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An Interactive Genetic Algorithm for the Study of Product Semantics

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Abstract: This study uses an Interactive Genetic Algorithm (IGA) for eliciting users' perceptions of products. It aims to understand perceptions, and to determine the product's attributes that contribute to reinforce - or inhibit - a given semantic dimension. The product proposed to illustrate the study, defined in collaboration with the Renault Company, is a digital instrument panel, integrated in a car dashboard, and the semantic dimension considered is its "sportiness". After a parameterization of the instrument cluster, an interactive assessment test, based on IGA, is conducted on different products' pictures with a panel of 30 participants. The IGA test proposes a set of 8 parameterized designs, which are iteratively presented to each participant with their pictures via an interactive interface. From these designs, the user has to select the most representative ones according to the considered semantic dimension (sportiness). From iterative choices of the user, the results show that the design of the product converges toward representative designs of the semantic dimension. We present in the paper the analysis of the results of the IGA test, using Hierarchical Ascendant Classification (HAC), univariate and multivariate analysis. The effect of the design variables and their different modalities on the sportiness of the product is discussed. The agreement between the different participants is also studied, to uncover different typologies of products and identify design trends. The results show that IGA can be an interesting alternative to classical rating tests on experimental designs, used in conjoint analysis or in Kansei Engineering.

Keywords: interactive genetic algorithms, product semantics, user centered design, multivariate analysis.

1. INTRODUCTION

Emotions elicited from product appearance may enhance the pleasure of using things and design for emotions is now an important topic in engineering design (Barnes & Lillford, 2009) The development of successful products requires the control of product semantics, the “symbolic qualities of man-made forms in the context of their use and application of this knowledge to industrial design” (Krippendorf & Butter, 1984). To manage the risks of design projects, companies must control that a product matches the design brief, defined by specific semantic dimensions. For example, the digital instrument cluster of a sporty car must inspire “sportiness" to customers, and the company must control since the early stages of the project that the design decisions are in agreement with this connotation along the design process. The challenge for designers is to understand what “sportiness” means to customers, in order to translate it into relevant design attributes. Even if designers are trained and skilled to understand customers, capture trends, and make innovative proposals, discrepancies may occur between designers’ and user’ product perception (Hsu et al., 2000). Furthermore, design decisions concerning the materials or the manufacturing processes may be in conflict with the initial designer intend. Therefore, to assist designers and engineers in their design decisions and to confirm their proposals, an active research field in product design concerns the analysis of end-users’ evaluations, in order to extract useful information for product innovation (Hsiao, 2002) (Orsborn et al., 2009).

In this context, a first category of contributions concerns the modeling of customers’ perceptions and preferences (Hoyle et al., 2009). Conjoint analysis, the typical decomposition method of preference, initiated in marketing, has now several applications in design (MacDonald et al., 2009) (Wassenaar et al., 2005). Conjoint analysis shares similarities with the Japanese Kansei engineering, a design method to account for user’s feelings and perceptions (Nagamachi, 1995). From subjective measurements of the user’s “Kansei”, obtained generally with the semantic differential method and adjective pairs, different statistical models are proposed to translate the user’s perceptions into design elements and take design decisions. The design of a car control panel using multivariate analysis and partial correlation coefficients is for example proposed in (Jindo & Hirasago, 1997). In the same spirit, the influence of slight changes in product attributes on user’s emotions using an ANOVA model is presented in (Artacho et al., 2010). All these approaches have in common subjective assessments of users, and assume a mathematical model (defined a priori) between the perceptions/preferences and the design attributes.

A second category of methods for the analysis of users’ evaluations is not model-based and uses human-computer interactions. In this case, an algorithm gradually refines the propositions made to the users, for example with interactive evolutionary computation (IEC), a category of methods where the user plays the role of the evaluator in an evolutionary process (Takagi, 2001). In IEC, the user assesses the fitness of the population (adaptation of the population to the problem), by choices or ratings for example. Particular cases of IEC are IGA (Interactive Genetic Algorithms), where genetic operators such as recombination, crossover, and mutation are used to modify design samples (Kelly, 2008). This method has been used to capture aesthetic intention of participants for the design of cartoons (Gu et al., 2006), car’s silhouettes (Yannou et al., 2008), for preference modeling (Kelly et al., 2011). IGA have also been tested in previous studies for the design of table glasses (Poirson et al., 2011) or cars’ dashboards (Poirson et al., 2013). These studies confirmed their utility to extract designs trends and to obtain a final product representative of a determined semantic dimension.

