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Abstract. When a group of agents is faced with collective decisional tasks, the agents may have to cooperate to establish which alternative appears to be a convenient consensus. The influence an agent may have upon the other ones may change the collective decision. Modelling of influence in a social network assumes that each player has an initial inclination for one of the alternative that may be different from his final decision. The point of departure of such studies is the concept of the Hoede-Bakker index, which computes the overall decisional power of a player in a social network when the decision is binary. We propose to extend the notions of decision power and influence indices when the decision is not simply binary, but associated with a scale of success: an individual can more or less adhere to the collective decision. Initially, the idea was motivated by the collective evaluation process in sensory analysis. Indeed, sensory analysis is a set of methods for measuring sensory perceptions. When the panel is made up of trained individuals who master the vocabulary of the domain, sensory analysis has been the subject of numerous evaluation protocols. On the other hand, when the evaluators are inexperienced evaluators not mastering the descriptors, the sensory characterization may strongly be impacted by influential panelists. In this paper, we are interested in measuring such a qualitative influence. Framing our work in game theory models, we propose to extend the notion of influence index to the qualitative process of graded decision in sensory analysis, justifying our choices on the basis of our feedback on the process of sensory analysis by a collective of panelists.

Keywords: Decision-making power - Index of influence - Social network - Sensory analysis.

1 Introduction

In industry, when a sensory analysis of an odor, a taste or a color is performed by a panel of evaluators, each description is made using conceptual descriptors of interest for the domain under study. These descriptors are disambiguated concepts extracted from a knowledge structure corresponding to a taxonomy [1][2]. The variability of the sets of descriptors provided from one evaluator to another requires a synthesis of the conceptual descriptions to be established, taking into account their diversity [3]. This synthesis can then be used to verify that the effect sought/desired by the industrialist at the initiative of this analysis was indeed perceived by the evaluators (e.g. to check if the taste of a product is consistent with a specific target). It is thus necessary to note that the human being, in spite of the subjectivity and the uncertainty which characterize

his sensory perception, is positioned as a tool of measurement and decision making in the chain of reliability of the industrialist by the means of the sensory analysis. When it is a panel of experts mastering the solicited sense and the associated controlled vocabulary, the sensory characterization reflects the sole perception of the experienced evaluator. On the other hand, if the evaluators are less experienced, with less trained senses and less familiar with the use of controlled vocabulary, then they will be more inclined, if given the opportunity, to pay attention to the characterizations of other evaluators to refine the expression of their perception. The less experienced will be inspired by the copy of their "elders" for example. The consumers who will buy the perfume, the dish or the paint, and who are therefore the real target of the industrialist, clearly belong to the second category, they are neophyte evaluators sensitive to advertising, to internet influencers or simply to a truth asserted by their neighbor, a proven reference in their eyes. Who among us has not suddenly attributed `blueberry` or `truffle` aromas to a wine after having inquired about its sensory description on the label of the bottle? We wish to instrument the analysis of influence phenomena in this process of qualitative description and to define the models that could be used to measure the influence of an evaluator or a group of evaluators in the sensory domain, the characterization of influencers having obvious economic repercussions.

We will therefore begin by referring to measures of decision-making power derived from game theory. Modelling of influence in a social network assumes that each player has an inclination to say YES or NO which, due to influence of other players, may be different from the final decision of the player. The point of departure of such studies is the concept of the Hoede-Bakker index, which computes the overall decisional 'power' of a player in a social network. The main drawback of the Hoede-Bakker index is that it hides the actual role of the influence function, analyzing only the final decision in terms of success and failure. Several extensions of this work have been proposed to address this issue, in particular by Grabisch and Rusinowska. These measures of decision-making power have been established for decisions where only two antagonistic alternatives are considered (Yes or NO). We then formally define the decision process at stake in sensory analysis: the choice of a semantic summary that synthesizes the descriptions of the sensory analysis panelists. We then propose to transpose the notions of decision power and influence indices when the decision process involves many possible decisions and it is possible to endow this set of decisions with an order relation. Beyond this application to the domain of sensory analysis, this model allows to extend the notions of decision power and influence indices when the decision is not simply boolean, but gradual: an individual can more or less adhere to the collective decision.

