Degree of subject's indecisiveness characterized by eye movement patterns in increasingly difficult tasks.

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***Abstract**: The development of eye-tracking-based methods to describe a person's indecisiveness is not commonly explored, even though research has shown that indecisiveness is involved in many unwanted cognitive states, such as a reduction in self-confidence during the decision-making process, doubts about past decisions, reconsidering, trepidation, distractibility, procrastination, neuroticism and even revenge. The purpose of our work is to propose a predictive model of a subject's degree of decisiveness, either "indecisive" or "decisive". To reach this goal, we needed to extract descriptors that clearly distinguished both states. Using eye-tracking methodology, we then studied the reactions of different subjects in response to several types of stimuli.*

KEYWORDS: indecisiveness; eye tracking; eye movements; decision strategy.

Introduction

Indecisiveness is, for some people, a character trait that manifests as a difficulty in settling between several simple or complex alternatives. It is an irritating character trait from a theoretical point of view, as it can be difficult to explain or decipher; it also becomes irritating from a practical point of view, as it seems particularly resistant to modification, sometimes even increasing while one tries to reduce it. Indecisiveness has been the topic of a large body of work. For example, relative to decisive people, Frost and Shows (1993) found that indecisive people take more time to make simple decisions; Rassin and Muris. (2005) noticed that indecisive people seek more information before making decisions; and Veinott. (2002) noticed that indecisive people more often postpone more difficult choices.

This study of indecisiveness is part of the ANR[†] project ORIGAMI2 ("*Observation du Regard et Interprétation du Geste pour une Analyse Marketing Non Intrusive*", or "observation of gaze and interpretation of gesture for a non-intrusive marketing analysis"). ORIGAMI2 aims at a complete analysis of the customer's decision-making process through the combination of various data acquisition tools. The analysis of a decision-making process involves three steps. First, the stimuli with which the customer is interacting must be identified. Second, the customer's behavior must be interpreted based on his hesitations, time spent staring at different objects, etc. Finally, behavior patterns that take place during the decision-making process need to be identified. Our present work is related to the second and third steps, with the goal of building a predictive model of a person's degree of

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Website : http://www.agence-nationale-recherche.fr/en/

indecisiveness through the use of eye-tracking methodology. First, we needed to extract relevant descriptors.

Several authors have proposed scales to quantify indecisiveness. We used Frost and Shows's Indecisiveness Scale. This tool is composed of fifteen statements (e.g., "I have a hard time planning my free time"); for each statement, the subject must choose from five answers, which range from "strong disagreement" to "strong agreement". The choice of the IS as a reference is a way of reaching our *gold standard*: the segmentation of the population into two groups, "decisive people" and "indecisive people". We will explore later how we made such a distinction.

In the first part of this paper, the operating procedure is presented. Next, the pre-processing of the data and the construction of descriptors is described. In the third part, the results regarding the selection of the best descriptors are presented. Finally, a comparison with other results in the literature is made.

I. Experimental procedure

The experimental procedure for each subject was standardized. First, the subject had to fill out Frost and Shows's multiple-choice questionnaire. Next, he was asked to complete three tasks in a random order. Finally, he had to fill out the multiple-choice questionnaire described by Zaichkowsky (1984), which measures the degree of motivation. We used a corneal reflection-based eye-tracker[†]. The subject's head rested on a headrest that was located 70 centimeters from a monitor that was 47.7 by 29.7 square centimeters. Stimuli were displayed with a resolution of 1680 by 1050 square pixels, and data were acquired at 500 Hz.

During the experiment, the subjects gave their answers orally while the experimenter took notes.

1. Measuring the degree of indecisiveness with Frost and Shows's scale

As described in the introduction, Frost and Shows's questionnaire gives us a way of segmenting the population into two classes: decisive subjects and indecisive subjects. It is a 15-statement questionnaire, and each response is chosen within the following parameters:

- strong disagreement (score = 1)
- disagreement (score = 2)
- reasonable agreement (score = 3)
- agreement (score = 4)
- strong agreement (score = 5)

For 6 of the 15 statements, the scoring is reversed (score for strong disagreement = 5, score for disagreement = 4, etc.). Frost and Shows define the subject's degree of indecisiveness as the mean value of the 15 scores.