We present in this paper a study using IGA to investigate product semantics. An experiment is conducted with a panel of participants who is charged to assess the degree of “sportiness” of the digital instrument panel of a car dashboard. The objective is to show how IGA can be used to understand a specific semantic dimension and to extract representative design attributes. We propose in this paper to show how the results of an IGA test can be analysed to understand the relations between design attributes and a semantic dimension of the product, assessed by the participant. An additional objective of the paper is to show how to account for inter-individual differences in the perception of the semantic dimension.

The paper is organized as follows. A short background on Interactive Genetic Algorithms is presented in section 2. After a description of the parameterisation of the digital instrument cluster, Section 3 presents the organisation of the IGA test. Section 4 presents the results. Conclusions are drawn in section 5 on the main contribution of this paper and recommendations in product design.

2. BACKGROUND ON INTERACTIVE GENETIC ALGORITHMS

2.1. Principles

Genetic algorithms are evolutionary optimization methods (Goldberg, 1989). Based on the principle of Darwin’s natural evolution theory, the algorithm proceeds to a selection of parents, which will spread in the next generation their genetic dominant heritage, suitable for a desired objective. Classically, the fitness evaluation of the individuals is calculated numerically with a mathematical function known beforehand. A particular category of GA, Interactive Genetic Algorithms (IGA), introduces the user in the optimization loop to assess the fitness. For each iteration, the user selects solutions (products) that he/she considers as the most interesting for the desired objective. After a number of iterations (convergence loop), the method may converge toward solutions that fulfill the users objective. These algorithms are used for example to explore design spaces and to encourage creativity (Kim & Cho, 2006) (Qian & Ben-Arieh, 2009). Since the user decides the individual fitness, there is no need for a prior and unique formulation of the fitness function. For some applications, such as exploring the semantic dimensions of a product, this advantage is crucial.

2.2. Implementation of the IGA

After a definition of the variables of the product and their corresponding levels, a coding of the designs, represented by a chromosome, is proposed. Our implementation of the IGA uses a binary coding and discrete-valued variables. The IGA creates an initial population of designs by generating randomly the chromosomes, and presents them to the user as digital drawings. According to the instructions given to the user for the experiment, the user then has to select a subset of these individuals (1 or 2), representative of the semantic dimension studied. A new population of individuals is then created using one of the three following operators, applied to each individual of the population and selected according to tuning parameters:

- **Crossover**. The individual is crossed with a second parent in the population to form a child. Thanks to a “roulette wheel” method, the individuals selected by the user are favored to be parents in the next population. The roulette wheel is managed by the parameter *Rw* (the chance that a selected individual will be parent in the crossover operation is multiplied by the weight *Rw* >1). The probability of selection of this operator “crossover” is managed by the parameter *Rc*. This operator contributes to the convergence toward products with the desired perception.
- **Mutation**: random mutation of one variable of the individual. The probability of selection of this operator “mutation” is managed by the parameter *Rm.* This operator controls the diversity of the designs among the population.

- **Duplication**: simple duplication of the individual. The probability of selection of this operator is 1-(*Rc* + *Rm).* This operator allows the conservation of products with interesting features.

This iterative process runs until the program has reached the maximum number of generations allowed by the experimenter. The number of individuals in a population (8 in our study) is chosen by the experimenter according to the number of variables and levels, and the size of the screen to represent the designs. To tune the different parameters of our IGA, an automatic process has been implemented (Poirson et al., 2010). This process uses simulated "virtual" users and a "target" product in the design space. To simulate the choices of a virtual user, a distance function between the individuals of the population and the target is computed. By launching several simulations in the same conditions (Monte Carlo method), an average estimate of the convergence rates of the IGA is computed, given the value of the parameters. This process allows the experimenter to determine the "optimal" tuning of the parameters, given a maximum number of generations. To not fatigue the user, we considered that a participant could process a maximum of 30 generations. A more complete description of the implementation of our IGA can be found in (Poirson et al., 2013).