The paper is organized as follows: Section 2 introduces theoretical notions on which is based our approach as well as notations; it next reports state of the art studies of influence based on the Hoede-Bakker decision power index and its extensions. This index computes the overall decisional power of a player in a social network when the decision is binary; Section 3 introduces the decision-making process involved in a collective sensory analysis evaluation to illustrate the concepts of collective decision making and influence in a group; Section 4 is our main contribution: it extends the Hoede-Bakker index to non-binary and gradual decisions, when alternatives can be associated with a graded success scale. Section 5 presents the experiment we are building, unfortunately

it is still in progress and we did not have time to include it in this article, it is just meant to illustrate our project.

2 Decision-making power of an agent

Different models have been introduced in game theory to represent influence in social networks. We are inspired here by the study of influence based on the Hoede-Bakker decision power index [5] and its extensions. This section is a simple synthesis of what has been written in game theory about the notion of influence; we use the notations and definitions that have become established in this literature. This index allows us to calculate the global decisional power of an actor in a social network. This index has been generalized by the works of Rusinowska and De Swart [6] and then in [4][7]. The reasons for the existence of influence phenomena, *i.e.*, why an individual changes his decision, are more psychological considerations and are outside the scope of the studies proposed by [8]. All definitions and notations in this section are simply taken from [7] and [8] for the sake of consistency. In these studies, the debate concerns the choice between two options, noted ± 1. The social network considered is composed of a group of n actors $\{a_1,..,a_n\}$. Each actor has an a priori inclination to opt for $+1$ or -1. A vector of inclinations, noted i, is a vector of $+1$ and -1 : j^{th} component of i, noted $i_j \in \{-1;+1\}$, represents the inclination of actor a_j. Let $I = \{-1;+1\}^n$ be the set of the 2^n possible inclination vectors.

In this influence model, the basic assumption is that each actor has an a priori inclination, which, under the influence of the other actors, may be different from his final decision. In other words, each vector $i \in I$ of inclinations is transformed into a vector of decisions Bi by a function, denoted B, that models the influence in the social network. The j^{th} coordinate of Bi is $(Bi)_j$, $j \in N := \{1,...,n\}$ and represents the a posteriori decision of the actor a_j. Then, to each decision vector b is associated a group decision $gd(b) \in \{-1;+1\}$ where $gd : I \to \{-1;+1\}$ is an aggregation function. The function gd is called the *group decision function* and models the decision of the collective of actors (a majority for example).

An *influence function* B can correspond to a common collective behavior.

For example, in [7] an influence function of the majority type, noted $Maj^{[t]}$ and parameterized by a real t, is introduced. More precisely, for a given vector of inclinations $i \in I$: $Maj^{[t]}(i) = \begin{cases} 1_N \text{ if } |i^+| \geq t \\ -1_N \text{ if } |i^+| < t \end{cases}$ where $i^+ = \{j \in N / i_j = +1\}$.

The definition of the decision power index of an agent a_j proposed by Hoede-Bakker in [5], where only success with respect to the option $+1$ is considered, was generalized by Rusinowska and De Swart [6] by studying success for both options $+1$ and -1.

Definition 1: Given an influence function B and a group decision function gd, the generalized decision power index of an actor a_j, denoted GHB_{a_j} is defined by:

$$GHB_{a_j}(B, gd) = \frac{1}{2^n}\left(\sum_{i/i_j=+1} gd(Bi) - \sum_{i/i_j=-1} gd(Bi) \right) \quad (1)$$

The main drawback of the Hoede-Bakker index and its generalization is that it masks the actual role of influence. Indeed, it analyses the decision of an actor in terms of success or failure according to whether or not the group's decision coincides with the actor's initial inclination and not with his final decision. Based on this idea, Grabisch and Rusinowska [7] proposed to distinguish the influence function from the group decision function in order to formulate a new index of decision-making power which is based this time on the concordance between the group's decision and the actor's final decision (in this proposal, they also assign a probability of occurrence to each vector of inclinations which we will not develop here):

$$GHB_{a_j}(B, gd) = \frac{1}{2^n}\left(\sum_{i/(Bi)_j=+1} gd(Bi) - \sum_{i/(Bi)_j=-1} gd(Bi) \right) \quad (2)$$

