# A regression-based method for the prediction of the indecisiveness degree through eye movement patterns

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# A Regression-Based Method for the Prediction of the Indecisiveness Degree Through Eye Movement Patterns


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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 indecisiveness. To reach this goal, we first need to extract statistically relevant. Using eye-tracking methodology, we build a list of patterns that best distinguish decisive people from indecisive people; this segmentation is made according to the state of the art. The final list of eye-tracking patterns is also coherent with the state of art. A comparison between Multiple Linear Regression (MLR) and Support Vector Regression (SVR) is made so as to select the best predictive model.



## Keywords
Indecisiveness degree, eye-tracking, eye movements, decision-making strategy, regression model, purchase behaviour.


## 1. INTRODUCTION
Indecisiveness is, for a kind of person, a character trait which manifests itself through difficulty to settle between several simple or non-simple alternatives. The goal of this work is to build a predictive model of the indecisiveness degree of a subject, based on eye tracking methodology. For our experiments, we simulate two decision making situations in laboratory. The first one consists in performing a simple task. The second one consists in performing a more complex task. In each task, the subject has to choose one alternative between several alternatives. We define the complexity of a task with the number of available alternatives. We aim at offering solutions to the following issues. (i) Predict the indecisiveness degree of the subject. (ii) From what moment can the indecisiveness degree be predicted? (iii) Does the complexity of the task influence the quality of the prediction?



Our study on indecisiveness is lead under a marketing project. This project aims at completing an analysis of the customer's decision-making process by combining various data acquisition tools. The analysis of decision-making process goes through three steps. First, the stimuli in interaction with the customer need to be identified. Then the interpretation of the customer's behaviour is achieved, thanks to his hesitations, the time staring at different objects, etc. Eventually, behaviour patterns in purchasing situation can be determined. Our present works are related to the second and the third steps.

In the first section of this paper, we make a brief state of art of works that are related to eye tracking and indecisiveness degree fields. In the second section, we present the architecture of our approach, with the regression algorithms that are used. In a third section, we describe the data collection step, before ending with the different results.

## 2. RELATED WORKS IN EYE TRACKING AND INDECISIVENESS DEGREE
Eye tracking technology is used not only in fundamental research, with the modelling of visual attention, but also in applied research. Bojko [1] uses the eye tracking methodology so as to evaluate the design of several web pages. Later, Peirreira Da Silva, Courboulay, Pringent, and Estraillier [10] find that preys/predators systems can help modelling visual attention. In psychological and psychiatric research, we can quote the works made by Sasson and Elison [13]. The authors study the behaviour of young children with autism spectrum disorders. Jainta and Baccino [4] use the pupil responses of several subjects during the reading process to emphasize the pupil's responses to low-level aspects of visual inputs.

All over this paper, the indecisiveness degree is defined through the scale of Frost and Shows [3]. This scale is built from a multiple-choice questionnaire with valuated answers. Thanks to a threshold on the scale, the authors divide the population into two groups: the group of decisive people and the group of indecisive people. They show for example that an indecisive person, relatively to a more decisive one, needs more time to make a simple decision. Several works come from this scale. Ferrari and Dovidio [2], show that an indecisive person, relatively to a decisive one, looks deeper in alternatives he finally chooses. Rassin, E., and Muris, P. [11] notice that indecisive people seek for more information before deciding. Veinott, E.S. [17] notice that they most often postpone the most difficult choices.

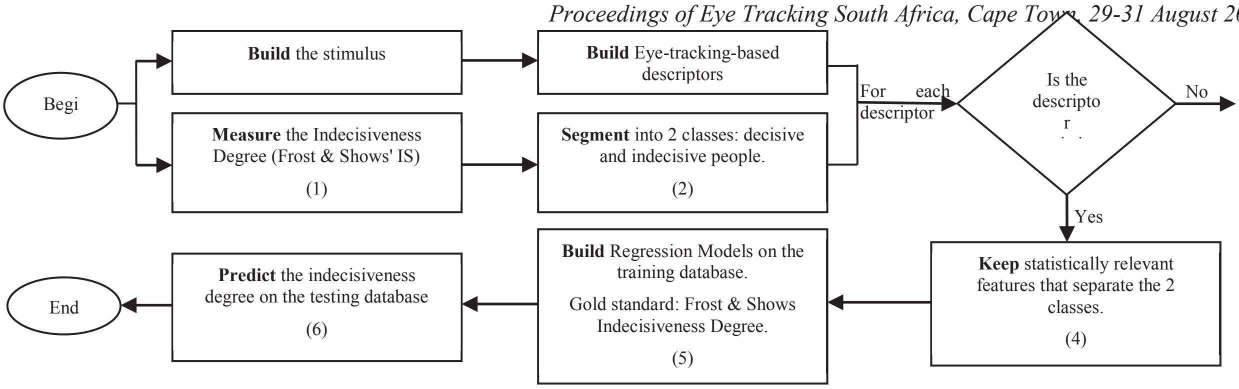


**Figure 1. Architecture of our approach.**

It has also been demonstrated by Huang and Kuo [6] that the decision making process can be split into two steps: a first step, which is dedicated to the search of information and orientation, and a second step of evaluation. Earlier, Patalano et al. [9] also distinguish a first step and a second step in a decision making situation. They show that the exploratory strategy is different from the decisive class to the indecisive class. Moreover, these differences depend on the fact that we only take into account the first step or the second step of the decision making situation.