According to Frost and Shows, subjects whose scores are less than 2.5 are labeled "decisive", while those whose scores are greater than 2.5 are labeled "indecisive". In contrast, Patalano et al. (2009) used the median score of the population as a threshold for segmentation. We, however, questioned which solution, either Frost and Shows's value of 2.5 or the median score, was more statistically relevant. The value of 2.5 is logical, but the actual statistical distribution of our population's degree of indecisiveness cannot be known; therefore, choosing the median score, as proposed by Patalano, appears to be more appropriate but may not always be an absolutely correct choice. We believe that one should also consider whether the variance should be taken into account. In part III.2, an alternative way of segmenting the population is presented that is based on intra-class variance, as described by Otsu (1979).

[†] Website : http://www.smivision.com/en/gaze-and-eye-tracking-systems/products/red-red250-red-500.html

2. Participants

The goal of this work was to describe and characterize each subject's degree of indecisiveness. It was necessary to recruit a large number of subjects, which can be difficult in a controlled environment. In particular, it was necessary to recruit enough subjects to obtain reliable data. Germeijs and De Boeck (2002) used 291 subjects, while Rassin et al. (2007) used 39, 56 and 62 subjects; the number of subjects depends on the requirements of the experiment. We recruited 28 French-speaking subjects. The subjects had no ophthalmological problems nor any particular difficulties in reading and understanding documents displayed on a screen. The following table shows the distribution of the ages of female and male subjects.

	18 to 20	21 to 30	31 to 40	41 to 50	51 to 60	61 to 70	Total
Women	1	9	0	2	2	1	15
Men	1	4	1	7	0	0	13
Total	2	13	1	9	2	1	28

Table 1. Distribution of the ages of male and female subjects.

3. Description of tasks

After filling out Frost and Shows's questionnaire, each subject was given three tasks to perform. We chose to arrange each task's alternatives in columns. The complexity of each task was determined by the number of alternatives: two alternatives in task 1, three in task 2 and four in task 3. Accordingly, task 1 was the least complex task and task 3 the most complex. In tasks 1 and 2, the subject had to choose between menus (2 menus in task 1 and 3 menus in task 2). In task 3, the choice was between 4 academic programs. Tables 1, 2 and 3 show the stimuli for each task.

Because of the relatively small number of participants, we chose to increase the number of tasks. In addition to the advantage of acquiring more data, increasing the number of tasks allowed us to reduce intra-subject variability, which is an important parameter to consider when one is working with human subjects and needs to generalize features. The robustness of certain descriptors was tested relative to task complexity, and the results are presented in part II.3. Similarly, increasing the number of tasks allowed us to filter our subjects, allowing us to avoid "noise" (part II.1) even before building the database.

The three tasks were randomly presented to the subjects. We chose to arrange the alternatives in columns. The instructions given for task 1 and 2 were as follows:

"*You are a student. It is lunch time. Every day, information about the day's menus is displayed on a touch screen in the campus restaurant. A menu selection can be made by touching the screen. Please indicate which menu would best suit you (menus can be vegan).*"

Menu 1	**Menu 2**
Starter	Hot dish
Hot dish	Dairy product
Dairy product or dessert	Dessert
Bread	Bread

Table 2. Stimulus on the screen for task 1.

Menu 1	Menu 2	Menu 3
Salad with a side dish Dairy product Bread	Cold sandwich. 30 cm Dessert or dairy product	Hot sandwich. 15 cm Dairy product Dessert

Table 3. Stimulus on the screen for task 2.

Program 1	Program 2	Program 3	Program 4
Sports : compulsory module.	Sports : compulsory module.	Sports : compulsory module.	Sports : non-compulsory module.
Frequency : 12 hours per semester.	Frequency : 24 hours per semester.	Frequency : 48 hours per semester.	Frequency : as you wish.
BONUS = + 1 points on the final general semi-annual mark, *if and only if* practicing 12 hours in the semester.	BONUS = + 2 points on the final general semi-annual mark, *if and only if* practicing 24 hours in the semester.	BONUS = + 4 points on the final general semi-annual mark, *if and only if* practicing 48 hours in the semester.	BONUS = + 6 points on the final general semi-annual mark, *if and only if* practicing > 60 hours in the semester.

Table 4 Stimulus on the screen for task 3.

