A COMPARISON OF CONJOINT ANALYSIS AND INTERACTIVE GENETIC ALGORITHMS FOR THE STUDY OF PRODUCT SEMANTICS

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Abstract

An active research field in product design concerns the analysis of end-users' evaluations on virtual products, in order to understand the product semantics. This study compares two methods for eliciting user's perceptions of a product: a classical model-based method, based on conjoint analysis, and a more innovative non model-based test, using interactive genetic algorithms. The product proposed to illustrate the study is a digital instrument panel integrated in a car dashboard, and the semantic dimension considered is the "sportiness". After the definition of the variables of the instrument panel, the two users' assessment tests are conducted with a panel of 30 participants. For both tests, the most influent variables on the "sportiness" of the instrument panel are selected, and representative designs of the sportiness are defined (the most or the least sporty). A comparison of the results of the tests is proposed, by examining the differences and agreements between them. The results show that the agreement between the two tests is important and that interactive genetic algorithms can be an interesting alternative to classical rating tests to study product semantics.

Keywords: Human behaviour in design, User centred design, Emotional design

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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 (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). 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 and 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 (Tseng et al., 2012).

We propose in this paper to compare two methods from these two categories and to investigate similarities and differences between their results. 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 first method under study is "model-based": after a rating task of an experimental design using the semantic differential method, individual conjoint analysis (CA) models are fitted to the data (Petiot et al., 2014). The second method, applied to the same example, uses Interactive Genetic Algorithms (IGA), and is based on iterative choice tasks. The main objective of the paper is methodological: the purpose is to compare to what extent the conclusions about the product, drawn from the results of the two methods, are similar. The main question is to determine whether the design attributes responsible of the "sportiness" of an instrument panel are similar when two different experimental protocols are implemented. More precisely, the methods are compared according to different criterions: (1) comparison of the attributes identified as the most salient on the perception of

the sportiness; (2) comparison of the products identified as the most or least "sporty"; (3) comparison of the individual discrepancy between the evaluations for each test.
The paper is organized as follows. After a description of the parameterisation of the digital instrument panel, Section 2 presents the organisation of the two tests (Conjoint Analysis tests (CA test) and Interactive Genetic Algorithm test (IGA test)). Section 3 presents the results and the analysis of the differences between the two tests. Conclusions are drawn in section 4 on the main contributions of this paper and recommendations in product design.

2 EXPERIMENT

2.1 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) is 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 (the picture of each modality is given in Appendix for information):

- 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.

2.2 Organisation of the tests

Two tests were proposed to a panel of 30 participants (8 women and 22 men, students or professors at the Ecole Centrale de Nantes): a rating test (CA test) and the research of the most "sporty" digital instruments panel with the IGA (IGA test). The panel was divided into 2 groups G1 and G2 of 15 participants each. The first group of subjects started with the IGA test and then continued with the CA test. The second group made the tests in the opposite order, so as to control a possible influence of the test order on the results. Each subject made both tests on a Personal Computer. An instructions sheet and a questionnaire were provided for each test, informing the subject that the participation was completely voluntary and that they could stop the test at any time. The total duration of a session was approximately 40 minutes per subject.

2.3 Description of the Conjoint Analysis test (CA test)

This test consisted in proposing to the participants a series of digital instruments panel designs, one after another. They had to give a score from 0 (not at all sporty) to 10 (very sporty) to each of the designs. The model used is a rating based Conjoint Analysis. The experimental design was optimised to take into account the main effect of each variable (model without interaction). 32 designs were defined with a DOE software using the D-optimality criteria, and presented to the participants, one after another. In order to limit the order effect on the rating, the presentation order of the products was controlled and followed a Williams Latin Square. The graphical interface for the ratings is presented in Figure **1** (left). It shows the image of the digital instruments panel (in scale 1:1), a scroll bar with a 10 points Likert scale, which allows the participant to assess each product, and a “next” button to validate the score and continue to the next design.