# 3. PROPOSED APPROACH

## 3.1 Architecture

On Figure 1 is presented the architecture of our approach. It must be said that the goal of this work is to build a predictive model of the indecisiveness degree. In the first step, thanks to Frost and Shows' [3] method, we need to segment the population into two groups: decisive people and indecisive people (2). All the same time, a list of eye tracking patterns is built, and a feature selection is made: the purposes here are to only keep the most statistically relevant descriptors and to minimize the information's redundancy. The descriptors that are extracted at step (4) are then used as the inputs of the regression model (5), whose output is the indecisiveness degree of the subject (6). We consider the fact that if each one of these descriptors is statistically relevant for the discrimination of both classes, then their combination in the regression model can help predicting the indecisiveness degree.

## 3.2 Indecisiveness scale and classes

The multiple-choice questionnaire of Frost and Shows [3] gives us an a priori of the population's segmentation into two classes: decisive subjects and indecisive subjects. It is a 15-statement questionnaire (e.g. "I have a hard time planning my free time") rated on a 5-point scale; to each statement the subject has to choose between the following proposals: 'strong disagreement' (score = 1), 'disagreement' (score = 2), 'neutral' (score = 3), 'agreement' (score = 4), 'strong agreement' (score = 5). Within the 15 statements, 6 have reversed scores. The authors define the subject's indecisiveness degree as the mean value of the 15 values.

The subjects, whose score are less than 2.5 will be labelled 'decisive'; those, whose scores are greater than 2.5, will be labelled 'indecisive'. Authors like Patalano et al.[9], use the median score of the population as a threshold for segmentation. We can however question ourselves whether choosing 2.5 or the median score is a statistically relevant solution or not. The value 2.5 is logical; but it cannot be denied that we do not know the statistical distribution of our population's indecisiveness degrees. Choosing the median score, as proposed by Patalano et al. [9], seems more appropriate, but not always an absolute choice. Taking into account the variance in the population could bring relevant information.

We use here a method that is based on the maximization of the between-class variance, from Otsu [8]. The optimal threshold $s_0$ is obtained maximizing the following expression:

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

$$where\ V(s) = p(C_1^s) * p(C_2^s) * (M_1^s - M_2^s)^2$$

The between-class variance between $C_1^s$ and $C_2^s$ is equal proportional to the weight of each class and the square of the difference of the mean values.

## 3.3 Eye-tracking descriptors

Eye-tracking descriptors are divided into two groups: descriptors that are built from fixations data (D1 to D19) and those that are built from saccades data (D20 to D24). Concerning the saccades, we differentiate the saccades that stay in an area ('within-alternative saccades') from saccades that go from an area to another ('between-alternative saccades'). What we call 'alternative' is one of the possible choices that are given to the subject. To one alternative corresponds one area one the scene. The list of the 24 descriptors is given in the following table.

These descriptors are built taking into account not only information about the chosen alternative, but also the N most observed alternatives. If the task is only made of N-1 alternatives, then all the N-1 alternatives will be taken into account. In our experiments, we interest ourselves in the 3 most observed alternatives.

The descriptors D1, D2, D3, D6, D7, D10, D11, D14, D15, D18, D19, D20 and D21 are either temporal data or spatial data. The other descriptors are calculated relatively to the previous list. D1 is the time between the beginning of the task and the end of the task. D4 is the proportion of the mean duration fixation on the chosen alternative over the duration of the task. D8, D12 and D16 are built in the similar way as D4, for respectively the first most observed alternative, the second most observed alternative and the third most observed alternative. The percentage of time that is spent on an area is calculated with the ratio between the time spent on the area and the total duration of a task. We only take into account fixation duration, not saccade duration.

The works of Patalano et al. [9] also emphasize the importance of the time spent looking at outside areas. The moments of fixation on these areas (D18) can be seen as moments of pure reflection.

Eventually, it has been shown that the differences in exploratory strategy depend on whether we analyse the first half or the second half of a decision making situation. The first half corresponds to discovering the stimuli and collecting the information. The second phase corresponds to the evaluation of those information and the elaboration of a choice. We made the hypothesis that, for each subject, the first half corresponds to the first sequence of fixations and that the second half corresponds to the second sequence of fixations.

**Table 1. Eye-tracking descriptors.**

| | |
|---|---|
| **D1** | Total time : time between the beginning of the task to the end of the task |
| **D2** | Time spent on the chosen alternative |
| **D3** | Mean fixation duration on the chosen alternative |
| **D4** | D3/D1 |
| **D5** | Percentage of time spent on the chosen alternative |
| **D6** | Time spent on the 1st most observed alternative |
| **D7** | Mean fixation 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** | Mean fixation 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** | Mean fixation 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 area |
| **D20** | Scanpath length |
| **D21** | Between-alternative scanpath length |
| **D22** | Between-alternative scanpath length' / 'Total scanpath length' |
| **D23** | 'Number of alternative-base saccades' / 'Total number of saccades' |
| **D24** | 'Number of alternative-base saccades to the chosen alternative' / 'Total number of saccades' |

Thus, both phases have the same number of fixations, but not necessary the same duration. The final predictive model of the indecisiveness degree will be built in three cases: (i) one model for the entire task; (ii) one model for the first half of the task; (iii) one model for the second half of the task. It is to be said that the descriptor D1 will not have the same signification in the three cases. In the case (i), D1 is the duration time between the first fixation on the scene and the moment when the subject orally announces his choice.