3. EXPERIMENT

3.1. Parameterization of the product

The product under study is the digital instruments panel of a car's dashboard. In modern cars, a display, made of a Thin Film Transistor (TFT matrix) can be used to show information to the drivers. This screen (see an example on figure **3**) is integrated in the dashboard and contains different elements showing driving information. The advantage of this display is that its design is customizable and that different trends can be programmed in vehicles.

According to the practice of car markers and after a qualitative analysis of different existing designs, 8 variables (V_1 to V_8) were defined to parameterize the design of the digital display. The definition of the 8 variables, and their associated modalities, is as follows (Table **1** shows the picture of each modality):

- V_1: Background colour: 3 modalities (light, dark and gradient)
- V_2: Strip colour: 3 modalities (light, dark and gradient)
- V_3: Theme colour: 3 modalities (neutral, orange and turquoise)
- V_4: Font weight: 2 modalities (thick and thin)
- V_5: Fuel gauge: 3 modalities (bar, simple analogic and full analogic)
- V_6: Speedometer: 3 modalities (numeric, simple analogic and detailed analogic)
- V_7: Revolution-counter (RPM counter): 4 modalities (circle bar, simple analogic, detailed analogic and absent)
- V_8: Motor temperature gauge: 3 modalities (continuous bar, divided bar and absent)

The designs proposed for the different modalities were defined on the basis of the current styles and designs available on today's vehicles. The modalities "absent" for the RPM-counter and the motor temperature gauge were included because these two elements are not compulsory in the instruments cluster design. So it is interesting to know if the presence of these two elements has an important influence on the perceived sportiness of the digital instruments cluster.

2D digital pictures were created to represent the digital instruments panel in a realistic way. The pictures of each modality were designed with an image editing software and saved in .png format, with a pixel density of 500 pixels per inch and a transparent background. All the possible combinations of panels (full factorial design of 3*3*3*2*3*3*4*3 = 5832 products) were created by assembling the corresponding modalities into a panel picture. The pictures were named with their chromosome of 8 digits (one per variable), For example, the instrument cluster defined by the code 22122122 (figure **3**) corresponds to a digital instruments cluster with a dark background (2), a dark strip (2), a neutral theme (1), a thin font (2), a simple analogic gauge (2), a numeric speedometer (1), a simple analogic RPM-counter (2) and a divided bar motor temperature gauge (2).

Table 1: Picture of the different modalities of the 8 variables

Variable	Modality 1	Modality 2	Modality 3	Modality 4
V_1: Background colour	Light	Dark	Gradient	/
V_2: Strip colour	Light	Dark	Gradient	/
V_3: Theme colour	Neutral	Orange	Turquoise	/
V_4: Font weight	**53 km/h** Thick	53 km/h Thin	/	/
V_5: Fuel gauge	Bar	Simple analogic	Full analogic	/
V_6: Speed mt.	53 Numeric	Simple analogic	Detailed analogic	/
V_7: RPM counter	Circle bar	Simple analogic	Detailed analogic	Absent
V_8: temperature gauge	Continuous bar	Divided bar	Absent	/

3.2. Tuning of the IGA parameters

For the tuning of the IGA parameters, a goal-seeking task with an automatic procedure with Monte Carlo simulations (simulated subjects) was implemented in a previous study (Poirson et al., 2013). Given the size of the design space (number of variables and modalities), the different parameters of the IGA to get the best convergence given the maximum number of iterations with simulated IGA tests were determined. The following conditions were set:

- 30 generations were allowed for the iterative selection. The participants could not stop the test before the 30th generation. Even if they estimated that the task was fulfilled and the selected design satisfied their perception of sportiness.
- In each generation, the participants had to select at least 1 design and a maximum of 2 designs among a population of 8 designs.
- After the 30th generation, the last 8 selected designs were shown again to the participants. Then, they had to select just one of them and give it a score of sportiness from 0 (not at all sporty) to 10 (very sporty), corresponding to the "quality" of the obtained solution, according to their expectations.
- Values of the IGA parameters: crossover rate Rc=0.6, mutation rate Rm=0.2, and wheel rate Rw=12 to 22 (Rw=12 for the ten first generations, and Rw increases of one unit every 2 generations from generation 11 to generation 30, until reaching 22 at the 30th generation. This process is proposed to speed up the convergence, by giving more importance to the selected designs at the end of the process).