The instructions for task 3 were as follows:

"*You are a student. Sports are becoming an important component of academic programs. Each student may choose between 4 programs, each with a different way of practicing sports. Please indicate which program would best suit you.*"

4. Measuring the degree of motivation with Zaichkowsky's scale

After completing the 3 tasks, the subject was required to complete Zaichkowsky's multiple-choice questionnaire. The purpose of Zaichkowsky's questionnaire is to measure the degree of motivation, on a scale that ranges from "low motivation" to "high motivation". The questionnaire is made up of 20 statements. The answers to each of the 20 statements are scored from 1 to 7; for 10 of the statements, the scores that correspond to each answer are reversed. Final scores can range from 20 to 140. A person whose score is under 69 is considered to have a low degree of motivation. A person whose score is between 70 and 111 is considered to have a medium degree of motivation. If his score is higher than 112, he is considered to have a high degree of motivation.

As was done by Zaichkowsky, J.L. (1984), we scored the answers to each of the 20 statements from 1 to 7. Accordingly, the final scores ranged from 20 to 140.

II. Filtering and database construction

Before analyzing the eye-tracking data, it was necessary to first filter the population.

1. Filtering based on Zaichkowsky's scale

To avoid distorting the results, or to at least minimize any distortion, it is necessary to exclude subjects whose motivation for the experiment is too low. To do so, we started by examining the distribution of the population based on Zaichkowsky's scale.

The figure below shows this distribution. Among the 28 subjects, 3 had a medium degree of motivation based on their effort during the experiment; the other 25 had a low degree of motivation. If we applied this criterion, we would have had to exclude 25 subjects from our database. We could not rely solely on Zaichkowsky's scale.

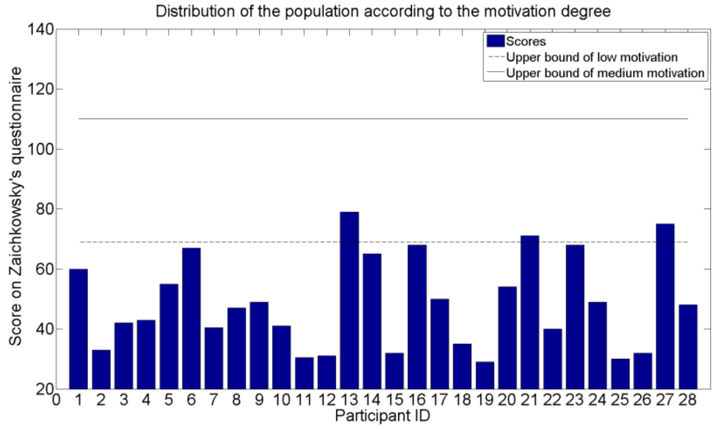

Figure 1. Degree of motivation.

2. Filtering based on both scanpaths and Zaichkowsky's degree of motivation

In addition to the distribution of the degree of motivation, we also examined each subject's scanpaths during the tasks. The following figure shows the scanpaths of two example subjects during the three tasks. Each rectangle stands for a text field on the stimulus.

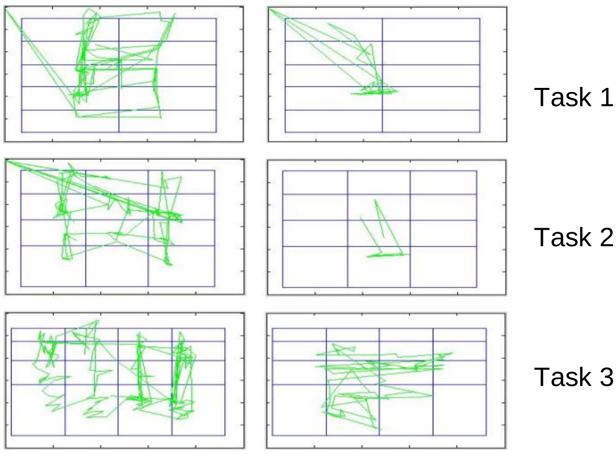

Figure 2. Scanpaths. Left: a good subject; right: a "noise" subject.

In the first subject's scanpaths (left), his eyes look over the three columns and come back several times to several locations. Based on these scanpaths, we could infer that this subject followed the instructions and seriously participated in the experiment. In contrast, the second subject (right) did not correctly view all of the alternatives; moreover, his scanpaths are less complex than those of the first subject. This subject was labeled "noise" in the database, and his participation was not taken into account. Altogether, among the 28 participants, 6 were labeled as "noise".

The mean score of the “noise” outliers on Zaichkowsky's questionnaire was 44.91, with a standard deviation of 15.75. According to Zaichkowsky's scale, they had a low degree of motivation with the experiment. The mean score of the other 22 subjects was 49.75, with a standard deviation of 15.36. The fact that these tasks were intended for students may explain these low scores. Despite the low degrees of motivation, Zaichkowsky’s scale supports the application of this filtering step.

