Statistical and Machine Learning Tools for Consonance Detection

1st Paolo Barile*
Computer Science dept. (DI)
Università degli Studi di Salerno
Salerno, Italy
pbarile@unisa.it
*Corresponding author

2nd Aysel Alizada
Management dept.
Sapienza University of Rome
Rome, Italy
aysel.alizada@uniroma1.it

3rd Clara Bassano
Pharmacy dept. (DIFARMA)
Università degli Studi di Salerno
Salerno, Italy
cbassano@unisa.it

***Abstract*—The study of emotions via Artificial Intelligence (AI) is considered a hot topic as technological development is gradually turning its gaze more and more toward understanding and emulating human beings. Emotion detection, however, runs the risk of being a useless investigative tool if it is not accompanied by solid theoretical foundations to reinterpret AI-detected emotions through a broader perspective. The Viable Systems Approach (ASV) may likely be the missing link between studying the emotional sphere and understanding the social dynamics that characterize human beings during each interaction. The concepts of consonance and resonance, typical of ASV, make it possible to describe patterns of information acquisition and to understand the dynamics underlying each individual's decision-making. The purpose of our study is to demonstrate, through field experimentation, the possibility of detecting consonance within groups of people in an automatic way, using statistical analysis techniques and Facial Expression Recognition (FER) algorithms. The trial was conducted in two phases: In the first one, a structured questionnaire categorized participants into distinct value clusters based on their strong beliefs; in the second one FER techniques were used to gauge the change in the initial level of consonance within the same clusters during a common contextual experience. Results demonstrated the possibility of detecting the initial level of consonance and its context-driven variation (resonance) both qualitatively and (at least partially) quantitatively. Research findings certified the feasibility of consonance measurement, opening the way to new usage perspectives for emotion detection tools in AI.**

***Index Terms*—Viable Systems Approach (VSA), emotion detection, Facial Expression Recognition (FER), consonance, resonance.**

I. INTRODUCTION

The new frontier of innovation in Artificial Intelligence (AI) is witnessing a significant shift from a purely technological approach to a more human-centric one. This pivotal change in perspective is essential for creating intelligent systems that not only comprehend human emotions but also authentically connect with individuals, fostering true synergy in user-machine interactions [1]. The development of fields such as Cognitive AI and Affective Computing has led to the advancement of emotional recognition technologies. These technologies enable machines to perceive and interpret the human emotional state through facial expressions, vocal tones, and other signals. The aim is to fully understand human dynamics through AI, enhancing our ability to interpret and replicate them for creating more user-friendly interfaces [2].

Prior to its application in computer science, the study of the human cognitive sphere was explored in various disciplines, particularly in the humanities and pseudo-science. The Viable Systems Approach (VSA) exemplifies the application of human dynamics in business economics to evaluate decision-making processes in managerial contexts [3]. Crucial to VSA is the concept of informational variety, defined as the range of information resources someone possesses at a specific moment. This is a dynamic quantity, continually evolving with the acquisition of new information through specific interpretation patterns [4]. At the heart of these patterns are value categories, the set of strong beliefs that define one's individuality. These categories guide the perception, interpretation, and response to new information, forming the foundational building block of individual behavior [5]. Another key concept in VSA is "consonance"; it describes how an individual acquires new information using interpretive schemes and integrates it through value categories. A high level of consonance among individuals indicates shared interpretive schemes and similar mental paths in information acquisition. Consonance is dynamic and evolves as new knowledge is gained. The presence of an informational context can reshape the learning path, redefining the level of consonance [6].

The objective of our research is to employ AI techniques in conjunction with VSA to explore social dynamics from a fresh perspective. We specifically implemented a methodology grounded in statistical and machine learning techniques. This approach was utilized to assess the initial levels of consonance and resonance — the latter being a form of context-modified consonance — within the same group of individuals.

The subsequent paragraph will provide an overview of how VSA has been utilized to study social dynamics in existing literature, emphasizing the relationship between emotions and value categories. The third paragraph will outline the experimental stages of our study, detailing the techniques we employed and the findings we garnered. Finally, the fourth and concluding paragraph will offer our final thoughts and reflections on the research.