3.3. Description of the IGA test

The test was proposed to a panel of 30 participants (8 women and 22 men, students or professors at the Ecole Centrale de Nantes). The graphical interface of the test (Figure **1**) presents the 8 images of the current population. For each population, the participants were told to select the most "sporty" digital instruments panel among the population of 8 designs, by simply clicking on the image. This task is repeated until the maximum number of generations is reached (30 generations).

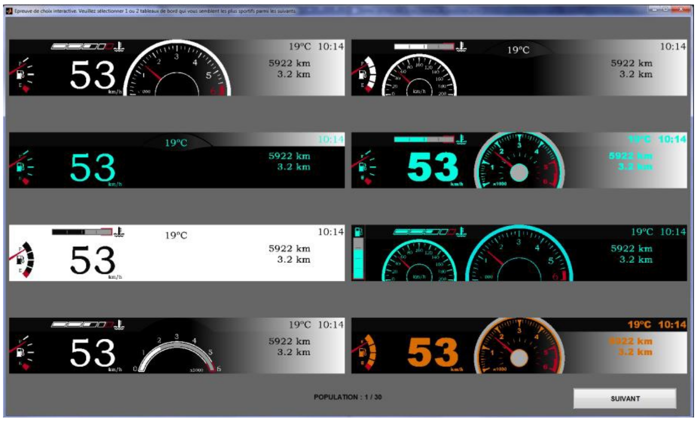


Figure 1: Graphical interface of the IGA test

At the end of the test, the participants answered a short questionnaire about their feelings concerning the test itself. Three questions were proposed: (1) the selection of 3 out of 12 positive and negative proposed terms to describe their feeling about the test (the terms proposed were "Amazing, Attractive, Boring, Clear, Complex, Complicated, Confusing, Intuitive, Repellent, Simple, Soothing, Stressful"), (2) a rating of their feeling during the test on a 5 levels Likert-sale (from 1-very unpleasant to 5-very pleasant), and (3) a free expression space to give comments about the test. The total duration of a session was approximately 20 minutes per subject.

4. RESULTS

The pictures of the 30 products representing the final choices of the 30 subjects at the end of the test are given in figure **2**. We notice that no one chose exactly the same digital instrument cluster.