(1) is not better than (2), they are two different views of what success means for a given individual in a collective choice. For example, do we associate ourselves more with the election of a president if the elected candidate corresponds to our choice at the beginning of the campaign ($i_j = gd(Bi)$) or if he is the one whose name is written on the ballot we put in the box ($(Bi)_j = gd(Bi)$)?

Let us now consider how to measure the degree of influence of an agent or a coalition of agents on the others. In general, we say that an agent is influenced by a coalition (a group of agents with the same inclination) if the agent's decision is ultimately different from his original inclination. Indeed, since the agent has changed his opinion and retained the option that he had initially rejected, we can imagine that he has undergone some kind of *external* influence that explains this change of opinion. We assume that this external influence comes from other agents who share the same inclination. In a so-called direct influence, the agent's inclination is therefore different from that of the coalition, but in the end his decision coincides with the coalition's inclination (Grabisch and Rusinowska also define an influence by opposition where the agent who initially shares the coalition's inclination changes his mind to oppose the latter).

The notations that are essential to the definition of the concept of influence in [7] and that will later be used in our model are given below.

The set of inclination vectors for which all agents in a coalition S have the same inclination is defined by:

$$I_S = \left\{ i \in I / \forall k, j \in S \left[i_k = i_j \right] \right\} \quad (3)$$

We note i_S, for $i \in I_S$, the value of $i_k, \forall k \in S$. For any coalition S and any $j \in N$, we define:

$$I_{S \to j} = \left\{ i \in I_S \,/\, i_j = -i_S \right\} \tag{4}$$

$$I^*_{S \to j}(B) = \left\{ i \in I_{S \to j} \,/\, (Bi)_j = i_S \right\} \tag{5}$$

$I_{S \to j}$ denotes the inclination vectors for which a direct influence of S on j can be observed (they correspond to decisions for which an influence of the coalition on the agent can be possibly observed since their a priori choices are opposed). $I^*_{S \to j}(B)$ denotes the inclination vectors for which the influence of S on j has potentially been exerted under the assumption of an influence function B (This is a subset of $I_{S \to j}$: only the vectors of $I_{S \to j}$ where the agent has joined the coalition's opinion a posteriori are retained).
We then introduce the index of possibility of direct influence of a coalition S on j:

$$\bar{d}(B, S \to j) = \frac{\left| I^*_{S \to j}(B) \right|}{\left| I_{S \to j} \right|} \tag{6}$$

We can still define an index of certainty of direct influence of a coalition S on j:

$$\underline{d}(B, S \to j) = \frac{\left| \left\{ i \in I^*_{S \to j}(B) / \forall p \notin S \left[i_p = -i_S \right] \right\} \right|}{2} \in \left\{ 0, \frac{1}{2}, 1 \right\} \tag{7}$$

Finally, we note the set of *followers* of S:

$$F_B(S) = \left\{ j \in N / \forall i \in I_S \left[(Bi)_j = i_S \right] \right\} \tag{8}$$

3 Decision model in sensory analysis

During a sensory analysis by a panel of evaluators, each description is made using disambiguated concepts extracted from a knowledge structure of interest for the business domain. The variability of the sets of descriptors provided by the evaluators complicates the task of the analyst who must merge them according to the similarity of the concepts in order to hope to obtain a more informative histogram (he must be able to bring together the concepts `Raspberry` and `Strawberry` which both evoke the concept `Red Berry`, a task with a high added cognitive value). The analyst must be able to propose a summary of the collective evaluation that is expressive while being synthetic by managing the abstraction and precision, the redundancy and similarity of the descriptors. To do this, he must manage the semantic relations that bring together or

differentiate the concepts and master the knowledge structure from which they are extracted.