After excluding the unreliable participants from the database, segmentation based on Frost and Shows's scale was performed.

3. Segmentation based on Frost and Shows’s indecisiveness scale

Both the 2.5 value given by Frost and Shows and Patalano's median value seemed to us to be arbitrary and only justified for a large number of subjects. We used a segmentation method based on the between-class variance, which was first proposed by Otsu (1979). This method is easy to implement and consists of two main steps:

- for each threshold s, ranging from s_{min} to s_{max} (here, 1 and 5), with a pre-defined step size, the intra-class variance $V_a(s)$ is given by the formula:

$$V_a(s) = p(C_1^s) * (M_1^s - M)^2 + p(C_2^s) * (M_2^s - M)^2$$

where:

C_i^s: the i^th class

M: the mean score of the population

M_i^s: the mean score of the i^th class

$p(C_i^s)$: the probability of the i^th class, equal to the number of subjects in the i^th class divided by the total number subjects

Minimizing the intra-class variance is equivalent to maximizing the between-class variance:

$$V_b(s) = p(C_1^s) * p(C_2^s) * (M_1^s - M_2^s)^2$$

- the optimal threshold s_0 is given by the expression:

$$V_b(s_0) = \max_{s \in [1;5]} \{V_b(s)\}$$

Figure 4 shows the distribution of the scores of the 22 subjects. Notably, our threshold and the median value (2.51) are similar. The numbers of subjects per class were quite similar: 9 decisive subjects and 13 indecisive subjects. The first class ("decisive") had a mean value of 2.13 with a standard deviation of 0.24, and the second class had a mean of 2.78 with a standard deviation of 0.19.

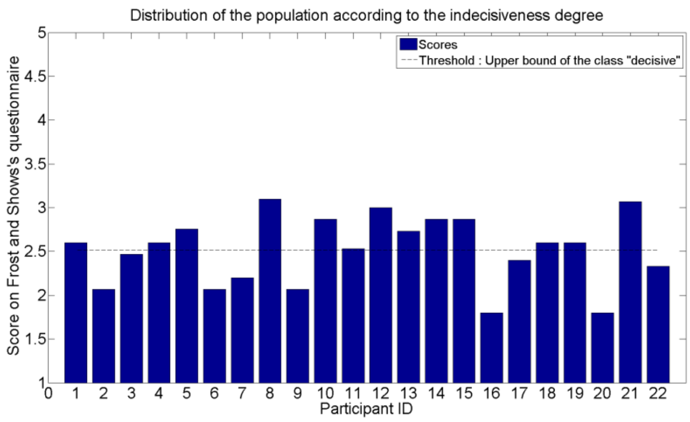

Figure 3. Degree of indecisiveness.

After segmenting the population into two classes, we next extracted the eye-tracking descriptors.

4. Eye-tracking descriptors

Eye-tracking descriptors were divided into two groups: descriptors based on fixation and descriptors based on saccades. We decided to focus not only on information about the alternatives that were chosen or looked at the most but also on information about the areas outside these regions. In an indecisive state, at least two alternatives must be taken into account; we wanted to study behaviors directed towards the three alternatives at which subjects spent the most time looking (or towards the two alternatives, when only two alternatives were available).

Fixations data	D1	Total time
	D2	Time awarded to the chosen alternative
	D3	Fixation's mean duration on the chosen alternative
	D4	D3/D1
	D5	Percentage of time awarded to the chosen alternative
	D6	Time awarded to the 1st most observed alternative
	D7	Fixation's mean duration on the 1st most observed alternative
	D8	D7/D1
	D9	Percentage of time awarded to the 1st most observed alternative
	D10	Time awarded to the 2nd most observed alternative
	D11	Fixation's mean duration on the 2nd most observed alternative
	D12	D11/D1
	D13	Percentage of time awarded to the 2nd most observed alternative
	D14	Time awarded to the 3rd most observed alternative
	D15	Fixation's mean duration on the 3rd most observed alternative
	D16	D15/D1
	D17	Percentage of time awarded to the 3rd most observed alternative
	D18	Time awarded to the non-information areas
	D19	Percentage of time awarded to the non-information areas
Saccades data	D20	Total path length
	D21	Alternative-based path length
	D22	Ratio between alternative-based path length and total path length
	D23	Ratio between the number of alternative-based saccades and the total number of saccades
	D24	Ratio between the number of saccades to the chosen alternative and the total number of saccades

Table 5. Descriptors.