In general, all the descriptors do not bring the same amount of information. Moreover, they can be correlated each other. Certain correlations are more powerful than others. For example the descriptor 'Total time' (D1) and 'Total path length' (D20) are hardly more correlated than the descriptors 'time awarded to the 3rd most observed alternative' (D14) and 'Time awarded to the non-information area' (D18). Thus, it is necessary that, before building the predictive models, to select the most statistically relevant descriptors and to minimize the redundancy of the information.

## 3.4 Feature selection with ANOVA and PCA

Feature selection goes through two steps. In the first step, the goal is to select the descriptors according to their ability to separate efficiently the decisive class from the indecisive class. One factor analysis of variance (ANOVA) is performed. Secondly we run a principal component analysis (PCA), in order to minimize the redundancy of the information among the eye tracking descriptors.

Nevertheless, in our works, we do not use the data in the new space that is defined by the PCA for one reason: the new axes can have no signification, in a physical way. It is essential here that the final models were built on data that have a physical meaning. The idea is to select the descriptors in the main factorial design of the PCA. After having selected the descriptors, the prediction of the indecisiveness degree can be performed with a regression model.

## 3.5 Regression model

Let us take into account a learning set $S = \{(\boldsymbol{x_1}, f(\boldsymbol{x_1})), \dots, (\boldsymbol{x_n}, f(\boldsymbol{x_n}))\} \subset X{\times}Y$. $X$ is the space of the descriptors, of dimension $p$ (here, inferior or equal to 24). $Y$ is the output space, that is to say the space of the indecisiveness degrees. We decide to compare the performances of two regression algorithms: the multilinear regression (MLR), a naïve method, and the support vector regression (SVR). SVR is more robust to noise and allow dealing with non-linearly separable data.

### *3.5.1 Multi Linear Regression*

The MLR is a generalization, with $p$ descriptors, of the simple linear regression. The goal is to explain an output $f(\boldsymbol{x_i})$ thanks to a linear combination of the dimensions of the input vector $\boldsymbol{x_i}$:

$$(1) \quad f(\boldsymbol{x_i}) = \mathcal{E}_i + a_0 + \sum_{j=1}^{p} a_i x_{ij}$$

The terms $a_0, \dots, a_p$ are the parameters of the model that we need to estimate. The term $\mathcal{E}_i$ is the error of the model; it explains or resumes the missing information in the linear expression of the values of $f(\boldsymbol{x_i})$, thanks to the different dimensions $x_{i1}, \dots, x_{ip}$. This residual error can come from a specification problem of can come from the fact that there is not enough patterns to explain the observable variable $f(\boldsymbol{x_i})$

### *3.5.2 Support Vector Regression*

Support Vector Regression (SVR) is a supervised learning algorithm. In the case where the problem can be solved linearly, it can be shown that the indecisiveness degree $f(x)$, that corresponds to a descriptor $x$, only depends on the dot products between $x$ and the other data. This relation can be translated in the following equation:

$$(2a) \quad f(\boldsymbol{x}) = \frac{1}{n}\sum_{i=1}^{n} \lambda_i^* y_i \,\langle \boldsymbol{x} | \boldsymbol{x_i} \rangle + b^*$$

$\lambda_i^*$ et $b^*$ are proportional to Lagrange multipliers.

In practice, a subset of $X$ is enough to solve the problem; this subset is called subset of support vectors; hence the name of the method.

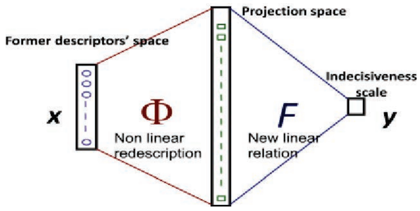


**Figure 2. SVR. Non linear case.**

In the case where the problem cannot be solved linearly, two ideas are used. The first idea (see Figure 2) is that by increasing the dimension of the data, we can reach a space where the resolution of the problem becomes linear: the data are projected in higher dimension space that is also called redescription space. The second idea consists in using a kernel $K$ in order to prevent us from calculating all the dot products in the redescription space. The new relation between the outputs and the inputs of the problem is explained in equation (2b):

$$(2b) \quad f(\boldsymbol{x}) = \frac{1}{n}\sum_{i=1}^{n} \lambda_i^* y_i \, K(\boldsymbol{x_i}, \boldsymbol{x_j}) + b^*$$

There are several kernel functions $K$. The most used kernels are the polynomial kernel $(3a)$, the gaussian kernel $(3b)$ and the sigmoidal kernel $(3c)$.