In previous work [9], we were interested in the case where this knowledge structure is a taxonomy $T = (\leq, \mathbb{C})$ where $\mathbb{C}$ is the set of concepts (or classes) and $(\leq)$ the associated partial order based upon an abstraction hierarchy (e.g., $\texttt{Raspberry} \leq \texttt{Red Berry}$) [10]. We have shown how to formally derive the notion of similarity between concepts from this hierarchical structure, the shared and differentiating features between two concepts and the information content of a concept in a given collection [9][10][11]. We have thus proposed families of functions allowing to model the similarity between two concepts ($sim : \mathbb{C} \times \mathbb{C} \to \mathbb{R}$) [12], then by extension the similarity between two groups of concepts, in other words between two conceptual annotations ($sim : 2^{\mathbb{C}} \times 2^{\mathbb{C}} \to \mathbb{R}$) [9].

Illustration 1. Intuitively, for concepts similarity:

$sim(\{\texttt{raspberry}\}, \{\texttt{blackberry}\}) \geq sim(\{\texttt{raspberry}\}, \{\texttt{truffle}\})$

$sim(\{\texttt{blackberry}\}, \{\texttt{blackcurrant}\}) \geq sim(\{\texttt{blackberry, humus}\})$

And for group of concepts similarity:

$sim(\{\texttt{raspberry, blackberry}\}, \{\texttt{strawberry , blackcurrant}\}) \geq$

$sim(\{\texttt{raspberry, blackberry}\}, \{\texttt{truffle, humus}\})$

In [18], we then proposed an automated approach to synthesize conceptual descriptions into a single synthetic conceptual description using the taxonomy-induced order relation. The analysis of the semantics of the conceptual descriptors allows managing redundancy, similarity and abstraction. The synthesis takes the most relevant and informative elements by eliminating redundant evocations, and manages the following dilemma: to be too abstract, one loses information; but to be too specific, one loses the synthesis criterion.

Illustration 2. A summary of $\{\texttt{mouse, rat, field mouse, ant, fly, mosquito, platypus}\}$ could be $\{\texttt{rodent, insect, platypus}\}$ considering the taxonomy of animals species.

If we now return to the problem of decision in sensory analysis:

- To each of the n evaluators e_i is associated with a set of concepts, *i.e.* a conceptual annotation noted $X_i \in 2^{\mathbb{C}}$.
- $\hat{X} = (X_1, X_2, .., X_n)$ is the sequence of annotations by n evaluators to be summarized.

Let X be the set of concepts provided by the evaluators, *i.e.*: $X = \bigcup_{i=1}^{n} X_i$.

The objective of Semantic Synthesis is to define a function SS which summarizes the sequence of conceptual annotations $\hat{X}$ into Y :

$$SS:\left(2^{\mathbb{C}}\right)^{n}\to 2^{\mathbb{C}}$$
$$Y=SS\left(\hat{X}\right) \tag{9}$$

Each set of descriptors $X_i \in 2^{\mathbb{C}}$ proposed by an evaluator e_i will be more or less similar to $Y \in 2^{\mathbb{C}}$. The more X_i is similar to Y , the more e_i will be comforted in the idea that the choice of his descriptors (his decision) has contributed to the collective characterization Y ; the more e_i will perceive his decisional power as high.

At this stage, we are thus able to calculate the similarity between the set of descriptors $X_i \in 2^{\mathbb{C}}$ proposed by the evaluator e_i and the summary $Y \in 2^{\mathbb{C}}$ that synthesizes the collective evaluation. The more similar X_i to Y (up to $sim\left(X_i,Y\right)$), the greater the decision power of e_i should be. It is this gradual decision process that we will now use to define the notion of influence in sensory analysis.

4 Model of influence in sensory evaluation

In this section, the model of [8] is extended to non-binary and gradual decisions: we extend the equations of [8] when the alternatives are more than two, can be ordered with respect to a similarity relation and then associated with a graded success scale.