Altogether, we extracted 24 descriptors for each subject: Of these, 19 were based on fixation data (D1 to D19) and 5 on saccade data (D20 to D24). The percentage of time spent on non-informative areas, the chosen alternative or the i^{th} most observed alternative $(1 \leq i \leq 3)$ is proportional to the ratio between the time spent on non-informative areas, the chosen alternative or the i^{th} most observed alternative, and the duration of the task. Thus, if $i = 1$, the percentage of time spent on the most observed alternative will be:

$$D9 = 100 * \frac{D6}{D1}$$

It should be noted that for task 1, we did not have descriptors based on the third most observed alternative (D14, D15, D16 and D17) because task 1 consisted of only two alternatives.

The alternative-based path length (D21) was calculated as the sum of the lengths of the saccades going from one alternative to another. This descriptor should be relevant in quantifying the participant's indecisiveness.

Such a large number of eye movement patterns were gathered to build, in future works, a predictive model that can be used to determine a person's degree of indecisiveness; this list is likely to evolve.

III. Eye-tracking results

In this part, the selection of the most relevant descriptors is presented. Then, the average behavior of decisive and indecisive subjects is discussed in relation to task complexity. An interesting conclusion about behavior is drawn based on either the first or second half of the task. Eventually, the results regarding the relationship between the degree of indecisiveness and the degree of personal motivation are presented.

1. First and second halves of a task

It has been shown that every decision-making situation can be divided into two main elementary parts (Patalano et al. (2009)). First, information about the proposed alternatives must be gathered; in our case, each subject was supposed to be looking at the stimuli as a whole. Second, a decision-making process is launched. The boundary between each part depends on the subject and is not always easy to define. Therefore, to simplify our measures, and as was done in Patalano et al.'s work, we assigned the first part of the decision-making process to the first half of fixation. Further studies can be made to refine this boundary.

The 24 descriptors were calculated three times: for the entire task, for the first half and for the second half. We then wanted to describe how a subject behaved, not only during the task as a whole but also during each half (see III.3).

2. Selecting relevant descriptors

To select the most relevant descriptors, a one-factor analysis of variance (ANOVA) was used. Because there were two classes ("decisive" and "indecisive"), the null hypothesis was that the patterns of each class originated from the same population; the alternative hypothesis was that they did not.

Table 6 provides the p-values for the main hypothesis for each of the 3 tasks. The values in column *F* are for the first half of the task, those in column *S* are for the second half, and those in column *T* are for the entire task. A p-value was considered significant if it was less than 0.05.

Only the descriptors whose p-values were significant for the full duration of at least one task were included: 13 descriptors from the fixation data and 2 from the saccade data. These names of these descriptors are depicted in bold in the table. It should be noted that no descriptor was statistically significant for each part of every task (*F, S* and *T*) and that only 6 were significant in two different tasks (D4, D8, D14, D17, D20 and D21). Because of this selection, we can now discuss the importance of task complexity and the relative importance the first or second part of a task in characterizing indecisiveness.