$$(3a) \quad K(\boldsymbol{x_i}, \boldsymbol{x_j}) = \left(c_1 + c_2\langle \boldsymbol{x_i} | \boldsymbol{x_j} \rangle\right)^2$$

$$(3b) \quad K(\boldsymbol{x_i}, \boldsymbol{x_j}) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$$

$$(3c) \quad K(\boldsymbol{x_i}, \boldsymbol{x_j}) = \tanh\left(c_1 + c_2\langle \boldsymbol{x_i} | \boldsymbol{x_j} \rangle\right)$$

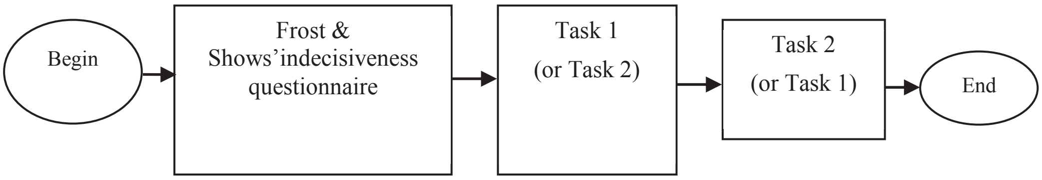


**Figure 3. Experimental design.**

What is important to emphasize with the support vector regression, in the linear case and the nonlinear case, is that : (i) the problem can be solved using only the dot products between the data, (ii) the solution is calculated considering only few set of data called support vectors. For further information about SVR, one can refer to the works of Rivas-Perea, P. et al [12].

Throughout the rest of this paper, we call P-SVR, G-SVR and S-SVR the regression models with the polynomial kernel, the Gaussian (or radial basis function) kernel and the sigmoidal kernel, respectively. The SVR is used for its robustness against noise and the possibility of dealing with data that are not linearly separable in their representation space. Just like the MLR, SVR allows us working directly on data that have a physical meaning.

# 4. DATA COLLECTION

## 4.1 Equipment

For the experiment, a population of 22 subjects is recruited, with the same proportion of men and women. They are all between 18 years old and 70 years old. We use a corneal reflection-based eye tracker[†]. The subject sits in front of a table. His chin rests on a headrest that is located at 70 centimetres from a monitor. The dimension of the monitor is 47.7 by 29.7 square centimetres. The stimuli are displayed with a resolution of 1680 by 1050 square pixels, and data are acquired at a frequency of 500 Hz. The eye tracking sensors are located just below the monitor. Eye tracking data can be seen on the experimenter's screen.

## 4.2 Experimental design

The experimental design falls into three steps (see Figure 3). In a first step, the subject has to fill the multiple-choice questionnaire of Frost and Shows [3]. In a second step, participants had to choose one alternative (or situation) among two alternatives. Lastly, they had to choose one alternative among four alternatives. Choice tasks were counterbalanced across subjects. Frost and Shows' [3] questionnaire is always presented at the beginning of the experiment. All the answers are given orally to the experimenter. The idea of analysing the subject through several tasks of different complexity relies on the fact that the indecisiveness degree of a person is connected to the situation in which this person is. The dissimilarities between the decisive population and the indecisive population depend on the complexity of the situation.

Here is the instruction that is given to each subject for the first task (task 1):

"*You are a student. It is lunch time. Every day, information about the day's menus are 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 (menu can be vegan).*"

**Table 2. Stimulus on the screen for task 1.**

| Menu 1 | Menu 2 |
|---|---|
| Starter<br>Hot dish<br>Dairy product or dessert<br>Bread | Hot dish<br>Dairy product<br>Dessert<br>Bread |

The stimulus of task 1, as it is seen on the monitor by the subject, is presented in Table 2. One column stands for one alternative.

Here is the instruction that is given to each subject for the second task (task 2). The corresponding stimulus is displayed in Table 3.

"*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.*"

**Table 3. Stimulus on the screen for task 2.**

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

Just like in task 1, the 4 alternatives of task 2 are presented in columns.

As for Frost and Shows questionnaire, the 15 items are also presented on the monitor in front of the subject, one item a stimulus.

# 5. RESULTS

## 5.1 Segmentation of the population, based on Frost and Shows' indecisiveness scale

Figure 4 on the next page shows the distribution of the 22 participants according to the scale of the indecisiveness degrees. The index in abscissa stands for the running order of the candidates.

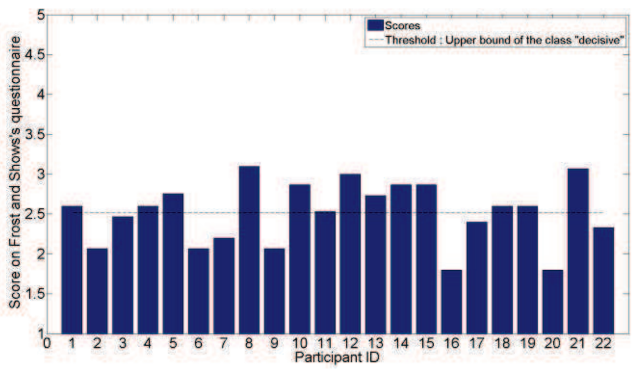


**Figure 4. Degree of indecisiveness.**

The number of subjects per class are rather similar: 9 decisive subjects and 13 indecisive subjects. The first class ("decisive") has a mean value of 2.13 with a standard deviation of 0.24; the second class ("indecisive") has mean value of 2.78 with a standard deviation of 0.19.

