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Designing the appearance of environmentally sustainable products

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Abstract

The study presented in this paper uses a mathematical model to measure the degree in which a product will be perceived as environmentally friendly from its physical attributes. A model based on genetic algorithms and neural networks was developed to predict the judgement of the users about environmental friendliness of different tables. Opinions of real users about a large set of tables were used to train the model. The results of the study suggest that, using this procedure in advanced stages of product design process, designers can determine the set of product's physical attributes that best convey the idea of "environmentally sustainable" to the customer. The analysis of the obtained model allows establishing how different product's attributes influence users' perception. From these results, the utilization of users' affective response models to design the appearance of environmentally sustainable products is discussed.

Keywords: Product design; product appearance; environmentally sustainable products; design tools.

Highlights

- A model to measure product' sustainability appearance from its attributes is developed.
- The objective is to optimize product design to transmit environmental friendliness to users.
- The approach presented can be used in advanced stages of product design.

1. Introduction

Consumer awareness and concern for environmental issues has grown in recent years. The global survey on Corporate Social Responsibility (CSR) conducted in 2012 in Nielsen (2014) revealed that 55% of consumers will pay extra for products and services from companies committed to positive social and environmental impact, and that 52% made at least one purchase in the past six months from one or more socially responsible companies. The same percentage of consumers checks product packaging to ensure sustainable impact. The results of a different survey conducted in 2007 by McKinsey to consumers from the eight world's major economies show that 87% consumers are concerned about the environmental and social impacts of the products they buy (Bonini et al., 2008). These consumers would prefer companies that promote measures for the production of safer and healthier products, consider the impact of their business practices on local communities, ensure the safety and health of their workers and implement policies of environmental sustainability (Gershoff and Frels, 2015; Luchs et al., 2010; Nielsen, 2011). Companies have significant opportunities to differentiate themselves by acting responsibly to improve not only corporate image but also willingness of socially committed consumers to buy their products. Therefore, companies should better understand consumer expectations and perceptions (Albino et al., 2009; Bonini et al., 2007; Gershoff and Frels, 2015).

The surveys mentioned above show a positive relationship between environmental attitude of consumers and Green Consumer Behavior; yet the market share of environmentally sustainable products is lower than expected when compared to the percentage of customers who claim to be interested in sustainable products (Dupré, 2005; Peattie and Crane, 2005; Rex and Baumann, 2007). The reason may be that consumers do not always know which environmental features characterize a sustainable product (Lin and Huang, 2012), or that many environmentally sustainable products do not meet consumers' expectations due to the gaps that exist between consumers' expectations and their perceptions of those products (Peattie and Crane, 2005; Tseng and Hung, 2013).

Companies apply communication strategies and conventional marketing practices in order to improve acceptance of sustainable products in the market (Delmas and Burbano, 2011; Rex and Baumann, 2007). Other measures consist of analyzing how certain aspects of the sales environment or packaging can influence consumer decision to purchase green products: price presentation (Lee Weisstein et al., 2014), eco-labeling (Atkinson and Rosenthal, 2014), using green color (Pancer et al., 2015), etc. However, companies have paid less attention to product design and appearance.

Previous studies show that environmental sustainability could be communicated to consumers through product's appearance (Hassi and Kumpula, 2009; Hosey, 2012), and that superior product aesthetic design has a positive effect on confidence and choice likelihood for sustainable products (Luchs et al., 2012). Even, some authors propose that products appearance can influence their environmental sustainability (Zafarmand et al., 2003). Luchs et al. (2012) suggests that it is especially important for firms interested in marketing sustainable products to develop market-leading product aesthetic design capabilities. However, very little work focuses on how to design the appearance of environmentally sustainable products, and little research on design tools for this objective can be found in the literature on sustainability. Some guidelines for environmentally friendly product's form design are found in Hassi and Kumpula (2009). For example, small products, plainness, natural material appearance, quality appearance or simplicity seem to be attributes related with positive environmental appearance of products. Murto et al. (2014) use a basic design tool (image boards) in shaping the appearance of products in early phases of design to draw conclusions about how consumers infer sustainability from products appearance.

Although these works suppose an important advance, there are more sophisticated design tools to achieve the objective of relating products' attributes with consumers' opinions. Using these tools could be useful to understand the way in which consumers establish relationships between the attributes of products and the environmental sustainability. In product design, the ability of a product to evoke emotions in the observer is becoming increasingly more important, since it has a decisive influence on purchasing decisions (Chuang and Ma, 2001; Creusen and Schoormans, 2005; Desmet, 2003; Holbrook, 1985). In the current market, a great variety of products of the same type can be acquired to sufficiently meet users' needs. Therefore, product's shape, aesthetic features, visual appearance and ability to convey to the user the objectives for which it was designed, are all key to the success or failure of a product (Bloch, 1995; Chuang et al., 2001; Crilly et al., 2004). Additionally, sales platforms such as the Internet limit the user-product relationship to visual interaction, meaning that it is the appearance of a product which defines the image the user has of it (Dahan and Srinivasan, 2000; Vriens et al., 1998).

This justifies the efforts carried out by many authors (Chen and Yan, 2008; Chen et al., 2006, 2002; Diego-Mas and Alcaide-Marzal, 2016; Han et al., 2000; Hasdoğan, 1996; Lai et al., 2006, 2005; Lin et al., 2007; Park and Han, 2004; Tsai et al., 2006; Yang and Shieh, 2010) to provide mathematical models which match the attributes of a product to the consumers' affective responses (hereinafter CAR models). These models can be used to estimate how a user will assess a product in the early stages of the design process. Product's design can then be adapted to evoke the desired emotional response prior to its launch.

