17}$$

Considering ξ_i, ξ_i^* $\mathrm{I} = 1, \ldots, \mathrm{n}$ are the measurements of training samples deviation outside the ε-insensitive region. The minimization problem can be expressed as follows [265]:

$$\mathrm{Min}\ \frac{1}{n}\ \|\omega\|^2 + C\sum_{j=1}^{n}(\xi_i + \xi_i^*) \ \ \text{for} \begin{cases} y_i - f(\mathrm{x}_i, \omega) \le \varepsilon + \xi_i^* \\ f(\mathrm{x}_i, \omega) - y_i \le \varepsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0 \quad \mathrm{i} = 1, \ldots, \mathrm{n} \end{cases} \tag{18}$$

Soft computing refers to complex and flexible systems built to represent real applications [266], such as systems design problems [267–269], engineering design problems [270, 271], product design problems, and modelling the product design-response evaluation relationship [272, 273], where the Artificial Neural Networks (ANN) and optimization algorithms have known wide development [274, 275].

The fuzzy theory allows interpreting the uncertainty and vagueness of consumer choices in a mathematical form. It was found suitable for solving PDR problems. Hotta and Hagiwara [276] suggested a method for personal response modelling by adjusting group Kansei model rules to fit personal design response data; this is achieved using a set of fuzzy rules. Shen and Wang [272] suggested a creative thinking process to design a product that matches customers' preferences based on fuzzy theorem and ANN. Kang [260] employed the Fuzzy theory with the "Quality function deployment" method to associate the customer aesthetic qualities with product design characteristics. Dong et al. [277] addressed the topic of individual Kansei variance, suggesting a method based on fuzzy clustering and basic-emotion systems to transform the Kansei words into multisensory design elements.

Metaheuristic optimization algorithms have widespread use in various research fields due to their ability to solve challenging problems [278–280]. Product design studies also employ these algorithms in problems such as product form and attribute optimization [235]. Moreover, multi-objective optimization algorithms helped understand the association rules between product design and consumer response [281] and find the optimal design response for a group of diverse consumers [204].

7.7 Forward and Backward Kansei Engineering

The modelling applications focus on mapping the connection between design features and consumer perception. Modelling-based studies build mathematical predictive models that help predict design features corresponding to a specific perception (Forward), as well as the consumer perception corresponding to a design feature (Backward). It also allows estimating the perception of particular design features or combinations of design features.

An example of this type of research is presented by Xiong et al. [262], considering the application of mobile phone design. The approach first collected user perceptions from 40 participants about 32 mobile phone designs. Then construct a model based on Support Vector Regression (SVR) and Gaussian Radial Basis Function (RBF) to predict the users' perceptions of new designs. Shieh et al. also used the SVR method [236] combined with a multi-objective evolutionary algorithm for forward and backward modelling. Through their case study of vase design, they showed that clustering Pareto front solutions could suggest creative design ideas.

Chang and Chen [282] investigated the affective design elements of a car steering wheel, considering the aesthetic and ergonomic factors. Linear regression models were built to compare the consumer perception of individual components and the perception of the product as a whole. Akgül et al. [283] presented an approach for forward and backward modelling based on the Genetic Algorithm and Fuzzy linguistic summarization. In their case study, a cradle design was considered. In the backward model, the product design is input for one adjective as output. While In the forward model, one adjective is designated as the input corresponding to a complete design with a combination of eight variables.

A product design cannot be easily changed to satisfy the preference of a diverse customer base. Advanced models allow studying higher-level consumer response diversity and investigating design features that unify consumer perception to maximize customer satisfaction. Yamagishi et al. [284] presented an approach based on multiple regression analysis and hierarchical clustering for customer preference clustering. The most important design factors are selected based on the evaluation of each consumer cluster. And finally, find the design feature corresponding to the highest sensitivity in all consumer clusters. Kobayashi [187] developed a method based on multi-objective optimization to combine the design features that receive maximum unified customer perception, as intended by the designer. The Genetic algorithm solves two fitness functions, one for minimizing the variation of customer perception and the other for maximizing a specific perception.