After the segmentation of the population into two classes, the next step consists in selecting the less collinear descriptors that maximize the distance between the two classes.

## 5.2 Feature selection

It must be said that before building the final predictive models, it is necessary to select the most statistically relevant descriptors. So as to make it, two ideas are implemented: (i) choosing the descriptors that best distinguish both classes (ANOVA), and (ii) carry out a second selection so as to minimize the redundancy of the information (PCA).

Table 4 shows the p-values that are get for each descriptor (D1 to D24), for the first half of each task (column F), the second half of each task (column S) and the totality of each task (column T). As it is said in part 3.3 of this paper, we distinguish between the whole task, the first half of the fixations sequence and the second half of the fixations sequence. The ANOVA's are implemented in each of the three cases. So, what is called "total time" (D1) is different in each one of the three cases. In column F, D1 is the time band containing the first half of the sequence of fixations, D2 is the time that is spent on the chosen alternative in the first time band, etc. In column S, D1 is the time band containing the second half of the sequence of fixations, D2 is the time that is spent on the chosen alternative in the second time band, etc.

It is normal that the lines of the descriptors D14 to D17 remain empty for task 1. Indeed, these descriptors correspond to the information about the 3rd alternative, and task 1 is only made of 2 alternatives. The descriptors whose number or value is printed in bold (15 descriptors) are those being considered statistically relevant in the discrimination between the decisive class and the indecisive class.

There are more descriptors that are selected in task 2 than in task 1. In the most complex task, respectively 10, 8 and 10 descriptors are selected for the first half the task, the second half of the task, and the totality of the task. The amount of descriptors is twice less important in the simplest task. This can mean that, for the simplest task, the separation between the two classes is less clear than for the most complex task. This deduction is only available if our list of 24 descriptors is an exhaustive list, which we cannot guaranty. Another explanation can be given with Figure 5. The fact that overall duration (D1) in task 1 does not well separate the two groups of participants suggests that this task is very fast: indeed, the average duration for task 1 is about 10 seconds, whereas the average duration for task 2 is about 14 seconds.

The second point that can be made with Table 4 is that, whatever the portion of the experiment (F, S or T), the number of statistically relevant descriptors remains the same. We can, from here, advance this hypothesis: as for the classification of the subjects into two groups, it may be sufficient taking into account only the first half or the second half of the decision making situation. This point allow drawing a first draft response to one of the questions that are asked in the introduction of the paper: from what moment in a given task is it possible to predict the indecisiveness degree of a subject? It is possible that the first half or the second half of the task fits the role. A more detailed answer is given in the section **5.3** of this paper.

Let us look deeper some results of Table 4. On the following figure is displayed the distribution of the durations of tasks (D1), for the 2 groups of subjects and for the entire task (column "T" in Table 4).

**Table 4. The p-values of each descriptor, for the first half of the task (F), the second half of the task (S) and the entire task(T)**

| | Task 1 | | | Task 2 | | |
|---|---|---|---|---|---|---|
| | F | S | T | F | S | T |
| **D1** | 0.213 | 0.401 | 0.297 | **0.002*** | **0.003*** | **0.002*** |
| **D2** | 0.392 | 0.977 | 0.579 | **0.009*** | 0.126 | **0.016*** |
| **D3** | 0.236 | 0.928 | 0.244 | **0.013*** | **0.020*** | **0.010*** |
| **D4** | **0.020*** | 0.185 | **0.027*** | 0.058 | 0.124 | **0.035*** |
| D5 | 0.782 | 0.446 | 0.403 | 0.553 | 0.238 | 0.204 |
| **D6** | 0.452 | 0.394 | 0.504 | **0.020*** | **0.030*** | **0.005*** |
| D7 | 0.371 | 0.342 | 0.245 | 0.735 | 0.901 | 0.744 |
| **D8** | **0.022*** | **0.025*** | **0.019*** | **0.030*** | **0.017*** | **0.031*** |
| **D9** | 0.422 | 0.726 | 0.207 | **0.026*** | 0.515 | 0.187 |
| **D10** | 0.307 | 0.464 | 0.221 | **0.001*** | **0.005*** | **0.002*** |
| D11 | 0.668 | 0.082 | 0.361 | 0.994 | 0.542 | 0.500 |
| **D12** | 0.094 | 0.765 | 0.151 | **0.001*** | 0.137 | **0.047*** |
| D13 | 0.595 | 0.552 | 0.177 | 0.777 | 0.479 | 0.802 |
| **D14** | | | | **0.004*** | 0.066 | **0.015*** |
| D15 | | | | 0.066 | 0.368 | 0.237 |
| **D16** | | | | 0.102 | **0.017*** | **0.010*** |
| **D17** | | | | **0.047*** | 0.647 | 0.987 |
| D18 | 0.401 | 0.696 | 0.774 | 0.074 | 0.180 | 0.083 |
| D19 | 0.693 | 0.775 | 0.834 | 0.098 | 0.507 | 0.174 |
| **D20** | **0.006*** | **0.003*** | **0.001*** | 0.137 | **0.046*** | 0.059 |
| **D21** | 0.117 | **0.002*** | **0.007*** | 0.431 | **0.023*** | 0.085 |
| D22 | 0.410 | 0.154 | 0.187 | 0.373 | 0.271 | 0.889 |
| D23 | 0.347 | 0.368 | 0.262 | 0.198 | 0.430 | 0.287 |
| D24 | 0.225 | 0.146 | 0.131 | 0.253 | 0.278 | 0.804 |
| | 3 | 3 | 4 | 10 | 8 | 10 |