Han & Hong (2003) contends that the user's affective response is based on a cause-effect relationship with the attributes of the product. In other words, certain product attributes lead to a certain user response. This is a basic assumption for the development of a CAR model, given that the model can be created by systematically analyzing the relationship between the users' responses and products' attributes (Yang and Shieh, 2010). Nevertheless, establishing such relationships is not easy given that there are several fundamental problems that must be solved. One problem is that the mental process carried out by the user from the time he receives the information regarding the product until the time he makes a judgment on it, is in practice, unknown. Other problems relate to how to codify the inputs and outputs of the models or to determining the mathematical technique whose use is most appropriate for obtaining the model. However, the fundamental problem relating to the development of CAR models stems from the variety of different users' opinions regarding a single product. Generally, the models are based on the premise that there is a cause and effect relationship between the attributes of the product and the user's response. Nevertheless, these relationships vary from one user to the next since their opinions are not based entirely on the attributes of the object. Individual and external conditioning factors such as personal taste, cultural environment, level of education, and personal motivations and aims will all lead the perception of each user to vary (Allenby and Ginter, 1995; Engel et al., 1995; Hoch et al., 1995). In the case of a model developed to predict if a product is perceived as environmental friendly, the personal environmental attitudes of consumers could be considered important external conditioning factors.

Diego-Mas and Alcaide-Marzal (2016) proposes a procedure to develop single users' affective responses models (SUAR models) that address some of the problems in CAR models' development. In the present paper, a SUAR model is developed to predict if a product will be perceived as environmentally friendly based only on its physical attributes. There were several objectives in this work. One of them was to introduce this kind of design tools in environmentally-friendly product design. These models have been proved to be useful for predicting user's impulse to purchase or judgements related to essential functionalities of the product. However, environmental friendliness of a product is a more specific judgement, and the relationships between product attributes and users' perception could be harder to find. If this main objective is achieved, a secondary objective will be to provide insights on the process by which consumers infer beliefs about environmental sustainability from the appearance of products. To do this, the relationships between inputs and outputs of the obtained model will be analyzed. Finally, previous aforementioned studies address the appearance of products in terms of seeking inspiration and locating guiding principles for the continuation of a development process. Our work focuses on more advanced stages of the product design process, when designers are dealing with different product options, and could take advantage of these tools to select the most appropriate set of product's attributes to transmit environmental friendliness.

Section 2 in this paper will be devoted to an overview of SUAR models. Section 3 will show a case study in which a SUAR model is developed to predict if users perceive a product as environmental friendly based on its attributes. Results will be shown in Section 4 and will be discussed in Section 5.

2. Overview of SUAR models

The development of CAR models stems from supposing that the user's affective response is based on a cause-effect relationship with the attributes of the product. However, the fundamental problem relating to the development of these models is the variety of different users' opinions regarding a single product due to individual and external conditioning factors. Taking the above into account, a SUAR model approach develops several CAR models for several single users. These individual models do not suffer from the dispersion of users' opinions and it is supposed that they will be more accurate. The disadvantage is that these models would only be valid for one user. However, although the perceptual relationships to be modeled are different for different users, if the opinions of a group of users regarding a selected sample of products are similar enough, it can be concluded that their perception processes and specific conditioning factors are similar. Consequently, by grouping users based on the similarity of their judgments, a mathematical model can be generated for a user representative of each one of those groups. With a certain margin of error, these models would be valid for all users included in their cluster. The mean market response could be determined weighting the response from each model by the relative size of the cluster containing the user from which the model was obtained. Several conditions must be fulfilled to develop models with this procedure (Diego-Mas and Alcaide-Marzal, 2016). Well-defined user clusters are needed. These clusters must be dissimilar between them and, at the same time, the opinions of the users inside each cluster must be similar. If this condition is not achieved, individual models will not be representative of the users in their cluster.

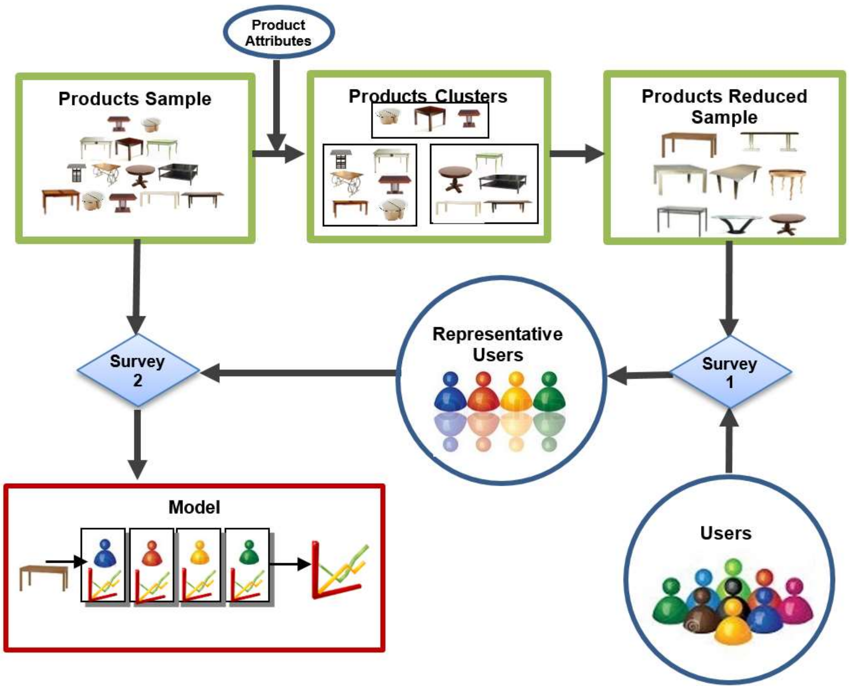
It should be recalled that other approaches, like using the mean opinion of all users to train a model, could obtain results that outperform this approach when trying to predict the market global response. However, apart from less effort to develop the model, a SUAR model has the advantage of being that the distribution of opinions of the users can be known.