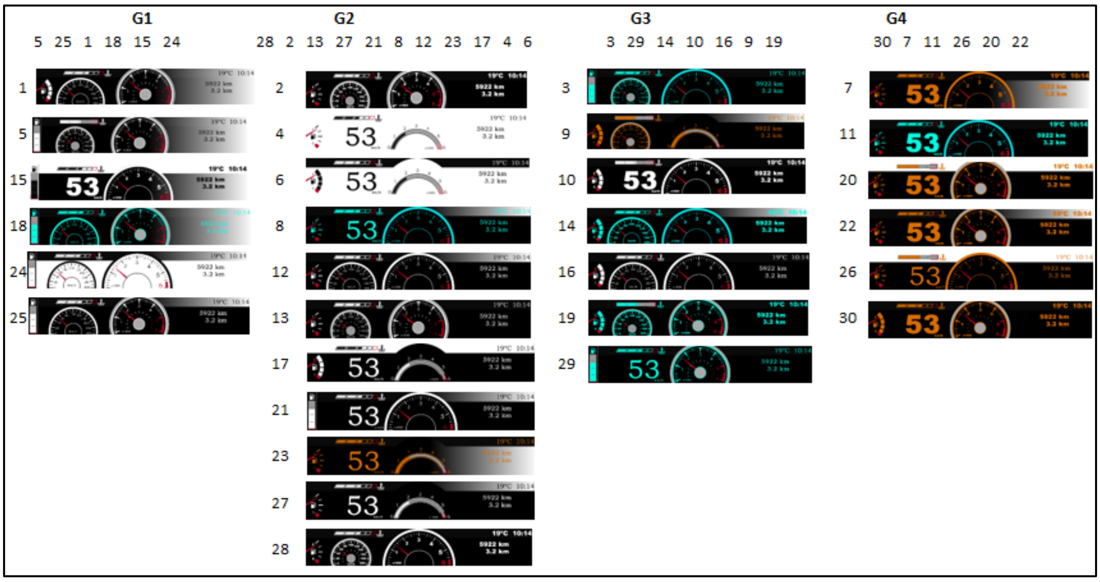


Figure 2: pictures of the 30 “sportiest” product of the 30 participants

The scores of sportiness given by the subjects of their final choices indicate an estimation of the quality of the obtained solution, according to their expectations in terms of sportiness. In our case, the average score was 7.6/10 with a standard deviation of 1.3. Only one subject gave a score lower than 3/10. The others score were higher or equal to 6/10. This relatively high score let us think that the subjects found satisfying product, and that the IGA test allows a convergence toward “sporty” instrument panels. To analyze more in detail the chosen products, we consider that the final choices of the subjects in the IGA test are represented by a matrix *X*, with subject *i* in row (*i*= 1 to 30) and the value of the variable *j* in column (*j*=1 to 8).

4.1. Global univariate analysis of the chosen designs

Table **2** shows the occurrences of each modality of the variables in the matrix *X*. For example, for the variable background (V_1), 3 participants chose the modality 1 (Light), 21 the modality 2 (Dark) and 6 the modality 3 (Gradient) for their final product.

Table 2: Occurrences of the different modalities of the variables in the final choices of the subjects for the IGA test

	V1: Background	**V2: Strip**	**V3: Theme**	**V4: Font**	**V5: Fuel gauge**	**V6: Speedometer**	**V7: RPM-counter**	**V8: temperature gauge**
Modality 1	*3*	*5*	**16**	*11*	*8*	**16**	6	6
Modality 2	**21**	**13**	7	**19**	**13**	*7*	**13**	**24**
Modality 3	6	12	*7*		9	7	11	*0*
Modality 4							*0*	
Multinomial test Signif.	***	N.S	N.S	N.S	N.S	N.S	***	***

***: p<0.01 N.S: not significant

With the occurrences of each modality in the final choice, we are able to define the product corresponding respectively to the most chosen modalities (in bold in table **2** – picture given figure **3**) and the product corresponding to the least chosen modalities (in *italic* in table **2** – picture given figure **4**– in case of ex aequo, one modality is chosen arbitrarily).

Figure 3: Digital instruments cluster with the most chosen modalities in the matrix X: most "sporty" product in average

The most "sporty" product in average according to the IGA test has a dark background, a dark strip, a neutral theme, a thin font, a simple analogic gauge, a numeric speedometer, a simple analogic RPM-counter and a divided bar motor temperature gauge.

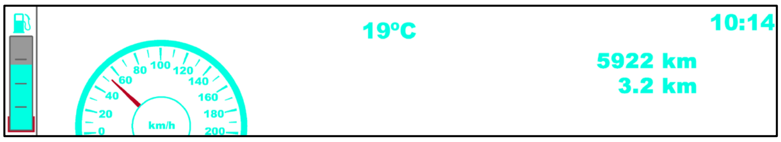


Figure 4: Digital instruments cluster with the least chosen modalities in the matrix X: least "sporty" product in average

The least "sporty" product in average according to the IGA test has a light background, a light strip, a turquoise or orange theme, a thick font, a bar gauge, an analogic speedometer, no RPM-counter and no motor temperature gauge. The data in Table **2** presents furthermore important differences in the scores of the modalities for certain variables. In particular, the modality "absent" for the RPM-counter (V7 - Modality 4) and the motor temperature gauge (V8 - Modality 3) were never selected in the final choice. These two modalities were however presented to the subjects during the test. Therefore, it can be concluded that these two optional elements of the digital instruments cluster are in fact mandatory in order to confer a sporty character to the instrument cluster. To define the variables subjected to the most consensual choice concerning their modalities, a multinomial goodness of fit test of the distribution of the occurrences was carried out. The results are presented in Table **2**. Three variables (V1 V7 and V8) obtain occurrences significantly different from a random distribution at the 1% level. These 3 variables are subjected to a consensus concerning the sportiness of the digital instruments cluster:

- For the background V1: the modality 2 (dark) is over represented comparatively to the two others,
- For the RPM counter V7: the modality 2 (analogic) is over represented comparatively to the modality 4 (absent),
- For the temperature gauge V8: the modality 2 (divided bar) is over represented comparatively to the modality 3 (absent).