	Task 1: complexity			Task 2: complexity			Task 3: complexity		
	F	*S*	*T*	*F*	*S*	*T*	*F*	*S*	*T*
D1	0.213	0.401	0.297	0.076	0.080	0.076	**0.002***	**0.003***	**0.002***
D2	0.392	0.977	0.579	0.197	0.606	0.320	**0.009***	0.126	**0.016***
D3	0.236	0.928	0.244	0.029*	0.854	0.573	**0.013***	**0.020***	**0.010***
D4	0.020*	0.185	**0.027***	0.651	0.377	0.559	0.058	0.124	**0.035***
D5	0.782	0.446	0.403	0.433	0.620	0.975	0.553	0.238	0.204
D6	0.452	0.394	0.504	0.290	0.062	0.150	**0.020***	**0.030***	**0.005***
D7	0.371	0.342	0.245	0.700	0.394	0.940	0.735	0.901	0.744
D8	**0.022***	**0.025***	**0.019***	0.421	0.143	0.377	**0.030***	**0.017***	**0.031***
D9	0.422	0.726	0.207	0.087	0.914	0.563	**0.026***	0.515	0.187
D10	0.307	0.464	0.221	0.170	0.172	0.074	**0.001***	**0.005***	**0.002***
D11	0.668	0.082	0.361	0.774	0.465	0.950	0.994	0.542	0.500
D12	0.094	0.765	0.151	0.105	0.135	0.117	**0.001***	0.137	**0.047***
D13	0.595	0.552	0.177	0.555	0.911	0.773	0.777	0.479	0.802
D14				**0.029***	0.150	0.111	**0.004***	0.066	**0.015***
D15				0.171	0.120	0.490	0.066	0.368	0.237
D16				0.685	0.903	0.725	0.102	**0.017***	**0.010***
D17				**0.035***	0.781	0.655	**0.047***	0.647	0.987
D18	0.401	0.696	0.774	**0.045***	0.572	0.100	0.074	0.180	0.083
D19	0.693	0.775	0.834	0.140	0.823	0.219	0.098	0.507	0.174
D20	**0.006***	**0.003***	**0.001***	0.193	0.410	0.282	0.137	**0.046***	0.059
D21	0.117	**0.002***	**0.007***	0.181	0.168	0.148	0.431	**0.023***	0.085
D22	0.410	0.154	0.187	0.273	0.297	0.142	0.373	0.271	0.889
D23	0.347	0.368	0.262	0.953	0.529	0.646	0.198	0.430	0.287
D24	0.225	0.146	0.131	0.651	0.741	0.975	0.253	0.278	0.804
	3	3	4	4	0	0	10	8	10

Table 6. The p-values of each descriptor for the first half of the task(P), the second half (S) and the entire task (T).

3. Degree of indecisiveness and task complexity

The following figures display the standardized total durations of the tasks (descriptor D1) and the standardized durations spent looking at the chosen alternative (D2).

Let us consider task duration. Relative to the average decisive subject, the average indecisive subject spent more time on a task (figure 4). Moreover, he spent more time looking at the alternative he ultimately selected (figure 5), with a higher mean fixation duration. We noted that the longer the duration of the task, the larger the difference between the indecisive class and the decisive class. However, this observation did not apply for all of the 24 descriptors.

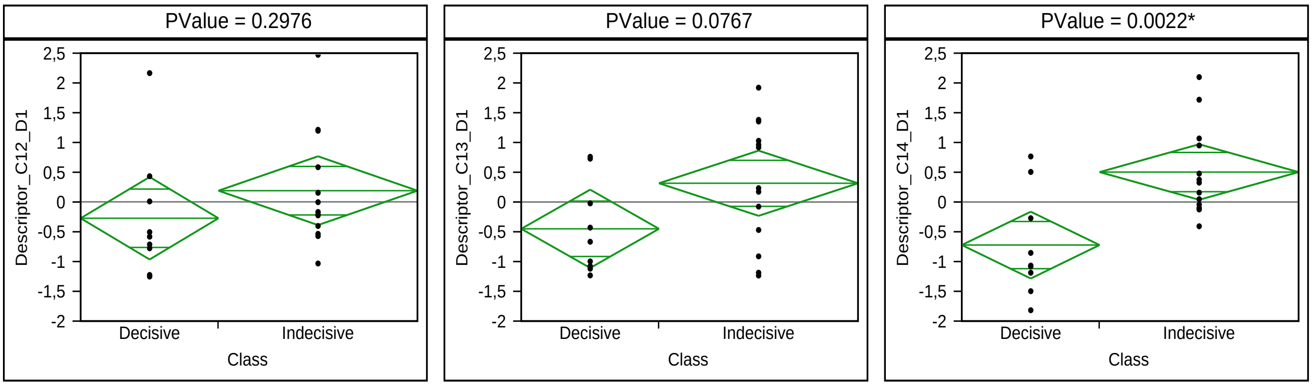

Figure 4. Standardized total durations of the tasks (D1) for tasks 1 to 3 (from left to right).