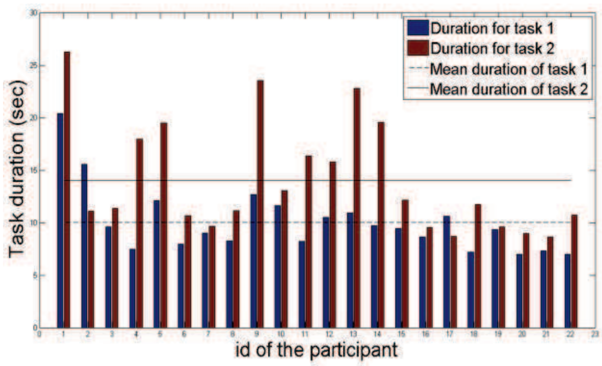


**Figure 5. D1: duration of task 1 and task 2 for each subject.**

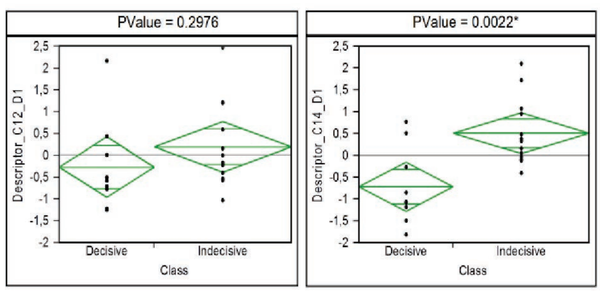


**Figure 6. Standardized total durations of the tasks (D1), for tasks 1 (left) and 2 (right).**

Let us now consider the time that is awarded to the chosen alternative (D2), for the totality of each task (column "T" in Table 4).

For the less complex task (on the left), there is no significant difference between the decisive subjects and the indecisive subjects: the p-value is 0.5791. For the most complex task (on the right), it can be seen that the average indecisive subject, relatively to the average decisive subject, pays more attention to the alternative he finally chooses. The p-value here is 0.0160. This is coherent with the results of Ferrari and Dovidio [2]: the decisive subject selects more information about the chosen alternative.

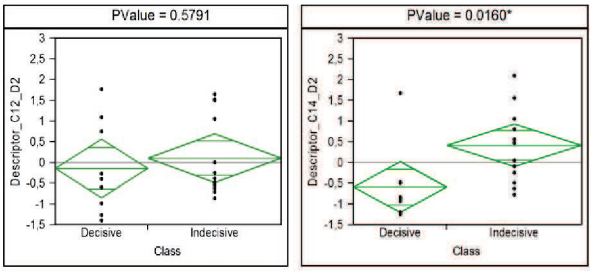


**Figure 7. Standardized durations spent looking at the chosen alternative (D2), for tasks 1 (left) and 2 (right).**

Let us eventually consider the length of the between-alternative path (D21), for the second half of each task (column "S" in Table 4). The results are displayed in Figure 8. We find the same result as Patalano et al [9], i.e. that the relationship between the exploratory strategy and the indecisiveness degree depends on the fact that we only consider the first or the second half of a decision making situation. Indeed, for task 1 and for task 2, the average indecisive subject, relatively to the average decisive subject, makes more jumps from one alternative to another, in the second half of a task. We did not find the same result in the first half of the tasks.

Overall, 13 descriptors from saccades data and 2 descriptors from fixations data are selected. After the section of the most statistically relevant descriptors, the next step consists in minimizing the redundancy of the information. On Table 5 are presented the results of the second selection by PCA.

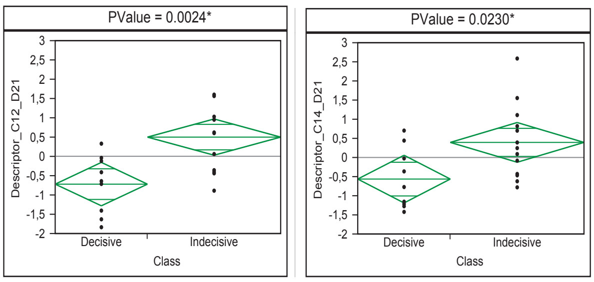


**Figure 8. Alternative-based path lengths in standardized values (D21) for parts S of the first task (left) and the second task (right).**

**Table 5. Selected descriptors for the regression models.**

| | Whole task | First half | Second half |
|---|---|---|---|
| Task 1 | D4, D8, D20, D21 | D8, D20 | D8, D20, D21 |
| Task 2 | D1, D2, D6, D10, D14 | D1, D2, D6, D10 | D1, D6, D10, D20 |

It is logical that a fewer amount of descriptors is needed in the less complex task, regardless of the portion of the task (first half, second half or whole task). For example, in its entirety, task 1 requires 4 descriptors, whereas task 2 requires 5. It also should be noted that, in general, the whole task requires more descriptors than the first half or the second half of the task. The second half of each task requires more descriptors than the first half. This could be put in perspective with the fact that in the second half of decision making situation, the evaluation process is launched [6].