We therefore imagine evaluators participating in $|D|$ sensory evaluations $D^{(i)}$, $i=1..|D|$. The idea is to determine which of these evaluators has the most influence on the group in view of these $|D|$ sensory exercises with the mathematical tools of section 2 transposed to the decision-making process of sensory analysis: "The more similar the conceptual description proposed by e_i to the descriptions retained by the collective, the greater its decision-making power". For each sensory evaluation $D^{(l)}$, each evaluator e_i proposes a conceptual description $D_i^{(l)}$. Then, the evaluations of all the evaluators are brought to the knowledge of each one. After having read the descriptors used by the other evaluators, the evaluator e_i can modify his a priori choice and propose a new a posteriori semantic annotation $BD_i^{(l)}$ for the evaluation $D^{(l)}$ (e.g., some evaluators less familiar with the controlled vocabulary did not find the precise words during their initial characterization, the descriptions of the other evaluators can then allow them to correct some inaccuracies). The semantic summary of the $D_i^{(l)}$ annotations (respectively $BD_i^{(l)}$) is noted $SS\left(D^{(l)}\right)$ (respectively $SS\left(BD^{(l)}\right)$) where $D^{(l)}$ (respectively $BD^{(l)}$) is the vector of a priori (respectively a posteriori) evaluations of the n evaluators (a vector whose coordinates are thus elements of $2^{\mathbb{C}}$). This process of sensory qualification is repeated on $|D|$ evaluations by the panel.

In the game-theory model of decision-making power in Section 2, the statistics for the coincidence of decisions between an evaluator e_i and the collective are for the 2^n possible inclination vectors, with the influence function B and the collective decision process *gd* known a priori. Here, we do not try to define the B function a priori, we simply observe the vectors $D^{(l)}$ and $BD^{(l)}$ on the $|D|$ evaluations and the statistics established do not concern all the possible vectors ($2^{\mathbb{C}^n}$), but the $|D|$ observations of the experiment. The semantic synthesis function SS can be seen as playing the role of the aggregation function *gd* in Section 2. It is thus an estimation of the decision power and influence on a case base reduced to the observations that we propose. The following models focus on defining the decision power of an evaluator e_k based on $|D|$ sensory analyses for a given SS annotation synthesis process.

On the other hand, the model in Section 2 is concerned with a Boolean decision where the two alternatives are necessarily opposite. Here, the idea that the more similar the conceptual descriptions proposed by e_i are to the descriptions chosen by the collective, the greater its decision-making power, suggests that this gradual aspect must be integrated into the modeling of the power index and the associated influence indices.

We can first introduce a threshold η (η can be interpreted as the radius of a circle with center $SS\left(BD^{(l)}\right)$) such that if $sim\left(BD_k^{(l)}, SS\left(BD^{(l)}\right)\right) \geq \eta$ then the final evaluation of e_k coincides with the final characterization of the collective and then count the number of evaluations among the $|D|$ sensory analyses where this constraint is realized. We then define the decision power of e_k as follows:

$$GHB_k(B, SS) = \frac{1}{|D|}\left(\sum_{i=1}^{|D|}\left[sim\left(BD_k^{(i)}, SS\left(BD^{(i)}\right)\right) \geq \eta\right]\right) \quad [1] \tag{10}$$

To take into account the gradual aspect, the following formulation can be preferred:

$$GHB_k(B, SS) = \frac{1}{|D|}\left(\sum_{i=1}^{|D|} sim\left(BD_k^{(i)}, SS\left(BD^{(i)}\right)\right)\right) \tag{11}$$

where the decision-making power of e_k is all the greater as its a posteriori annotations approach the collective annotations retained.

We can then define the sets: I_S , $I_{S\to j}$ and $I^*_{S\to j}$ according to the same principle of similarity to the group decision.

Let S be a coalition of evaluators. I_S is the set of a priori conceptual annotation vectors where all evaluators of S agree among the $|D|$ sensory analyses, *i.e.*, they are all inside

[1] [*Constraint*] = 1 if *Constraint* is true else 0.

or outside the "circle" of radius η with centre $SS\left(D^{(i)}\right)$ around the annotation chosen by the collective (in any case this radius can be chosen different from the radius in equation (10)):

$$I_S = \left\{ D^{(i)}, i \in 1..|D| / \forall k, j \in S, \left(sim\left(D_k^{(i)}, SS\left(D^{(i)}\right)\right) - \eta \right) \left(sim\left(D_j^{(i)}, SS\left(D^{(i)}\right)\right) - \eta \right) \geq 0 \right\} \quad (12)$$

We note for $D^{(i)} \in I_S$ and any $k \in S$, $sign\left(sim\left(D_k^{(i)}, SS\left(D^{(i)}\right)\right) - \eta\right) = s_i$.