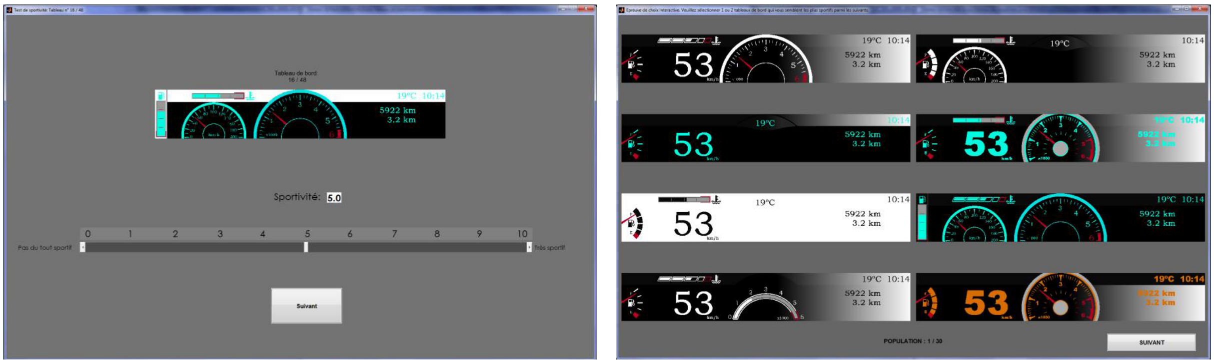

Figure 1. Graphical interfaces of the CA test (left) and the IGA test (right)

2.4 Description of the IGA test

Interactive Genetic Algorithms (IGA) are particular Genetic Algorithms where the user is introduced in the selection process to assess the fitness of the population. In an iterative process, 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 fulfil the users objective. 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. 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 operators crossover, mutation and duplication. The probability of selection of each operator is managed by the parameters *Rc* (crossover), *Rm* (mutation) and *1-Rm-Rc* (duplication), and *Rw* (the chance that a selected individual will be parent in the crossover operation is multiplied by the weight *Rw* >1). A more complete description of the implementation of our IGA can be found in (Poirson et al., 2013) as well as the procedure for the Monte Carlo simulations for the tuning of the IGA parameters. 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 were invited to make selections until the 30th generation.
- 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).

The graphical interface of the IGA test (Figure **1** - right) presents the 8 images of the current population. For each population, the participants were told to select the digital instruments panel among the population of 8 designs, by simply clicking on the image. This task was repeated until the maximum number of generations (30 generations).

3 RESULTS

3.1 Conjoint Analysis (CA Test)

For each of the 30 participants, an individual ANOVA model was fitted to the data. The results show that the fitting of the model to the data was rather good (for 25 subjects, $R^2 > 0.8$; R^2: determination coefficient of the ANOVA - for the 5 remaining subjects, $R^2 > 0.6$).

3.1.1 Importance of the variable

After a computation of the part-worth utilities of each participant, the importance of each variable V_j was computed. In average, given that there are 8 variables, the medium importance is 100/8 = 12.5%. Three variables had an average importance I_j greater than the medium value and can then be considered as important for the sportiness:

- RPM-counter (V_7) – 32.9%
- Speedometer (V_6) – 15.2%
- Background (V_1) – 14.0%

It signifies that in average, the participants are the most sensitive to these variables for the perception of the sportiness of the instrument panel. The 5 other variables (font, strip, theme, fuel gauge and motor temperature gauge) were in average less important.

3.1.2 Ideal and anti-ideal average product

To sum up the results, the average part-worth utilities can be computed from the individual part-worth utilities of each modality (**Table** 1). The average “ideal” product (resp. “anti ideal”) is defined by considering, for each variable, the modality with the highest (in bold in **Table** 1) (resp. lowest (in italic in in **Table** 1)) average part-worth utility (Figure **2**).

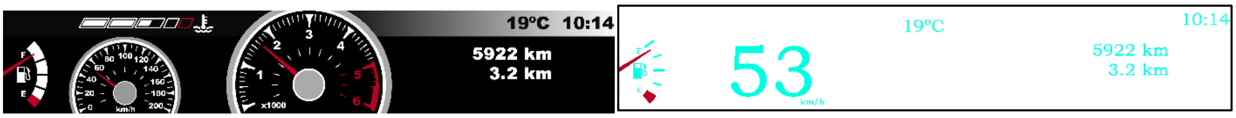

Figure 2. Average “ideal” (left) and “anti-ideal” (right) product for the sportiness (CA model)

Table 1. Average part-worth utilities of each modality and each variable (Conjoint analysis model)