In addition, the descriptors that are built from saccades data (D20 and D21) appear more in task 1 than in task 2. This can be explained by the fact task 1 is only made of 2 alternatives. In task 2, only the length of the scan path in the second half of the task, is selected. After the selection of the descriptors in each case, the regression models can be built.

## 5.3 Selecting the best regression model

Two regression models are implemented and compared: the classical linear regression (MLR) and SVR with kernels. On Table 6 are presented the results for both algorithms. As a deviation indicator in the predicted indecisiveness degree, a common measure is used: the Mean Square Error (MSE) . The MSE is defined by the arithmetic average of the squares of the differences between the predicted values and the expected values.

The results for task 1 are printed on the first line; those for task 2 are on the second line. The first column consists in the results that correspond to the totality of a task. The second column consists in results that correspond to the first part of a decision making situation, i.e. the search of information and orientation. The third column consists in results that correspond to the step of evaluation. We use the "leave-one-out" cross-validation method (LOOCV). Given $N$ observations (here, $N$=22), the LOOCV method consists in building a model on $N$-1 observations and validating it on the $N^{th}$ observations. The process is repeated $N$ times.

Let us consider the first two columns of Table 6. The question that is asked here is the following: can the prediction of the indecisiveness degree be improved by only taking into account the first half or the second half of a decision making situation? As regards task 1, no relevant improvement is seen by only considering the first half of the task instead of the totality. For the MLR model, we go from 18% of deviation for the totality, to 20% of deviation for the first half. The observation remains the same for the SVR models. As regards task 2, the deviation for the MLR model decreases its MSE from 25% to 23%. The MSE for the P-SVR model remains constant at 15%. In addition, if we compare the results of the first task to those of the second task, we can notice that the deviations in predicting the indecisiveness degree are less important in the first task. In the light of these results, we can draw the following conclusions: (i) the indecisiveness degree, under Frost and Shows' [3] definition, is more predictable on the less complex task; (ii) for the most complex task, it is sufficient to only analyse the first half of the decision making situation.

**Table 6. MSEs for the regressions' cross-validations.**

| | MSE for the whole task | MSE for the first half | MSE for the second half |
|---|---|---|---|
| Task 1 | MLR : 19%<br>P-SVR : 9%<br>R SVR : 18%<br>S-SVR : 8% | MLR : 20%<br>P-SVR : 19%<br>R SVR : 20%<br>S-SVR : 15% | MLR : 20%<br>P-SVR : 16%<br>R SVR : 19%<br>S-SVR : 26% |
| Task 2 | MLR : 25%<br>P-SVR : 15%<br>R SVR : 17%<br>S-SVR : 14% | MLR : 23%<br>P-SVR : 15%<br>R SVR : 20%<br>S-SVR : 18% | MLR : 24%<br>P-SVR : 24%<br>R SVR : 20%<br>S-SVR : 42% |

Let us consider now the first column and the third column of Table 6. The only improvement that we can notice is about the MLR model, on task 2: it goes from 25% of deviation for the whole task, to 24% of deviation for the second half of the task.

Let us eventually consider the second column and the third column of Table 6. It can be noticed that, for task 1, the regression on the second half leads to less errors than the regression on the first half. Indeed, the MSE of the MLR remains the same; the MSEs of the P-SVR model and the R-SVR model decrease. Only the MSE of the S-SVR increases. The observation is reversed in task 2. Except for the R-SVR, whose MSE remains constant from the first half to the second half of the task, the other models give less deviations on the first half than on the second half. In view of these results, we can draw the following conclusions : (iii) for the less complex task, the indecisiveness degree under Frost and Shows definition is more predictable prioritizing the second half of the task ; for the most complex task, this observation is reversed.

In the following table is presented the best regression model for each task, according to the mean square errors that are showed Table 6. The corresponding MSEs are printed into brackets.

**Table 7. Best regression models for each task.**

| | Best models | | | | | |
|---|---|---|---|---|---|---|
| | Whole task | (MSE) | First half | (MSE) | Second half | (MSE) |
| Task 1 | S-SVR | (8%) | S-SVR | (15%) | P-SVR | (16%) |
| Task 2 | S-SVR | (13%) | P-SVR | (15%) | R-SVR | (20%) |

Table 7 illustrates the fact that the SVR model gives better results than the classical regression model MLR. This validates the use of SVR instead of MLR. For the less complex task (with two alternatives), it is preferable to consider the whole decision making situation, while trying to predict the indecisiveness degree under Frost and Shows definition. For the most complex task (with four alternatives), the deviations in the predicted degrees for the first half of the task are close to the deviations for the whole task. It is sufficient, for task 2, to only restrict the analysis in the first half.