It is possible to model the gradation of coalition membership by fuzzyfying I_S. The idea is to model the fact that a synthesis $SS\left(D^{(i)}\right)$ is more or less unanimous in the coalition S. The degree of membership of $D^{(i)}$ to I_S gives an account of the cohesion of the evaluations around $SS\left(D^{(i)}\right)$ within the coalition (respectively of the distance of the evaluations to $SS\left(D^{(i)}\right)$) and can then be defined as follows :

$$\begin{cases} \mu_i = \frac{1}{|S|} \sum_{k \in S} sim\left(D_k^{(i)}, SS\left(D^{(i)}\right)\right) \text{ if } s_i \geq 0 \\ \mu_i = \frac{1}{|S|} \sum_{k \in S} \left(1 - sim\left(D_k^{(i)}, SS\left(D^{(i)}\right)\right)\right) \text{ if } s_i < 0 \end{cases}$$

A fuzzy extension after normalization can then be proposed for I_S :

$$\tilde{I}_S = \left\{ \left(D^{(i)} \in I_S ; \mu_i \right) \right\} \quad (13)$$

If we are interested in the influence of S on e_j, we select among the vectors of I_S those where $D_j^{(i)}$ is not on the same side of the "circle of radius η and center $SS\left(D^{(i)}\right)$" as the $D_k^{(i)}$, $k \in S$:

$$I_{S \to j} = \left\{ D^{(i)} \in I_S / s_i . \left(sim\left(D_j^{(i)}, SS\left(D^{(i)}\right)\right) - \eta \right) \leq 0 \right\} \quad (14)$$

One can also quantify the opposition of e_j to S : for a given evaluation $D^{(i)}$ if the conceptual characterizations of the evaluators of S are very similar to (respectively far from, *i.e.*, outside the circle of radius η) $SS\left(D^{(i)}\right)$, e_j is all the more opposed to S than $D_j^{(i)}$ is different from (respectively similar to) $SS\left(D^{(i)}\right)$.

This statement allows us to define a degree of membership for $D^{(i)}$ to $I_{S \to j}$:

$$\begin{cases} \lambda_i = \mu_i \left(1 - sim\left(D_j^{(i)}, SS\left(D^{(i)}\right)\right)\right) \ if \ \ s_i \geq 0 \\ \lambda_i = \mu_i sim\left(D_j^{(i)}, SS\left(D^{(i)}\right)\right) \ if \ \ s_i < 0 \end{cases}$$

and then after normalization we introduce the fuzzy set:

$$\tilde{I}_{S \to j} = \left\{ \left(D^{(i)} \in \tilde{I}_{S \to j}; \lambda_i \right) \right\} \tag{15}$$

Among the vectors selected in opposition to the coalition S ($I_{S \to j}$), we select those that change the side of the circle (they are outside the circle initially and inside in the end or vice versa) after being possibly influenced by S :

$$I^*_{S \to j} = \left\{ D^{(i)} \in I_{S \to j} / \left(sim\left(D_j^{(i)}, SS\left(D^{(i)}\right)\right) - \eta \right) \left(sim\left(BD_j^{(i)}, SS\left(D^{(i)}\right)\right) - \eta \right) \leq 0 \right\} \tag{16}$$

We can quantify the "reversal" undergone by e_j under the possible influence of S : the reversal is all the more consequent when $D_j^{(i)}$ is similar to (respectively different from) $SS\left(D^{(i)}\right)$ and $BD_j^{(i)}$ different from (respectively similar to) $SS\left(D^{(i)}\right)$. This makes it possible to define a degree of membership for $\tilde{I}^*_{S \to j}$:

$$\begin{cases} \upsilon_i = \lambda_i sim\left(BD_j^{(i)}, SS\left(D^{(i)}\right)\right) \ if \ \ s_i \geq 0 \\ \upsilon_i = \lambda_i \left(1 - sim\left(BD_j^{(i)}, SS\left(D^{(i)}\right)\right)\right) \ if \ \ s_i < 0 \end{cases}$$