2.1. Developing the model

Figure 1 shows the procedure to obtain the model. After having determined the type of product and the opinion for which a model is to be created, a sufficiently large and varied sample of products of this type is selected, and an image of each product is then obtained. Then, the attributes defining the appearance of the product are determined. The attributes can be qualitative variables (such as color) or quantitative (number of different colors). In the case of the qualitative attributes, the different levels for each of the attributes (red, green, blue, etc.) is then determined. The number of attributes should be sufficient to completely define each product.

A large enough group of potential users for the product chosen is selected and divided into clusters. The criterion to group the users is the judgment made with respect to the different products subject to study. A small set of products representative of the different types available in the market (Products Reduced Sample) is shown to the users. To conform the Product Reduced Sample (PRS), the products are grouped according to their attributes, and depending on the number of clusters, one or two products are chosen from each cluster.

Figure 1. Procedure to obtain the users' response model



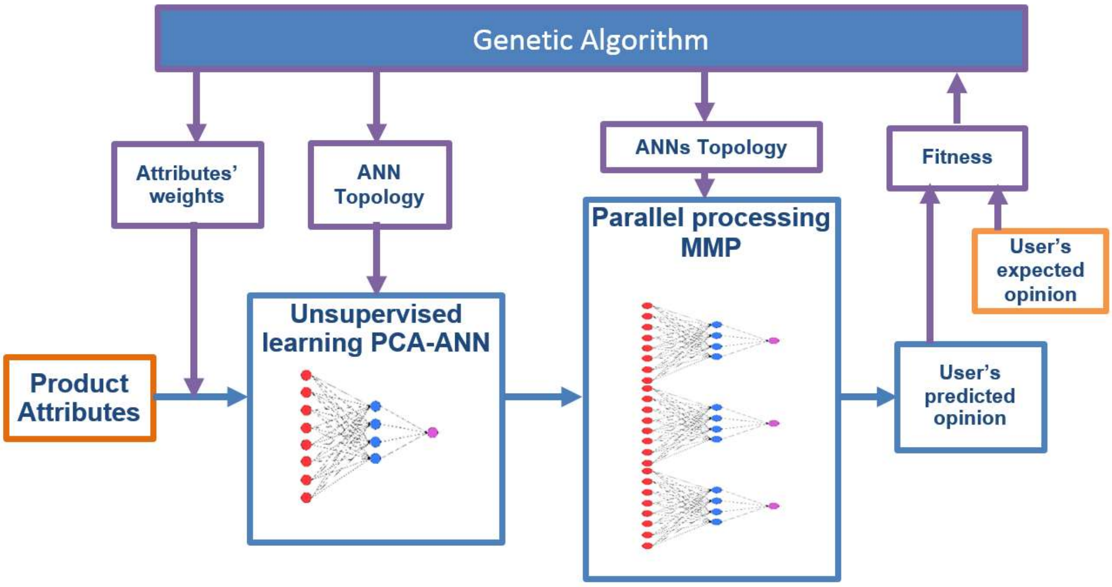
After having obtained users' responses regarding the PRS, they can be grouped into clusters and a representative user from each group can be chosen. Each of the representative users is interviewed again, and this time they are requested to give their opinion on the complete sample of products. The data obtained is then used to obtain a model of each of the representative users.

The individual mathematical models use Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs). An ANN is a mathematical model that represents a distributed adaptive system built by means of multiple interconnecting processing elements, just as real neural networks do. ANNs are used in many fields of research (design, psychology, robotics, biology, production or computer science, to name a few) (Principe et al., 2000) due to their ability to adapt, learn, generalize, organize or cluster data. Given their ability to learn (in comparison with sequential systems), they are instruments which are suitable for generating models such as those described in Section 2, there being various uses of ANNs in this area

(Chen and Yan, 2008; Dasgupta et al., 1994; Hsiao and Tsai, 2005; Ishihara et al., 1997; Lai et al., 2006, 2005; Tsai et al., 2006; Yang and Shieh, 2010).

The training process of ANNs is as follows: the users' answers to the products sample are grouped into three sets of data: the training set, which is used to train the model, the cross validation set, which is used during the training to avoid overfitting (Sarle, 1995) and the test set, which is used to verify the adjustment of the model once trained. The training set is presented to the network and the outputs obtained in each case are compared against the desired output to calculate the network error. Then, the weights of neuron connections are modified according to the selected training algorithm in order to minimize this error. This process is repeated until a criterion previously established is reached, for example, when the error value gets to a threshold or stops decreasing.

Figure 2. Generation of neural networks using genetic algorithms



Each individual model is composed of two ANNs, one unsupervised learning ANN and another parallel processing ANN (Figure 2). The information regarding product attributes, which has been appropriately filtered and weighted, reaches an ANN, which must then pre-process and combine it to give rise to new significant information, transforming the input samples into a new space where the information about the samples is retained, but the dimensionality is reduced. The type of network is an unsupervised learning network which performs a principal component analysis (PCA-ANN). This network enables significant characteristics of a group of data which have not been previously classified to be differentiated since the network attempts to find redundancies and patterns internally based on which to group the information. An ANN of this type will have as many inputs as attributes established to define the product. The number of outputs will be determined during the training of the model. The outputs of the PCA-ANN will be used as inputs for a second ANN, a Modular Multilayer Perceptron (MMP). This kind of networks are actually several networks which process the inputs in parallel and re-combine the outputs to obtain a common result (Principe et al., 2000).