II. Literature review

In human learning processes, value categories play a pivotal role in shaping our informational framework. They act as filters, determining the way individuals process and assimilate new information. Each person's unique set of value categories guides their understanding and interpretation of the world around them, molding their perceptions and reactions [7]. Emotions, on the other hand, are an expression of the way our minds react to informational stimuli and a tangible manifestation of the acquisition of new knowledge that modifies the informational variety that characterizes us. When looking into the idea of consonance or resonance, emotions become more easily identifiable indicators than value categories [8]. They help us understand how much harmony, agreement, or disagreement people feel in their interactions with their surroundings in a more immediate way [9]. Given these premises, it is easy to identify the study of emotions as the meeting point between ASV and AI. The analysis of human decision-making approaches that ASV sets out to analyze through value categories can be achieved through AI models that make use of emotion detection. In this view, consonance can be analyzed through two different perspectives that proceed in the same direction. As for AI, the science of reading our emotions and responding to them has made enormous improvements. Machine learning, thanks mainly to image processing advances, have played an important role in this success. Facial Emotion Recognition (FER), a technique that analyses facial signals to identify human emotional states, represents one of the most widely used and effective techniques for the purpose [10]. In the context of Human-Computer Interaction (HCI), FER has the power to completely change how people and machines interplay, allowing for a more intuitive, responsive, and personalized user experience. When it comes to VSA and emotions, instead, the literature is still nascent. Authors like Leonard [11] have started to peel back the layers on how knowledge management within a VSA can benefit from the rich insights provided by emotion analysis. Further, Hoverstadt [12] has proposed frameworks for integrating systemic organizational health with the continuous feedback given by intelligent analysis systems. More recently, Di Mascio et al. [13] have begun to address how organizational systems can be designed to account for the emotional states of their members, suggesting that VSA principles can be applied to manage the complexity of human emotions within systems. Another noteworthy example is the study by Angelis et al. [14], which hints at the intersection of VSA with the emotional aspects of work systems. Finally, Espejo and Gill [15] were among the first to hypothesize using the concepts of consonance and resonance typical of ASV through an HCI perspective. They highlighted how VSA can inform the design of HCI by ensuring that the systems are adaptable and sustainable. While these studies do not directly address emotional considerations in HCI, they lay the groundwork for integrating systemic thinking into the design and management of interactive systems.

III. Experimental and results

The search for an experimental model that can enable the determination of the level of consonance between different people is based on the use of the relevant value categories as ”measure units”; it is assumed, for example, that two individuals who share the same values (e.g., respect and justice) will have a higher level of consonance between them than a different pair who base their behaviour on other values (e.g., ambition and power) [16]. The initial level of consonance between people can, therefore, be considered a measurable entity in a context-free manner.

Resonance, on the contrary, requires a specific interaction scenario to be detected, representing the change in the initial level of consonance as a function of new context-driven information. The only possible empirical method for determining resonance, therefore, necessarily involves an assessment of the level of consonance between the same people at two separate moments [17]. The study of emotions, being inherently linked to arbitrary aspects derived from specific contexts, may be particularly suitable for the measurement of context-derived resonance, but not for the study of the initial level of consonance.

Given these premises, the analysis of resonance was approached through two separate experimental phases, aimed respectively at measuring the initial level of consonance by means of value categories and at detecting the context-driven change in the level of consonance by means of facial emotions.

A. Consonance detection

In the first phase of the experiment, sixteen selected value categories (ambition, consistency, creativity, culture desire, fidelity, trust, justice, loyalty, merit, honesty, power, responsibility, respect, solidarity, tradition, and utility) were used to define the participants' initial level of consonance (uncontested) through a quantitative statistical method based on the use of a structured questionnaire delivered online. It was decided to place the consonance analysis in the academic setting, selecting economics students between the first and third year from different Italian universities (University of Salerno, University ”Federico II” of Naples, University ”La Sapienza” of Rome) as the target audience for the questionnaire. It was submitted to about 600 students and collected a completion rate of around 75%.

The objective of the questionnaire was to investigate the value scale of each of the participants, so as to divide the respondents into groups, called “value clusters”, that share the priority of some value categories over others; based on theoretical studies [18], members of the same cluster should be considered to have a very high level of consonance as they see the same strong beliefs as preeminent. The questionnaire used is structured on a total of 48 questions (three for each of the sixteen selected value categories), in each of which two instances, which are conceptually opposed to each other with respect to the specific reference category, are presented. Participants were asked to assign a score, based on a 7-point

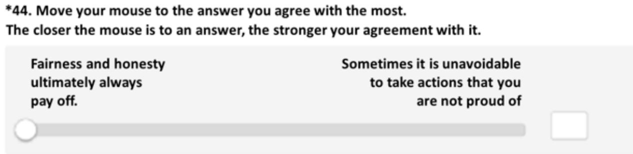

Fig. 1. Structure of one of the questions within the questionnaire.

Likert scale in which 1 represents total agreement with the left-hand instance and 7 total disagreement (Fig.1).

Prior to submitting the questionnaire to the study sample, it was necessary to test the validity of each question, going to verify that each pair of sentences was indeed a good indicator for assessing the degree of closeness to the relevant value category and that the component instances were in antithesis with each other. This ”pre-test” phase was carried out by submitting the questionnaire to a group of a hundred people with characteristics similar to the population to be studied; the statistical analysis of the pre-test responses allowed us to revise some indicators, eliminating those that were semantically redundant or invalid with respect to the indicated dimension, refine the wording and language of some questions, and remove some variables that were deemed irrelevant to the research.