And we introduce after normalization:

$$\tilde{\tilde{I}}^*_{S \to j} = \left\{ \left(D^{(i)} \in \tilde{I}_{S \to j}; \upsilon_i \right) \right\} \tag{17}$$

We then deduce the index of possibility of direct influence of a coalition S on j :

$$\bar{d}\left(B, S \to j\right) = \frac{\left| I^*_{S \to j}\left(B\right) \right|}{\left| I_{S \to j} \right|} \tag{18}$$

Or in the fuzzy version:

$$\tilde{\bar{d}}\left(B, S \to j\right) = \frac{\sum_i \upsilon_i}{\sum_i \lambda_i} \tag{19}$$

This index makes it possible to establish the possible influence of any coalition of evaluators on a particular individual. This type of information can be used to predict sensory perceptions based on the characterization of a group of reputable influencers. Influencers can also be used to control collective perception in sensorial marketing. These indexes allow us to answer the question we asked in the introduction about the influence of the sensory description on the label of a bottle of wine. If we are simply interested in the hedonic character of the sensation (pleasant or not), the problem is simpler and can be treated with the tools of section 2. Evaluating the influence through the characterization of a sensory evocation (neutral characteristic descriptors without appreciation judgment) is more complex because there are many possible decisions more or less close to each other.
Beyond this application to the domain of sensory analysis, this model allows to extend the proposals of [7] when the decision is not simply boolean, but gradual: an individual can more or less adhere to the collective decision.

5 Illustrative example

Verbalizing emotions allows moving from an emotional/reactionary state to a more reasoned state. The experimentation we have implemented consists in proposing to a group of users to verbalize and confront their emotions in front of a series of artworks. The protocol is divided into two phases: an annotation phase and a revision phase. During the first phase, all the users of the group have to express the emotions inspired by the artworks chosen in a priori series. The constraint of this exercise is to choose emotions from a controlled vocabulary represented by Plutchik's wheel of emotions. Plutchik created his "wheel of emotions" to better visualize the intensity and combination of emotions. On the left part of Fig. 1, in the center, we find the most intense emotion (e.g. ecstasy); then in the first crown, the basic emotion (e.g. joy) and finally, in the periphery, the least intense emotion (e.g. serenity). He then defined three levels of possible combinations: primary dyads (combinations of two adjacent basic emotions on the wheel), secondary dyads (combinations of basic emotions within one emotion) and tertiary dyads (combinations of basic emotions within two emotions). We transposed his wheel (left part of Fig. 1) into a multiple inheritance taxonomy structure (a digraph) to be able to calculate the similarities needed for the experiment and to get back to the model described in the article (right part of Fig. 1).