During the training of the model, it is necessary to determine which ANN structure is most appropriate for solving the problem. Specifically, the following should be established: the weight of each product attribute in the response, the number of PCA-ANN outputs (eigenvalues), the number of layers of the (MMP), the number of neurons by layer, the weights of the synaptic connections between the neurons and the type of transfer function of each neuron. Given that the number of parameters to be determined is large, it is advantageous to use a metaheuristic to solve the problem. For this purpose, a GA (Dam and Saraf, 2006; Kim et al., 2005) is used during training to establish the most appropriate combination of parameters (Figure 2).

GAs perform a stochastic guided search based on the evolution of a set of structures as it occurs in natural species evolution (Goldberg, 1989). The starting point is a set of problem solutions called *individuals*. This first set is randomly generated and called *initial population*. Each individual is an ANN, and it is coded by a finite length chain called *chromosome*. Each individual solution is evaluated using an evaluation function to determine its suitability for the requirements of the problem. The population undergoes several transformations that yield a new population (*new generation*). These transformations are guided by some genetic operators, the most common being *selection*, *crossover* and *mutation*, which combine or modify the chromosomes representing the individuals. *Crossover* and *mutation* operators are applied to create a new generation of *individuals* that inherit the best characteristics of their predecessors. For this purpose, the *individuals* that will participate in each of the genetic operators, and those that will survive and pass on to the following generation, are selected previously by mean of the *selection* operator. The process is repeated with the new set of *individuals* until a certain number of iterations is reached, or until a certain number of iterations without a new best solution have been performed, making the *individuals* evolve to better solutions to the problem.

Characteristics and development process of SUAR models could be reviewed in Diego-Mas and Alcaide-Marzal (2016).

3. Materials and methods

A case study was used to determine to what extent a SUAR model can predict consumer opinion on whether a product is perceived as environmentally friendly from its physical attributes. The product was selected taking into consideration that, a priori, the weight of the non-functional attributes had a significant impact on the users' assessments. The product finally chosen was tables, including end tables, coffee tables, console tables, dining tables and similar products. It could be considered that this product is simple enough, and its non-functional attributes, such as product appearance, affect the final selection of a product.

To get the consumers' opinion on the products, they were asked the question "Does this table appear to be environmentally friendly?". The question was asked while showing users each product. No labels, packaging or further information of the products were provided to the interviewed customers since the purpose of this work was to evaluate to what extent product design communicated environmental awareness to customers. According to Pancer et al. (2015), the presence of cues traditionally used to signal environmental friendliness increases the ability with which consumers are initially able to categorize the product as environmentally friendly, and this is a critical determinant of consumers' responses. However, at present there are many small and large manufacturers of home furniture that manufacture these products touting them as eco-friendly, claiming that they are made from raw materials that are harmless to the environment, avoid deforestation or use of protected species, and employ non-polluting manufacturing processes. In this way, the consumer knows that these products could be manufactured respecting the environment.

3.1– Product sample

Several specific journals of home furniture and websites of factories that manufacture tables were consulted to obtain product samples which represent all the different types of the product and its most common attributes. Rather than using real products, images of the products can be used to develop the model. Using images of the products makes it easier to develop the models without affecting the quality of the results, since photographic representation suffices to communicate most of the concepts and sensations in the same way that the real product would do (Artacho-Ramírez et al., 2008).

Images of 164 tables were gathered. The environmental sustainability of the tables was not a criterion for selecting them. Although our objective was to relate the product's attributes with the degree in which users perceive the table as environmentally friendly, tables without this condition could have attributes that elicit this sensation. Conversely, an environmentally friendly table may seem otherwise. After analyzing the sample of tables, and the information obtained by consulting specialized journals in home furnishings, 18 relevant product attributes were identified: Primary Material, Secondary Material, Primary Color, Secondary Color, Finish, Trend, Board form, Board embossment, Complexity, Geometry, Edges shape, Legs form, Extendable, Number of legs, Board levels, Legs frame, Reinforcements and Height. Each of these attributes had different numbers of possible levels. Finally, 75 attribute levels were identified. As an example, seven attribute levels were assigned to "Primary Material" (metal, wood, glass, plastic, marble, carton and other). One attribute level was then assigned to each of the 18 attributes for each of the 164 tables. Afterwards, in order to obtain the PRS, the 164 cases were clustered into groups based on their attributes levels using a TwoStep cluster algorithm (SPSS_Inc, 2007). This procedure enabled clusters to be created based on both continuous and categorical variables and the automatic selection of the number of clusters. The TwoStep cluster algorithm was applied to the sample of 164 tables, and the algorithm was enabled to determine the appropriate number of clusters, which was set at a maximum of 10. The products were clustered via the Bayesian information criterion and the similarity among clusters was measured using multinomial probability distribution among the variables. As a result of this analysis, 8 clusters were established, each of which contained from 12 to 34 tables. A table from each cluster was chosen randomly to form the PRS. The same selected tables formed the test set that would be used to generate the individual models. On the other hand, 32 tables were selected to form the cross validation set (approximately 20% of the available data) so that all the clusters were represented in the data set. The remaining 124 tables formed the training set.

3.2– Selection of Representative Users

114 people were chosen to be interviewed (51 men and 63 women) with age ranging from 21 to 46 years old. Although it is difficult to define the appropriate sample size for each study, according to Chambers and Wolf (1996) and Mammasse and Schlich (2014), sample sizes which are over 100 are generally considered appropriate for most market studies. Engelbrektsson (2002) and Karlsson et al. (1998) concluded that experience and knowledge were essential factors to assess specific matters about a product. Also, Schoormans et al. (1995) suggest that product expertise allows customers to understand product information faster, to fill in missing information, and to discriminate the important aspects of the product. In this study, respondents were not requested to be particularly interested in eco-products because the main purpose of the survey was to develop an overall model; yet they were requested to know the meaning of environmentally friendly and what features should be expected of a product to be considered eco-friendly.