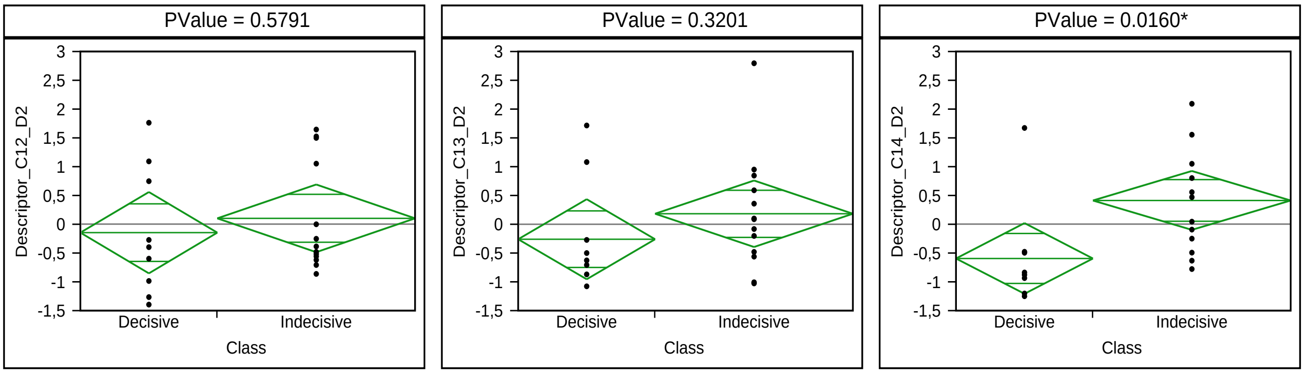

Figure 5. Standardized durations spent looking at the chosen alternative (D2), for tasks 1 to 3 (from left to right).

Let us then consider all of the descriptors for the full task durations (table 6, column *T*). We can see that for the most complex task, almost half of the descriptors were statistically significant. For the first and second tasks, 4 and 0 descriptors were relevant, respectively. We did not find that the relevance of the descriptors increased with task complexity. It would have been interesting to study the subjects' behaviors for a greater number of stimuli with increasing complexities.

4. Degree of indecisiveness during the parts *F* and *S* of the tasks

If we consider the alternative-based path length (figure 6), we can see that during the second half of a decision-making situation, the average indecisive subject, relative to a decisive one, has a greater alternative-based path; although there is no significant difference during the first half of the task. We obtained the same results with the descriptor "total path length". These results are consistent with the idea that after reading the instructions and exploring all of the alternatives, an indecisive subject, relative to a more decisive one, browses a greater distance before orally formulating his answer.

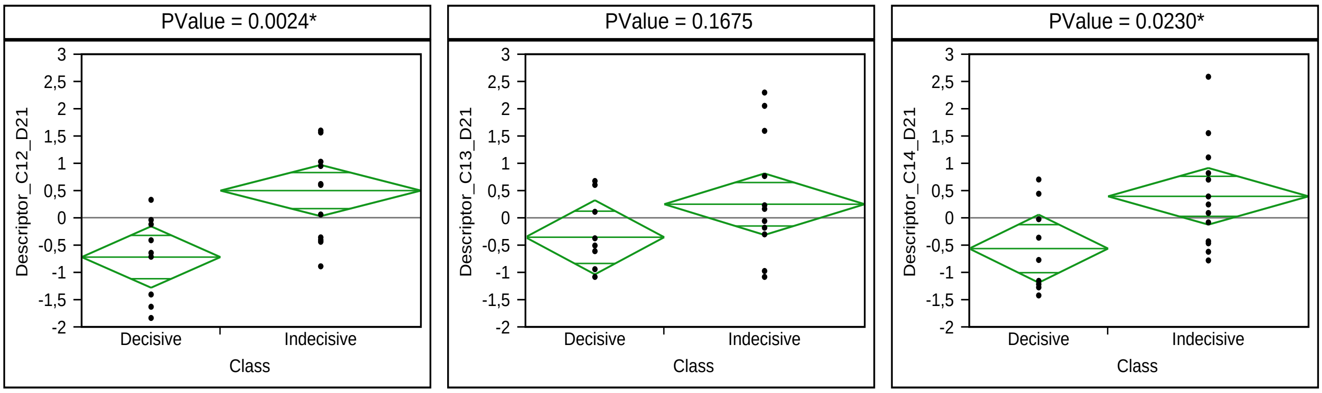

Figure 6. Alternative-based path lengths in standardized values (D21) for parts *S* of the first task (left), the second task (middle) and the third task (right).

The data presented in figure 6 are consistent with the hypothesis proposed by Patalano et al. (2009) that the relationship between the degree of indecisiveness and the exploratory strategy employed depends on whether the subject is in the first or second stage of the decision-making process.

5. Degree of indecisiveness and degree of personal motivation

In this section, we present data relating to the relationship between the degree of indecisiveness and Zaichkowsky's degree of personal motivation. To analyze this relationship, we began by performing an analysis of variance and then applied Kendall's nonparametric test (τ) to more precisely identify any interactions.