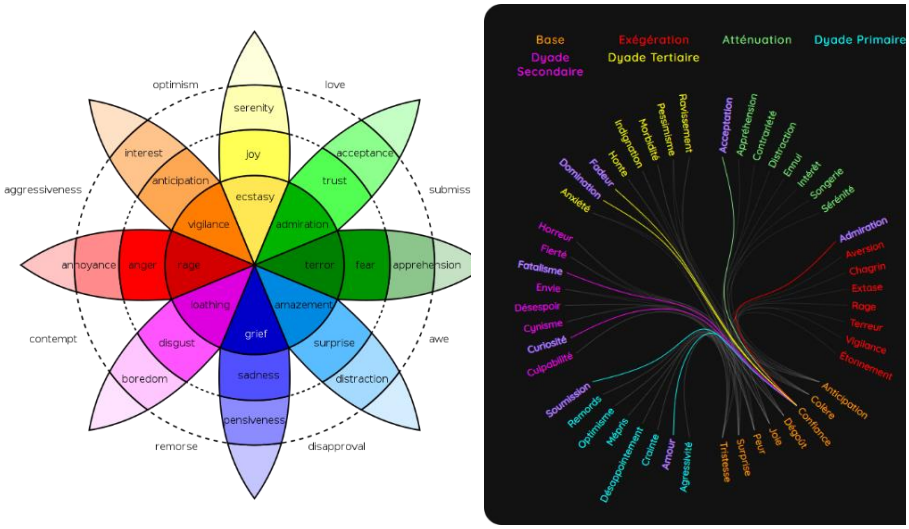

Fig. 1. The Plutchik wheel and its transposition into a graph of relations *(Types of inherited emotions: Base, Exaggeration, Attenuation, Primary Dyad, Secondary Dyad and Tertiary Dyad)*

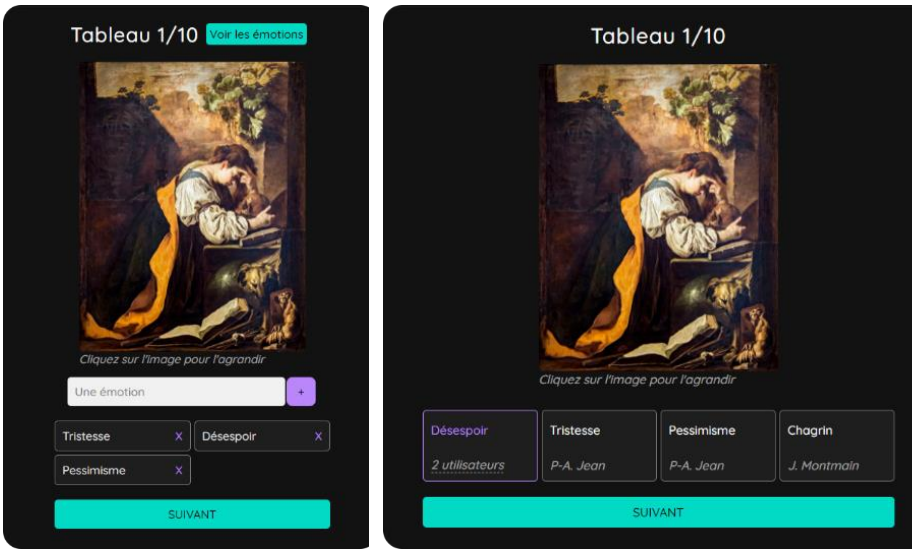

Fig. 2 The user interfaces during the first and second phase of the evaluation

For the experiment, each user for each artwork must fill in at least one emotion (left part of Fig. 2). The second phase can start when all the users of the group have finished filling in the evaluations of the first part. In the second phase (right part of Fig. 2), the same suite of artworks is presented again to each individual in the group. Each individual has the opportunity to revise his initial choices by taking into account the emotions expressed by the other users. In view of the emotions returned by the group and exposed to each individual, each user can give up some of his initial emotions or borrow some of the emotions retained by the others because they seem more relevant.
We did the first tests with a small group of informed users to test the formulas and the feasibility of the experimentation. In these first tests, a user intentionally played the role of a follower or a leader; the test then consisted in automatically finding the role adopted from the model we proposed, but we did not have time to set up an experiment with a network of 'naïve' users.

Conclusion

We started from Grabisch and Rusinowska's indices of decision-making power and influence defined for a binary decision. We proposed an extension to more sophisticated decisions with n alternatives that can be associated with a graded success scale. Based on Grabisch and Rusinowska's model, our extended fuzzy model allows to measure the influence that a coalition of individuals can have on a given individual when the decision process involves n alternatives, especially in the complex case where these alternatives can be ordered according to graded success scale. The basic idea behind our proposal is that the more an individual is initially opposed to the choice of a coalition, the more difficult it seems to make him/her adhere to the choice of the coalition; on the other hand, if this is the case, it means that the influence exerted by the coalition on the target individual will have been very significant. This is what our model aims to formalize. The sensory analysis on which we have already published seemed to us to be a tangible illustration of the model that we wish to justify and develop more theoretically in our future work.

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