In order to conduct the survey, a web application was developed which enabled each product to be presented to the respondent in random order together with the judgment the respondent was required to make (Does this table appear to be environmentally friendly?). The responses were to be given on a six-level Likert scale, and ranged from "Completely in agreement" to "Completely in disagreement". No neutral option was provided, therefore, respondents were forced to opt for one side of the scale. Subjects were permitted to take as long as they needed to answer the survey. The average time to complete the rating was one minute and six seconds. The subject's answers were numerically codified, being assigned a whole number ranging from -3 for "Completely in disagreement" to 3 for "Completely in agreement". The opinions of 114 potential users were obtained regarding 8 tables representatives of the different types of this product on the market. This information was used to group the users based on how similar their opinions regarding the products were.

For the purpose of obtaining the Representative Users (RUs), a k-means clustering analysis was carried out based on the responses given for each table using SPSS, 16.0. This analysis was performed to obtain groups of users with homogeneous opinions. The centers of the clusters were automatically selected and updated after each assignment of a case to a cluster. The number of case reassignment reiterations was limited to 15 and the distance between cases was measured using a simple Euclidean metric. K-means clustering requires the specification of the number of clusters into which the cases are to be divided. Therefore, various analyses were carried out with different numbers of clusters. The criterion for selecting the appropriate number of cluster was to obtain the maximum distance between the centers of the obtained clusters and the minimum distance between the users and the center of their clusters.

Based on these rules and the number of cases per cluster, 4 significant clusters were identified. Convergence was achieved in the sixth iteration in which there was no change in the cluster centers. Given that the iterative resolution of the analysis was not invariable with regard to the order of the cases, the stability of the solution was evaluated by comparing the results of the same analysis with different orderings of the cases. 21, 35, 25 and 33 users formed the final clusters. To choose a RU from each cluster, the distance of each user in a cluster to the center of this cluster was analyzed, the users closest to the center of each cluster being chosen. Four RUs were obtained in this manner.

3.3 – Obtaining individual models for representative users.

Each of the four RUs was interviewed and requested to take part in the study, for which they were financially rewarded. The survey previously conducted was then repeated, but now including the total sample of 164 tables. The survey was developed over different sessions to avoid the effect of boredom (Brace, 2013; Savage and Waldman, 2008). The tables were presented to each user in random order in order to prevent the possible effect of having presented the products in same order. The users' responses, on a Likert Scale of -3 to + 3 were standardized to range from -1 to + 1, and the standardized responses were then used for training the individual models. Populations of 30 chromosomes were used in the GA and the maximum number of generations was set at 100. The objective function employed was to minimize the mean square error (MSE) in the cross validation data set. The MSE was measured on the outputs of the standardized model ranging from -1 to 1. The crossover probability was set at 0.9 and the mutation probability at 0.01.

The GA must determine the number of layers of the ANNs, the number of neurons in each layer, the transfer function in each neuron (which could be linear, hyperbolic tangent or logistic sigmoid) and some parameters of the learning rule as step size and momentum (Dam and Saraf, 2006; Kim et al., 2005). The GA was allowed to vary the number of neurons in each layer of the PCA-ANN (number of principal components) from 3 to 15. Sanger's learning rule (Oja, 1992; Sanger, 1989) (also called Generalized Hebbian Learning) was used during unsupervised learning training stage. The MMP could have one or two hidden layers and the number of neurons by layer could range from 5 to 20 in the first layer and from 2 to 10 in the second layer (Sarle, 1995). The MMP learning algorithm was Back Propagation with Momentum (Rumelhart et al., 1986). The learning rate for the hidden layers could range between 0.1 and 0.4, and between 0.1 and 0.2 for the output layer. Momentum ranged from 0.1 to 0.3 for the hidden layers and from 0.1 to 0,.2 for the output layer. The maximum duration of the unsupervised learning phase was set at 3,000 epochs, with a learning rate of 0.01 decaying to 0.001. The minimum network training passes for the MMP were 500 and the cut off was 5,000.

4 - Results

The average GA run time required to obtain the individual models was 1 hour and 31 minutes on a PC with a 3.60 GHz processor and 12 GB RAM. Table 1 shows the characteristics of the models found. The MSEs in this table are the errors committed by the model when predicting the users' opinions on the tables of the test set. These products were not used for training the model, and using them makes it possible to measure whether the models are able to generalize their results. The models obtained for each RU differ not only in terms of the weight of the connections among neurons, but also in the number of principal components of the PCA-ANN, the number of hidden layers and the number of neurons in each layer of the MMP. On the other hand, the activation function type of neurons of each layer differs across models, being logistic sigmoid the most commonly employed.

Table 1. Characteristics of the best models obtained for each RU.

	RU 1	**RU 2**	**RU 3**	**RU 4**
Hidden Layers	1	2	1	1
Neurons in the PCA-ANN	14	9	12	12
Neurons in the MMP first hidden layer	15	16	18	17
Neurons in the MMP second hidden layer	-	9	-	-
Test MSE	**0.6751**	**0.3954**	**0.3211**	**0.7374**

Table 2 shows the obtained results. For each cluster of users, Table 2 shows the RU’s opinion, the prediction of the model corresponding to the cluster and the mean of the actual opinion of all user of the cluster. The RUs opinions are the actual responses for each product in the PRS of the user selected to develop the model of the cluster. The Model row shows the prediction for each product obtained using the model for the cluster. Finally, the Cluster mean row shows the mean of the responses for each product calculated using the opinions of all users belonging to the cluster. The last column of Table 2 presents two MSEs for each cluster. The first one is the MSE committed when using the model results to predict the RU's opinion. The second one is the MSE when using the model to forecast the mean opinion of all users in the cluster.