In conclusion, for the whole group, a dark background, an analogic RPM-counter and a divided bar temperature gauge constitute consensual cues of a sporty control panel. For the other variables (V2, V3, V4, V5 and V6), there was no significant consensus: either because there were conflicting opinions of the subjects on these variables, or because these variables are not important in the perception of the sportiness.

4.2. Partitionning of the final choices - typology

The objective of this section is to study more in detail the inter-subject differences in the final choice of the product. The previous section showed that three characteristics (black background V1, analogic RPM counter V7 and divided temperature gauge V8) were representative of a sporty instrument cluster for the whole group of participants, but different characteristics may be also representative for sub-groups of participants. In order to uncover a typology of products for sub-groups of subjects, a Hierarchical Ascendant Classification (HAC) has been performed on the Matrix *X*. The objective is to define a partition of the final choices according to their similarity. To estimate this similarity, the Euclidian distance cannot be used because the variables that define a product are nominal (modalities), not quantitative. A similarity measurements based on nominal variables must be defined. After a transformation of a chromosome into a binary coding using the full disjunctive form (contains a "1" when the modality is present and a "0" when it is absent), the Sokal and Michener similarity index was used with the complete linkage rule for the HAC (Hair et al., 1998). The corresponding dendrogram is shown in figure **5** with a partition in 2 groups A and B.

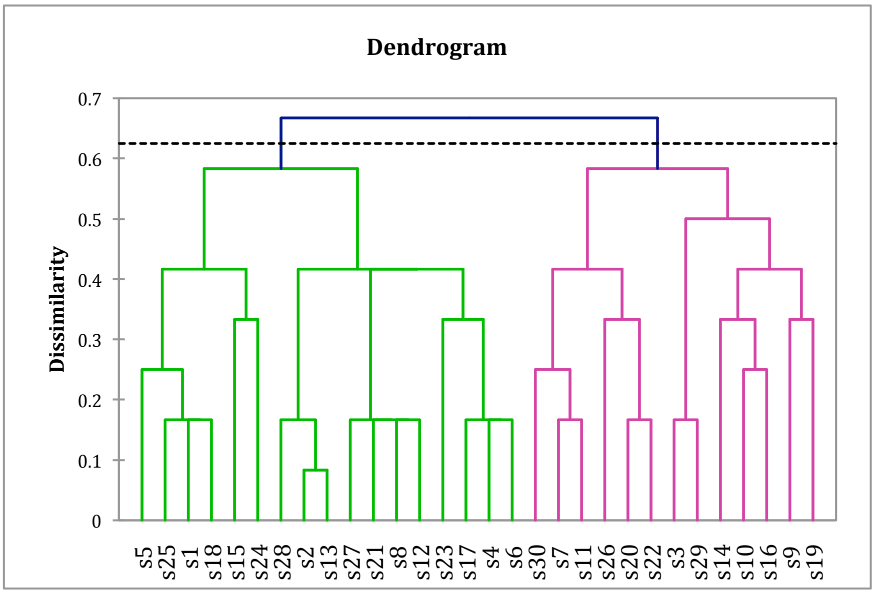


Figure 5: Dendrogram of the clustering of the 30 subjects according to their final choices

4.2.1. Characterisation of the two groups

Table **3** shows the occurrences of each modality of the variables, for each group A and B, and the results of the multinomial test of the distribution of the occurrences.