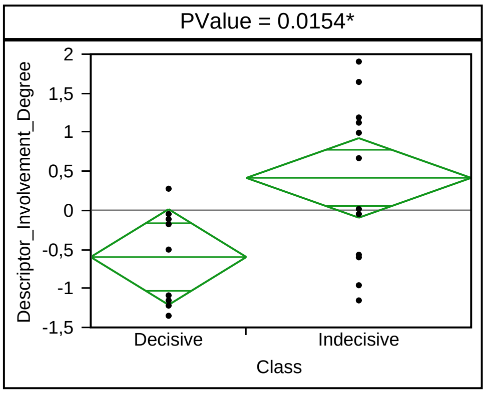

Figure 7. ANOVA: class and degree of motivation.

The ANOVA revealed that the classes were statistically separable based on the degree of motivation: the probability that all of the 22 degrees of motivation came from the same population was 0.0154, which is less than the value of alpha (0.05). We were interested in looking more deeply at this interaction.

Kendall's rank correlation coefficient is based on Spearman's. The calculation is quite simple. First, the n degrees of indecisiveness must be sorted. The rank values of the n degrees of motivation are then sorted according to the degrees of indecisiveness. After this step, only the degrees of motivation are taken into account. For the oth observation, we counted the number of observations that were greater than the oth (weight "+1") or less than the oth (weight "-1"). We then obtained a third column of n-1 values by summing the weights.

The maximum total weight, S, is equal to $\frac{n*(n-1)}{2}$ if the order is perfect, as it would then be the sum of the n first integer numbers. If the order is the perfect opposite, S will be equal to $\frac{-n*(n-1)}{2}$. In the case of a total absence of correlation, S is equal to 0. The Kendall rank correlation is given by the expression:

$$\tau = \frac{S}{\frac{n(n-1)}{2}} = \frac{2S}{n(n-1)}$$

τ ranges from -1 to 1 and can be related to Pearson's coefficient: the closer it is to 1, the more likely it is that a positive correlation exists, while the closer it is to -1, the more likely it is that a negative correlation exists. Finally, if τ is close to 0, there is a strong probability that there is no monotonic link between the two degrees.

We calculated Kendall's τ for the entire population (n=22), for the decisive group (n=9) and for the indecisive group (n=13):

$$\tau_{Total} = 0.35, \qquad PValue_{Total} = 0.03^*$$

$$\tau_{Decisive} = 0.59, \qquad PValue_{Decisive} = 0.04^*$$

$$\tau_{Indecisive} = -0.16, \qquad PValue_{Indecisive} = 0.49$$

Thus, according to our decisive database, we can conclude that the higher the degree of indecisiveness (below 2.5), the higher the probability that the degree of motivation will be high as well. As for the indecisive subjects, we can only conclude that there is a high likelihood that there is no monotonic link between the degree of indecisiveness and the degree of personal motivation.

Conclusions and discussion

We proposed an automated method for the segmentation of a population into two classes: decisive and indecisive. We emphasized a possible correlation between Frost and Shows's indecisiveness scale and Zaichkowsky's personal degrees of motivation. We successfully filtered the participants and identified 15 eye-tracking descriptors based on the ocular responses of the 22 subjects during the 3 different tasks.

Some of the results are consistent with the work of Frost and Shows (1993). For example, an indecisive person, relative to a more decisive one, takes more time to make simple decisions. We also found the same results as Ferrari and Dovidio (2000): an indecisive person, relative to a decisive person, seeks more information about the alternative chosen but not more information overall. It should be noted that the greatest number of relevant descriptors was found for the most complex task (task 3).

These analyses were applied to a population of 22 subjects. The lack of relevancy of certain descriptors, from a statistical point of view, may be due to the lack of power. Whether it is valid to base the first step of a decision-making process on the first half of fixation may also need to be evaluated further. Indeed, it would be interesting to identify a method of determining this threshold in each subject. For example, by applying a sliding temporal window to the saccade data, we could detect when the alternative-based saccade frequency exceeds the frequency of saccades directed to the alternatives.

As mentioned in the introduction, this indecisiveness study is part of our work on behavioral marketing. Marketing managers need to understand the behavior of customers during a purchasing act: what first catches the customer's eye, between what products does the customer hesitate, why does he hesitate, etc. Our work could also be translated into research fields that involve the subject's emotional state, such as motor racing competitions, fighter pilots' flights, or psychiatric disorders.

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