In order to predict the global rating of tables it is necessary to calculate the mean of the values predicted for each individual model weighted by the percentage of users represented by each model according to equation 1.

$$P_i = (\sum_{m=1}^{N_m} p_i^m . n_m)/N$$

Eq. 1

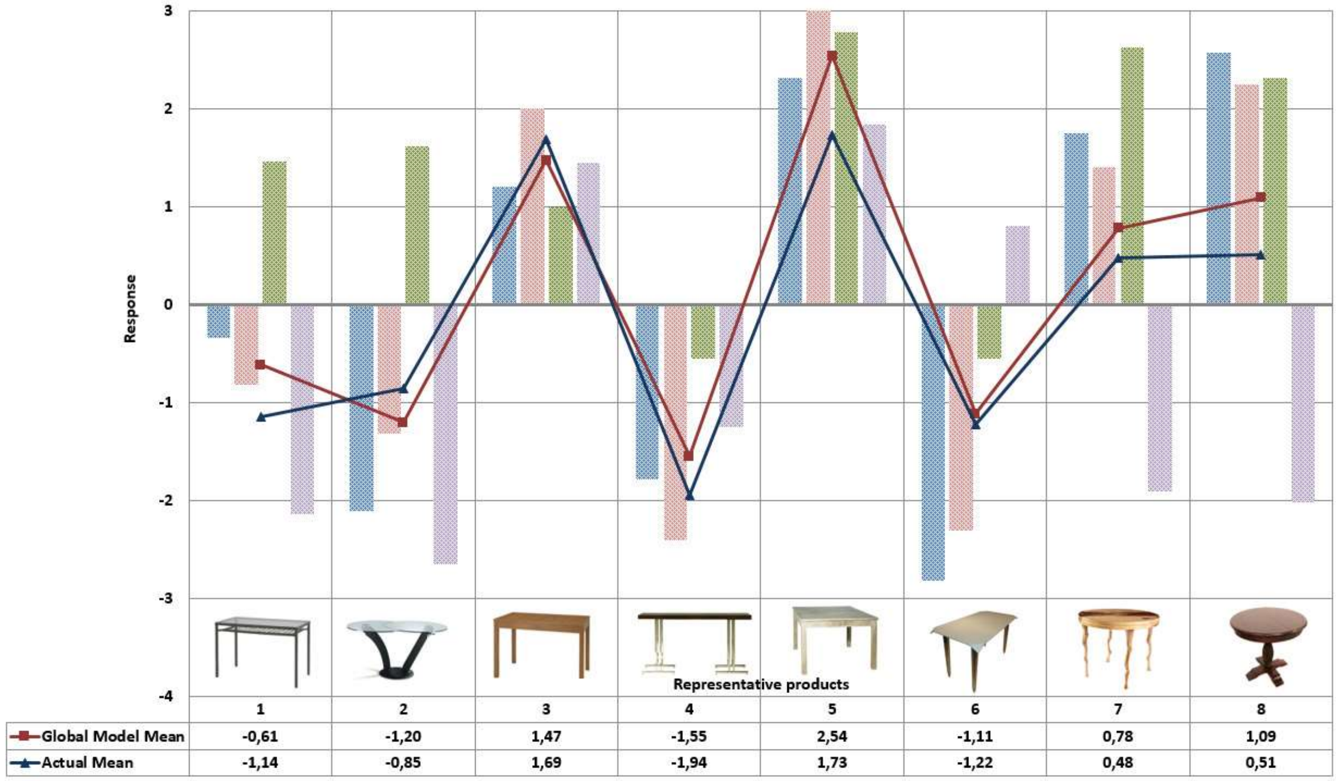
Where:

- P_i is the global rating predicted for the product *i*.
- N_m is the number of individual models developed.
- p_i^m is the assessment of product *i* predicted using the individual model *m*.
- n_m is the number of users belonging to the cluster of users *m*.
- N is the total number of users employed to develop the models.

Table 2. Representative users' opinions, models' predictions, and clusters' mean opinions on Reduced Product Sample.

		Product								
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	
										**MSE**
CLUSTER 1	RU1	-1	-3	2	-3	3	-2	1	2	0.6751
	Model	**-0.34**	**-2.10**	**1.20**	**-1.78**	**2.32**	**-2.82**	**1.75**	**2.57**	
	Cluster mean	-0.95	-1.67	1.66	-1.95	2.24	-1.71	1.57	1.05	0.5480
CLUSTER 2	RU2	-2	-2	2	-3	3	-3	2	2	0.3954
	Model	**-0.81**	**-1.32**	**2.01**	**-2.40**	**3.17**	**-2.30**	**1.41**	**2.25**	
	Cluster mean	-1.71	-1.60	1.63	-2.43	1.63	-1.86	1.35	1.71	0.4889
CLUSTER 3	RU3	1	1	2	-1	3	-1	2	2	0.3211
	Model	**1.46**	**1.62**	**0.99**	**-0.55**	**2.78**	**-0.55**	**2.63**	**2.32**	
	Cluster mean	1.12	1.16	1.32	-0.84	2.16	-1.2	1.52	2.08	0.3271
CLUSTER 4	RU4	-3	-2	1	-2	1	2	-1	-1	0.7374
	Model	**-2.14**	**-2.65**	**1.45**	**-1.25**	**1.84**	**0.81**	**-1.90**	**-2.02**	
	Cluster mean	-2.36	-1.06	2.06	-2.24	1.18	-0.24	-1.94	-2.30	0.6942