Table 3: For group A and B, occurrences of the different modalities of the variables in the final choices of the participants

		V1: Background	*V2: Strip*	*V3: Theme*	*V4: Font*	*V5: Fuel gauge*	*V6: Speedometer*	*V7: RPM-counter*	*V8: temperature gauge*
Group A (17 subjects)	Multinomial test Signif.	N.S	N.S	***	**	N.S	N.S	N.S	***
	Modality 1	3	3	**14**	3	6	**8**	5	1
	Modality 2	**9**	5	1	**14**	**8**	5	**6**	**16**
	Modality 3	5	**9**	2		3	4	**6**	0
	Modality 4							0	
Group B (13 subjects)	Multinomial test Signif.	***	N.S	N.S	N.S	N.S	N.S	**	**
	Modality 1	0	2	2	**8**	2	**8**	1	5
	Modality 2	**12**	**8**	**6**	5	5	2	**7**	**8**
	Modality 3	1	3	5		**6**	3	5	0
	Modality 4							0	

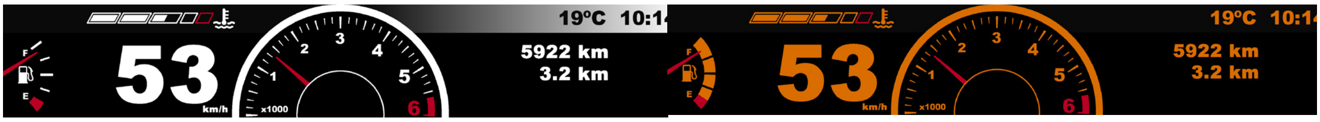
***: p<0.01 - **: p<0.05 N.S: not significant

For group B, the conclusions are similar to those of the whole panel: three variables (V1, V7 and V8) obtain occurrences significantly different from a random distribution. For these 3 variables, the modality 2 is over represented comparatively to the others. This group is relatively homogeneous and pulls the behaviour of the whole panel.

For group A, three variables are subjected to a consensus concerning the sportiness of the digital instruments cluster:

- Theme V3: the modality 1 (neutral) is over represented comparatively to the 2 others,
- Font V4: the modality 2 (thin) is over represented comparatively to the modality 1 (thick),
- As for group B and for the panel, for the temperature gauge V8, the modality 2 (divided bar) is over represented comparatively to the modality 3 (absent).

This analysis leads to a more detailed understanding of the concept of sportiness. For information, the images corresponding to the average product of the 2 groups (most sporty product in average) are given in figure **6**.



Group A Group B

Figure 6: picture of the most sporty product in average for group A (left) and B (right) – IGA test

We can see that the products are not so different visually. Except the colour, the differences concern details of the product, difficult to perceive at first sight. More subjects would be necessary to confirm these two trends concerning the sportiness.

4.2.2. Typology of the two groups

A supplementary analysis can be done on the two groups A and B in order to uncover the main characters that are representative of the differences between the groups (specificities). This analysis, different to those made in the previous section, aims to interpret now the differences between the groups. From the occurrence tables of each group, a computation of the rate of a modality in a group with respect to its rate in the whole population can be computed (Giordano et al., 2000). The rate γ_{ij}^{k} of a modality j for variable i in the group k is given by (equation 1):

$$\gamma_{ij}^{k} = \frac{n_{kij}/n_k}{n_{ij}/n} \qquad (1)$$

where n_{kij} is number of products with modality *j* in group *k* for variable *i*, n_k is the number of products in group *k*; n_{ij} is the number of products with modality *j* in the population for variable *i*, and n is the total number of products in the population. Over-represented modalities (abundant) are characterized by high values of γ_{ij}^{k}, whereas under-represented modalities (scarce) get low values. Given that there are only two groups, the rates are of courses opposite so the modality with the highest rate for A obtains the lowest rate for B. The analysis of the rate was performed to determine the specificities of each group in relation to the total population. Table **4** shows, for group A and B, the modalities V_{ij} that got the two highest rate γ_{ij}^{k}. A more tangible interpretation concerning the style of the digital instruments cluster and the design trend is also provided.

Table 4: Interpretation of the differences between the groups of digital instruments clusters obtained by the abundance analysis

Group	Modalities with the two highest rate γ_{ij}^{k}	Interpretation of the specificities of the group
Group A	V11, V31	Light background - neutral theme
Group B	V32, V81	Orange theme - continuous bar temperature gauge.