	V1: Background	*V2: Strip*	*V3: Theme*	*V4: Font*	*V5: Fuel gauge*	*V6: Speedometer*	*V7: RPM-counter*	*V8: temperature gauge*
Modality 1	*-0.80*	*-0.41*	**0.62**	**0.23**	-0.14	*-0.47*	1.62	0.29
Modality 2	**0.11**	-0.05	0.50	*0.00*	*-0.24*	-0.03	1.91	**0.40**
Modality 3	0.00	**0.00**	*0.00*		**0.00**	**0.00**	**2.10**	*0.00*
Modality 4							*0.00*	

The sportiest product in average according to the CA test has a dark background, a gradient strip, a neutral theme, a thick font, a full analogic gauge, a detailed analogic speedometer, a detailed analogic

RPM-counter and a divided bar motor temperature gauge. On the other side, the average anti-ideal product is characterised by a light background, a turquoise theme and a thin font, as well as the absence of the two optional instruments cluster elements (RPM-counter and motor temperature gauge). These two products give interesting cues on the modalities that drive the sportiness of the instrument panel, at the level of the group.

3.2 Interactive Genetic Algorithm (IGA Test)

The final choices of the subjects for 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). 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 modalities of the variables in the final choices of the subjects (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**) and the product corresponding to the least chosen modalities (in *italic* in table **2** – in case of ex aequo, one modality is chosen arbitrarily) (figure **3**).

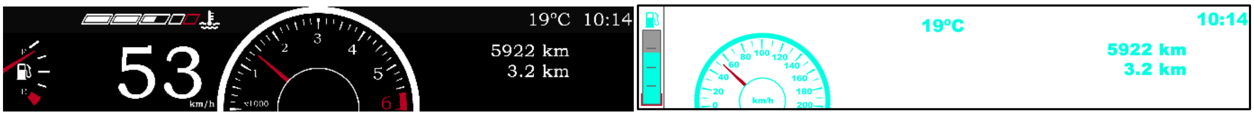

Figure 3. most "sporty" (left) and least "sporty" (right) product in average for the IGA test

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. 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 (V_7 - Modality 4) and the motor temperature gauge (V_8 - 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 (V_1 V_7 and V_8) 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 V_1: the modality 2 (dark) is over represented comparatively to the two others,
- For the RPM counter V_7: the modality 2 (analogic) is over represented comparatively to the modality 4 (absent),
- For the temperature gauge V_8: 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 (V_2, V_3, V_4, V_5 and V_6), 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.

3.3 Comparison of CA and IGA

The first way to compare the methods is to compare the variables considered as influent on the perception of the sportiness for the CA test and the IGA test. For the CA test, the most important variables are V_1, V_6, V_7 (value of the importance I_i higher than the medium value 12.5%), whereas V_1, V_7, V_8 are the most important for the IGA test (significant multinomial goodness of fit test). For both tests, 2 variables are important for the perception on the sportiness for the whole panel: background (V_1) and RPM-counter (V_7) and 4 variables V_2 V_3 V_4 and V_5 are not highlighted as important in both tests. For the CA test, Speedometer (V_6) is considered as important whereas this variable is not highlighted in the IGA test. Conversely, temperature gauge (V_8) is influent on the sportiness with the IGA test but not emphasized in the CA test.

The second way to compare the results of the methods is to compare the most/least sporty products. Table **3** indicates, for each test, the modalities Mi to characterize the most/least sporty instruments panel (most/least selected modalities in the case of the IGA, and with the highest/lowest part-worth in the case of the CA test). The most influent variables are presented in bold. The main conclusions in the comparison of the results are:

- **Agreement for 4 variables V1, V3, V7, V8**. For the variables V1 (background), V3 (theme) and V8 (temperature gauge), the most and least sporty products are exactly similar for both tests. For the variable V7 (RPM counter), the only slight difference concerns the modalities M2 or M3 of the most "sporty" product (M2 and M3 represent both an analogic RPM counter with very subtle differences). Furthermore, 3 of these variables (V1, V7, V8) are among the most influent in the perception of the sportiness,
- **Disagreement for the variable V6.** For V6 (Speedometer), the most "sporty" modality for the IGA test (M1 – numeric speedometer) is also the least sporty in the CA test. The tests lead to conflicting conclusions concerning these variables, all the more since this variable is influent in the perception of the sportiness,
- **Disagreement for 3 variables V2, V4 and V5.** For V4 (Font), the results are exactly opposite. A thick font (M1) is sporty for the CA test, whereas it is not for the IGA test. But the visual differences between the modalities are weak. Furthermore, the results are conflicting but these variables are not considered as influent on the perception of the sportiness, for the two tests. The differences are not a sign of a disagreement between the two methods.