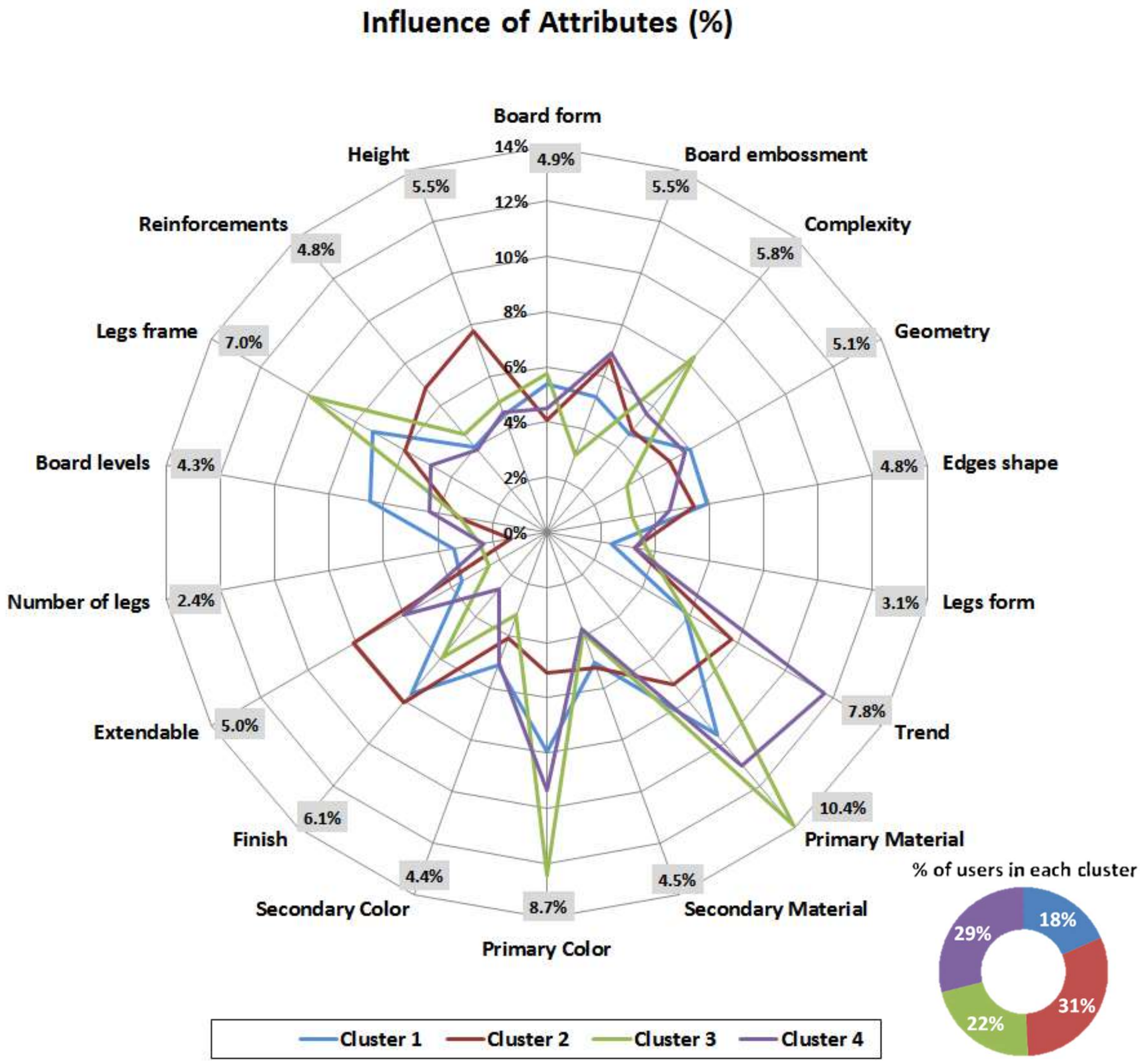
Figure 3. Mean rating of the Reduced Product Sample by all users (Actual Mean) compared to the rating obtained using the mathematical models (Global Model Mean).



These values were calculated using the opinion of all the 114 users interviewed in this study. The Global Model Mean represents the mean rating predicted by the SUAR model obtained in this study calculated using Equation 1. The MSE between the predictions of the SUAR model developed in this study and the actual mean of the responses was 0.2139.

Finally, using the model obtained for each cluster, a sensitivity analysis was performed in order to measure the influence of each attribute on the degree in which the product seems environmental friendly. In this case, it was measured the effect that each neural network's inputs was having on the network's output. This provides feedback as to which inputs are the most significant. To perform this analysis, the inputs to the network are shifted slightly (dither) and the corresponding change in the output is reported (Principe et al., 2000). Finally, the influence of each input on the output change is calculated as a percentage. Figure 4 shows the results obtained setting dither at 0.1. For each cluster of users the percentage of influence of each attribute is shown, as well as the mean value over the corresponding axe.

Figure 4. Percentage of influence of each attribute on the degree in which the tables seem environmental friendly by cluster. The mean percentages are shown over each axe.



5. Discussion

Sustainability can be transmitted to consumers through product attributes. Product aesthetics, oriented towards sustainable appearance, improves confidence of consumers in product sustainability and increases purchasing decisions of sustainable products (Luchs et al., 2012). It could be said that products should not only be eco-friendly, but should also appear to be so. Therefore, it is important for manufacturers interested in sustainable products to take advantage of the capabilities of product's appearance to communicate their sustainability friendliness and to give clear references to their environmental credentials.

Advances have been made in this regard (Hassi and Kumpula, 2009; Murto et al., 2014) that suggest guidelines or tools for early phases of product's design. These procedures are intended for exploratory stages of development, when designers are looking for inspiration and the particular characteristics of the product have not been defined. Our work is destined to more advanced design phases, when products are partially defined and designers are looking for a combination of a set of attributes that best transmit the sustainability friendliness. Finding this optimal product is not an easy task due to the complex relationships between products' physical attributes and users' perceptions. For example, white and green colors are usually associated with sustainability friendliness, but it strongly depends on the type of product and on other attributes like textures or shapes. Therefore, using mathematical models of the users' perceptions can be useful in this process.