These results show some specific features, representative of each group, which were not previously highlighted. For example, the light background for Group A and the orange theme for Group B. The light background is more represented in group A compared to group B. However, it doesn't mean that this modality is the most represented. In addition, the neutral theme is more representative of group A and the orange theme of group B. Theses analyses allow to differentiate the two groups and to determine which features are representative of the groups. These results are complementary to those obtained with the univariate analysis and allow a more in depth understanding of the semantic dimension "sportiness".

To conclude, the analyses allow us to extract the most influent variables on the perception of the sportiness. Especially, the variables Background (V1), RPM-counter (V7) and Temperature gauge (V8) have an important influence on the perceived sportiness and a consensus is observed. The variables Theme (V3) and Font (V4) have also an influence but there are different views. Finally, the Strip (V2), Fuel Gauge (V5) and Speedometer (V6) don't appear to influence the perception of the sportiness of digital instruments panels.

4.3. Participants feedbacks analysis

After the IGA test, the participants were allowed to give a feedback on their feelings and opinions on the progress of the test. The analyse of the answers to the questionnaires highlight the following results:

- **Selection of terms**: among the 12 terms proposed, more than half of the participants selected the following 3 positive terms: "Simple", "Intuitive" and "Clear" to describe their feeling about the test. The most selected negative term has been "Boring" with only 6 participants. We notice that among the 6 negatives terms, 2 of them were never chosen: complicated and repellent
- **Rating of feeling during the test**: half of the participants selected the level "4-pleasant" to characterize their pleasure during the progress of the test. Only three participants selected the level "2-Unpleasant" and nobody the level "1-very unpleasant".
- **Free expression about the test**: Among the principal free comments of the participants, we notice that they appreciated the convergence of the algorithm, but they sometimes complain against the fact that in the last generation, the proposed designs were very similar and the same design may be repeated several times.

The analysis of participants' feedbacks highlights the fact that in average, the test has been well accepted and perceived as pleasant and easy to understand.

5. CONCLUSIONS

This paper presented an experiment based on Interactive Genetic Algorithms in order to determine, with a panel of 30 participants, the product's characteristics that contribute to influence the sportiness of an instrument panel of a car dashboard.

A global univariate analysis was proposed for the analysis of the final choices of the panel. It allowed an extraction of consensual design features, representative of the desired semantic dimension, and the associated levels. In our case, 3 variables associated to their modalities were identified as influential on the sportiness of the digital cluster for the whole group. An image of the most/least sporty product can be obtained. To refine the results, a partitioning of the final choices was realized to identify 2 groups of participants with different opinions on the studied dimension. Abundance analysis and the same univariate analysis that was used for the global population was done to extract consensual design features for each group of subjects. These analyses leaded to a more refined understanding of the concept of sportiness, for each group.

The analysis of the feedbacks of the participants (answers to the questionnaires) showed that the test, based on a choice task, is well accepted by the subjects, easy to understand and to carry out, even pleasant. We showed that even with a short test with few selections, the IGA converge toward representative designs of the semantic dimensions, in a tractable number of generations, acceptable by the subjects. This gives to IGA the potential to study the influence of a large number of variables and modalities with a restricted evaluations number. Furthermore, the method does not postulate any model between the response and the design variables. Complex interactions between the variables can then be studied without an increase of the number of evaluations in the experiment (interactions exclusive OR, logical interactions like A&B, A&-B, …). These interactions between variables may be very important, in particular for the design of forms (Sylcott et al., 2013). The IGA method seems to be especially relevant for creativity stages where the designer wants to identify which variables, among a large of number, have an influence on the perception of the studied semantic dimension. The IGA tests can be a first step before a more refined study with a more classical protocol in Kansei engineering, based on conjoint analysis and semantic differential. On the other hand, the IGA test gives global results, for the whole population of participants, or subgroups, but not at an individual level. Consequently, concerning the influent variables, the test limits to average conclusions, valid for a panel of participants.

For further studies, we will investigate the potential of IGA methods as a creative tool used by experts rather than participants. Different coding of the products can be proposed to promote the diversity of products and innovation (encoding with a tree structure fro example).

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