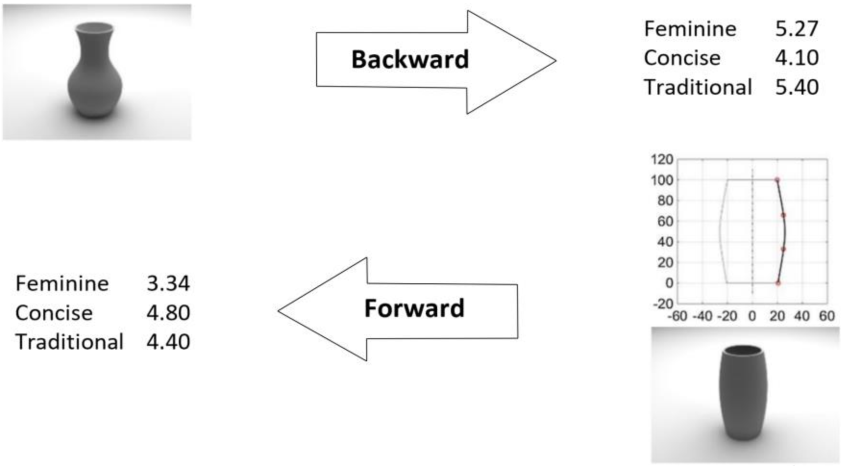

Figure 8. Illustration of the forward and backward modelling [236].

7.8 AI in product design response studies

The rapid advances in machine learning and optimization methods [285] plus the expansion of accessibility to big data [286] have led to the wide development of Artificial Intelligence (AI) applications in almost every domain. AI consumer for product design evaluation is an idea that several researchers are working on, we list below the most important axes of research.

In the axis of studying the profound connections between product design features and consumers' responses; Wu et al. [287] laid out the latest research and challenges in automatic aesthetic design evaluation using deep learning. Wang et al. [288] suggested a framework for mapping the consumer needs to design parameters using deep learning. McCormack and Lomas [289] studied the aesthetic evaluation using the Convolutional Neural Networks (CNN), trained on personal prior aesthetic evaluations. Zhou et al. [290] suggested a machine learning method for analyzing the consumers' design needs. Kobayashi et al. [291] proposed a method for associating the consumers' feedback to specific design features, using Gradient-weighted Class Activation Mapping (Grad-CAM) and CNN.

In the axis of simulating the consumers' response to product design; Pan et al. [292] introduced a deep learning approach based on the Siamese network of conditional GANs to predict the perception of different consumers of the product design aesthetics and visualize the corresponding design features. Dong et al. [277] suggested a fuzzy mapping method for modelling individual consumer affective needs. Zhou et al. [293] presented an approach that allows design aesthetics evaluation using CNN and aesthetic design generation using Generation Adversarial Network (GAN) with the help of manual sketching, thus reducing the investigative efforts. Yanagisawa et al. [294] proposed a database framework with embedded functions to estimate the product design's emotional responses.

And finally, in the axis of consumer-centred automatic design optimization, Kang et al. [295] presented an approach for real-time product form design interweaved with consumer preferences using the SVM method. Burnap et al. [296] proposed an automatic aesthetic design approach using GAN models of consumer design evaluation. Their application to car design showed that such an algorithm can suggest innovative design variations within the consumers' preferences.

8 Conclusion

Product design has reached an unprecedented level of sophistication; companies now understand that design is not only an issue of aesthetics and ergonomics but also an instrument to create complex consumer affect. Research has shown that such an affect exists and developed a broad understanding, both from the product design and human response sides. Vast progress has also been made in measuring and analyzing detailed consumer perceptions of product design.

Research has shown that we share some basic design preferences. For example, aesthetically, we like symmetry, curvature and complexity. We also tend to prefer design features that look familiar. And we highly value products after touching them or when they feel relatively heavier.

Measuring the real design response is challenging because some factors can influence the design evaluation, such as the environment of the product and the consumer mood at the moment of assessment. Also, how the product is evaluated can trigger one of the multiple potential cognitive biases. Researchers are required to pay extra attention to these biases, Low-level affect adjectives remain to be an efficient method for measuring the actual consumer's response to product design.

Several approaches have been created to analyze the product design response. We presented the commonly used methods and discussed their utility in current research. And discussed the current understanding of the connection between product design features and their corresponding affective responses, the tools allowing design researchers to produce new designs based on consumer design response models.

The Research has shown that there exist considerable individual differences. Recent research highlight that such differences can be linked to prior personal exposure to a design style and the personality scores in openness to experiences. Precision design studies are required to consider these individual differences.

Ethical Statement

Not applicable

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