Table 3. the most and least sporty product in average for the IGA and the CA test

		V1: Background	*V2: Strip*	*V3: Theme*	*V4: Font*	*V5: Fuel gauge*	**V6: Speedometer**	**V7: RPM-counter**	**V8: temperature gauge**
Most sporty	CA Test	**M2**	M3	M1	M1	M3	**M3**	**M3**	**M2**
	IGA Test	**M2**	M2	M1	M2	M2	**M1**	**M2**	**M2**
Least sporty	CA Test	**M1**	M1	M3	M2	M2	**M1**	**M4**	**M3**
	IGA Test	**M1**	M1	M3	M1	M1	**M2**	**M4**	**M3**

The pictures of the products confirm the fact that the results between the IGA and the CA tests are not conflicting. The most important and perceptible difference between the two tests concerns the Speedometer V_6: the IGA test would recommend a numeric speedometer, while the CA test a detailed analogic one. Further investigations on the behaviour of the participants would be necessary to explain these differences.

4 CONCLUSIONS

This paper presented two experiments on products' subjective assessments in order to determine the product's characteristics that contribute to influence the sportiness of a digital instruments panel: a rating test (CA test) and a test based on an Interactive Genetic Algorithm (IGA test).
For the CA test, the individual conjoint analysis models revealed the 3 most influential variables on the perception of the sportiness for the whole group. The analysis of the part-worth utilities allowed the definition of an ideal and anti-ideal product's images, which facilitated the understanding and gave interesting cues on the modalities that drive (or inhibit) the sportiness of the instrument panel.
For the IGA test, a global univariate analysis was proposed for the analysis of the final choices. This allowed the extraction of consensual design features, representative of the desired semantic dimension, and their associated levels. In our case, 3 variables associated to their modalities were identified as influential on the sportiness of the digital panel for the whole group. In the same way as the CA test, an image of the most/least sporty product can be obtained.
The comparison of the two tests was based on the comparison of the most influent variables, the comparison of the least and most sporty products, and the individual discrepancy between the results of the IGA test and the CA test. The results show a good agreement between the two tests for the influence of design attributes on the sportiness of digital instruments panel. Some recommendations can be made from the results of our study for the study of product semantics with users-tests.
First, each method (IGA or CA) has benefits and drawbacks and produces results that are different in nature: CA produces a mathematical model of the semantic dimension on the whole design space, while IGA gives a set of representative designs. If the objective is to quantify the influence of product's attributes on the perception of a semantic dimension, a CA test is the most adapted method. In its rating based form, CA produces individual models and allows a quantitative interpretation of the influence (importance of the variables, part-worth of the modalities). For example, this method is relevant at the development stage of industrial projects, for which designers need analytical data to "tune" the characteristics of the products or to confirm design choices. Several studies in Kansei engineering use CA models to define relevant design attributes. An important limit of CA models concerns the limitation in the number of variables and the interactions between the variables, which are generally ignored. These interactions between variables may nevertheless be very important, in particular for the design of forms (Sylcott et al., 2013). The numbers of products of the experimental design rapidly increases with the number of variables and interactions terms in the model. To limit the fatigue of the participants, the number of variables considered is necessarily bounded (not more then about ten). For applications in design, this can constitute a limitation.

Conversely, if the objective is to identify the most influent product's features on the perception of a semantic dimension, without intend to quantify accurately the influence or make inferences for different combinations of variables, the IGA test is relevant. The IGA test gives global results, for the whole population of participants but not at an individual level. Consequently, the test limits to average conclusions, valid for a panel of participants. On the other hand, this method allows the study of the influence of a large number of variables and modalities with a restricted evaluations number. Furthermore, the IGA test 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. The IGA method is especially relevant for creativity stages where the designer wants to identify which variables, among a large 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 CA. For further studies, we will investigate the potential of IGA methods as a creative tool used by experts rather than participants.

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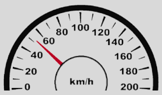
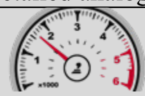
APPENDIX: PICTURES OF THE DIFFERENT MODALITIES OF THE 8 VARIABLES

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** km/h 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	/