The results obtained in this work lead us to conclude that the mathematical model found seems able to predict the degree in which a product will be perceived as environmentally friendly depending on its design attributes. The individual models obtained for each RU are capable of predicting individual users' judgments with enough accuracy. After having obtained the individual models, the mean response of all users can be obtained by weighting the responses of the individual models using the size of each cluster of users.

The development of models to predict users' opinion requires a lot of effort and survey time. Many users and many responses by user are necessary to generate the data to obtain the statistical models. This study has used a SUAR model, a different approach to generate models that looks for reducing the amount of time and effort to obtain a market model. It should be recalled that other approaches, like using the mean opinion of all users to train a model, could obtain results that outperform this approach when trying to predict the market global response. However, apart from less effort to develop the model, a SUAR model has the advantage of being that the distribution of opinions in each cluster of users is well known.

As stated before, several conditions must be fulfilled to develop models with this procedure. Well-defined user clusters are needed. These clusters must be dissimilar between them and, at the same time, the opinions of the users inside each cluster must be similar. If this condition is not achieved, individual models will not be representative of the users in their cluster. The obtained results show that this condition seems to be accomplished in our case study. The clusters of users are obtained using their opinions about a set of products. Therefore, it could be supposed that the users belonging to the same cluster share a similar decision making process to decide if a table seems environmental friendly (Diego-Mas and Alcaide-Marzal, 2016).

The results of the sensitivity analysis performed in this work show that users of each cluster use different criteria to judge if a table is environmentally friendly. The distribution of the attributes' weights is more uniform in clusters 1 and 2 than in clusters 3 and 4. Users from cluster 3 give much importance to Primary Material (13.88%) and Primary Color (12.42%). The most weighted attributes in cluster 4 are Trend (11.65%) and Primary Material (11.04%). In clusters 1 and 2 there are not attribute's weights over 8% except Primary Material in cluster 2

(9.61%). If we consider all clusters, Primary Material, Primary Color and Trend seem to be the most important product attributes when the users judge if a table is environmental friendly. On the other hand, the number of legs of the table seems to be of little importance.

From the sensitivity analysis and the results for each cluster some hypotheses could be stated. For example, although users in cluster 3 and 4 consider the Primary Material of a table an important attribute, they assess this attribute in different ways. While users in cluster 4 seem consider negative using metal or glass as raw material for a table, users in cluster 3 consider it positive. This difference could be associated with a different knowledge and perception about lifecycle, reuse and recyclability of these materials between users. Consumers do not always know what makes a product sustainable (Lin and Huang, 2012), and users' level of knowledge influences the way in which the product is perceived. For example, industrial designers perceive products in a different way than common users (Hsu et al., 2000). Another example of information that could be extracted from the sensitivity analysis is that the attribute Trend is one of the most weighted mainly due to users in cluster 4. For these users the table style seems to be good indicator of the environmentally friendliness of a table, and it seems from the results that old-fashioned tables are assessed negatively. However, these hypotheses must be validated in future researches. In this work, we looked for direct relationships between the attributes of the products and perceptions of generic users. Therefore, in the case study, the environmental concern or knowledge of the users has not been used as a criterion for selecting them. In the same way, the sample of tables was conformed without considering their actual environmental respect, and cues to signal environmental orientation of product (as labels or brochures) have not been used. It would be advantageous to analyze if the users in the same cluster share other similar characteristics in addition to their opinion over a set of products. For example, a future research could determinate if users particularly interested in environmental friendly products or having good knowledge about this kind of products belong to a specific cluster. If users of this cluster are supposed to be green consumers, green manufacturers could design tables specifically oriented to users of this cluster, given that it is supposed that these users translate their environmental concern into actively purchasing green products (Leonidou et al., 2010).

In product design field it is well-known that price has influence in product's perception and choice. Firstly, price could act as a filter to eliminate certain alternatives and, secondly, price may become a part of the decision process, particularly if price differences between the alternatives are perceived as significant to the customer (Monroe, 1982). Something similar occurs with brands (Dawar, 1994). In this paper, price and brand of the products were not included in the survey. This is because the objective was to develop a tool useful in early stages of the product design process, when it is difficult to establish the final price of the product. Moreover, the price could not be considered as a direct designer's choice, but the consequence of the selection of the raw materials and the production processes.

In the case study of this work a SUAR model has been developed to predict the degree in which users judge if a table is environmentally friendly. Although this kind of models have been applied to other products in previous works (Diego-Mas and Alcaide-Marzal, 2016), future researches must develop models for more complex products. The number of attributes to be considered in more complex products may be larger. Therefore it may be more difficult to obtain the mathematical models because of the larger number of model's input variables. Moreover, in complex products more complex relationships between the attributes may be present, making harder to fit the model.

6. Conclusions

This paper proposes a procedure to develop single users` affective responses models (SUAR models), based on artificial neural networks and genetic algorithms, to predict if a product will be perceived as environmentally friendly based on its physical attributes. The developed global model is formed by several sub-models, one for each cluster of customers. Therefore, it is possible to obtain the predicted perception of environmental friendliness of a product for each cluster of customers. A sensitivity analysis can be used to establish how product' attributes influence the perception.

The procedure described may prove useful to manufacturers and designers interested in developing environmentally friendly products. The model can be applied in design stages in which products have been partially defined, and where designers are looking for the best combination of product' attributes in order to transmit to the future customers the sustainability friendliness of the object. An initial conceptual design of a product could be introduced to the model obtaining the predicted perception. Then, the designer could vary the product design checking how the variations affect the customers' perception and, finally, obtaining the most suitable combination of attributes for the desired market response.

Using this kind of model manufacturers and designers interested in developing sustainable products can take advantage of the capabilities of product's appearance to communicate their sustainability friendliness to consumers, beyond the usual way of tagging the product as eco-friendly.

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