These remarks are coherent with the fact that the more complex a task, the more people will take time before making a decision, and the easier distinguishing antagonisms from the first half of the decision making situation. In other words, for the most complex task, differences in exploration are visible from the step of information step and orientation.

# 6. CONCLUSION AND DISCUSSION

The work that is presented in this paper is part of behavioural marketing project. Indeed, marketing managers need to know whether the customer hesitates in front of a product or not. The project aims at proposing a non-invasive model for the prediction of the indecisiveness degree of a person, under Frost and Shows definition.

We have analysed the behaviour of 22 subjects. We first defined 24 eye tracking descriptors. A statistical analysis enabled us to select 15 relevant descriptors.

So as to predict the indecisiveness degree of each subject, we implemented two regression algorithms. After a PCA on the descriptors, we got a prediction of the indecisiveness degree with a maximum deviation of 13%. Eventually, the predictive models were built with a maximum of 5 eye tracking descriptors. These results are very interesting for the behavioural marketing field and lead to a better understanding of the customer's decision-making process in a purchasing act. Nevertheless, these works can be translated into research fields that involve the emotional state of the subject, such as motor racing competitions, fighter pilots' flights, or psychiatric disorders.

An extension is being considered. In future works, we are going to introduce other eye tracking descriptors, like pupil opening, so as to improve the accuracy of the prediction. Additional studies have to be made, in order to detect the frontier between the step of information searching and the step of evaluation [6].

# 7. ACKNOWLEDGMENTS

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# 8. REFERENCES


[1] Bojko, A. 2006. Using Eye Tracking to Compare Web Page Designs: A Case Study. *Journal of Usability Studies*, Issue 3, Vol.1, May 2006, 112-120

[2] Ferrari, J.R. and Dovidio, J.F. 2000. Information search process by indecisives: Individual differences in decisional procrastination. *Journal of Research in Personality*, *34*, 127-137.

[3] Frost, R.O., Shows, D.L. 1993. The nature and measurement of compulsive indecisiveness. *Behaviour Research and Therapy*, Vol.*31*, N°7, 683–692.

[4] Jainta, S. and Baccino, T. 2010. Analysing the pupil response due to increased cognitive demand: an independent component analysis study. *International Journal of Psychophysiology: official journal of the International Organization of Psychophysiology*, 2010 Jul;77(1):1-7.

[5] Germeijs, V. and De Boeck, P. 2002. A measurement scale for indecisiveness and its relationship to career indecision and other types of indecision. *European Journal of Psychological Assessment*, *18*, 113–122.

[6] Huang, Y.-F, Kuo, F-Y. 2012. How impulsivity affects consumer decision-making in e-commerce. *Electronic commerce Research and Applications*, Vol. 11, Issue 6, November-December 2012, 582-590.

[7] Hsu, C.-W., Chang, C.-C. and Lin, C.-J. 2003. A practical guide to support vector classification. Technical report. *Department of Computer Science, National Taiwan University*.

[8] Otsu, N. 1979. *A threshold selection method from gray-level histograms*. *IEEE Transactions on Systems, Man and Cybernetics*, vol. 9, 62–66.

[9] Patalano, A.L., Juhasz, B.J. and Dicke, J. 2009. The relationship between indecisiveness and eye movement patterns in a decision making informational search task. *Journal of Behaviour Decision Making*, 23, 353-368.

[10] Peirreira Da Silva, M., Courboulay, V., Prigent, A., and Estraillier, P. 2012. Evaluation of preys/predators systems for visual attention simulation. *International Conference on Computer Vision Theory and Applications, VISAPP 2010*, 275-282.

[11] Rassin, E., Muris, P., Franksen, I., Smit, M. and Wong, M. 2007. Measuring General Indecisiveness. *Journal of Psychopathology and Behavioral Assessment*, 29, 61–68.

[12] Rivas-Perea, P., Cota-Ruiz, J., Garcia Chaparro, D., Arturo Perez Venzor, J., Quezada Carreon A., Rosiles, J.-G. 2013. Support Vector Machines for Regression: A Succint Review of Large-Scale and Linear Programming Formulations. *International Journal of Intelligence Science*, 2013, 3, 5-14, doi:10.4236/ijis.2013.31002

[13] Sasson, N.J. and Elison, J.T. 2012. Eye Tracking Young Children with Autism. *Journal of Visualized Experiments* (61), e3675, DOI: 10.3791/3675(2012).

[14] Scholkopf, B. 1997. Support Vector Learning. PhD thesis, *Technische Universitat Berlin*, R. Oldenbourg Verlag, Munich.

[15] Smola, A. 1998. Learning with Kernels. PhD thesis, published by *GMD*, Birlinghoven.

[16] Vapnik, V. 1998. Statistical Learning Theory. *Wiley*.

[17] Veinott, E.S. 2002. *The effect of understanding and anticipated regret on decision readiness*. Unpublished doctoral dissertation, University of Michigan, Ann Arbor.