A further validation step was carried out using the single factor analysis (SFA) approach [19], after the questionnaire was administered to the population of interest. SFA was applied to each of the sixteen batteries of questions with the aim of verifying whether the three items composing them actually detect the value category for which they were designed. This made it possible to eliminate some of the questions that were too complex and misleading. In interpreting the results of the SFA, the criterion of Comrey & Lee was adopted [20], which provides a cut-off point of approximately ±0.6 in the evaluation of factor loadings related to each variable in the battery. In addition, Kaiser’s criterion and two tests of statistical significance, the Kaiser - Meyer - Olkin (KMO) test and Bartlett’s test of sphericity, were considered [21].

Once validation was completed, the test responses were analyzed using multivariate analysis techniques (cluster analysis) based on the use of a k-means algorithm as a partition function. The approach used allowed respondents to be grouped into a small number (not knowable a priori) of value clusters, minimizing heterogeneity of individuals belonging to the same cluster and maximizing heterogeneity between different groups [22]. The final result of the evaluative phase was the definition of four distinct value clusters, each of which characterized by a series of values related to the sixteen reference value categories, describing the relevant strong beliefs of the people inside it (Table I).

The composition of the dominant scores highlights the relevance of different value categories depending on the cluster and offers a quantitative measure of the difference in consonance among the four different groups. The difference between the four clusters is even more evident from a qualitative

TABLE I
COMPOSITION OF VALUE CLUSTERS

	Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**
Ambition	-0.573	-0.28535	0.56562	0.3042
Consistency	-0.18285	0.0262	0.04994	0.12145
Creativity	0.00052	-0.60468	0.59286	0.00181
Culture desire	0.47765	-0.70054	0.53576	-0.38875
Fidelity	-0.36073	-0.3275	-0.07703	0.08717
Honesty	-0.41691	-0.61716	-0.55036	0.46228
Justice	0.37604	-0.74525	0.30573	0.18271
Loyalty	0.44805	-0.6809	0.25669	0.06468
Merit	-0.35038	-0.47208	0.59411	0.25667
Power	0.42116	-0.29161	-0.16925	0.16926
Respect	0.50485	-0.81835	0.48173	-0.15393
Responsibility	-0.18434	-0.50634	0.94034	-0.46163
Solidarity	0.68811	-0.75886	0.28339	-0.1736
Tradition	-0.56932	-0.19368	-0.06182	1.0000
Trust	0.63686	-0.42908	-0.21558	0.17295
Usefulness	-0.75152	0.17631	-0.02297	0.7555

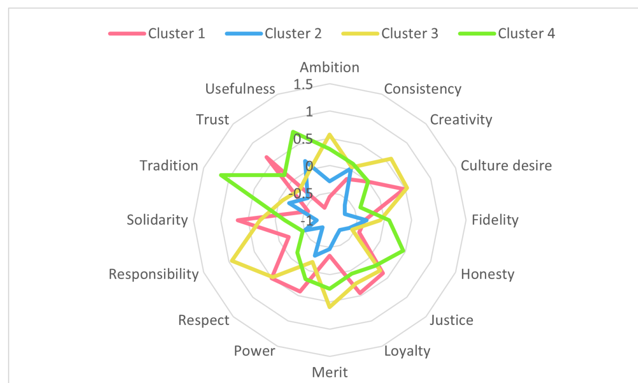

Fig. 2. Graphical representation of the initial level of consonance for the value clusters.

point of view, which can be appreciated through a graphical representation. Fig. 2 shows the radar graph representation for the four groups: each of the obtained shapes is very different from the others, and the graphs of the different clusters appear to be non-overlapping, a sign that the clustering process properly occurred.

B. *Resonance detection*

The first stage of the experimentation allowed the participants to be divided into the four clusters based on the level of consonance given by the analysis of the value categories. The following step was directly related to the results obtained from the questionnaire, as it aimed to measure the variation in the level of consonance for the same group of people according to a specific context.

For logistical reasons only sixty of the students responding to the questionnaire were selected for the second phase. This was possible because the choice of a subset does not affect the outcome of the survey, as long as the groups of people selected for each of the clusters are equally represented, avoiding problems of class unbalancing. Selected students were asked to take part in a short experiment for research purposes consisting of listening to a seminar lasting about forty minutes,

Fig. 3. Graphical representation of the context-driven level of consonance for the value clusters.

in exchange for a small bonus score on their exam evaluation. It is important to note that the target contest for the resonance study is not to be attributed to the content of the seminar itself, but rather to the common goal of all participants to pursue their bonus on the evaluation.

The metrics for measuring resonance were the emotions displayed by participants during the relevant contextual experience. Among the different emotion detection approaches available for the purposes of our study, Facial Emotion Recognition (FER) techniques were chosen, as they were considered more immediate, both at the level of experimental setup (positioning of cameras and optimization of brightness) and at the level of results analysis [23]. Specifically, the images collected during the experiment were processed using a deep-learning model based on a convolutional neural network (CNN), pre-trained on the ”FER 2013” dataset [24]. The use of CNN allowed for minimal data pre-processing and feature extraction procedures: the only operation required was cropping the acquired images to remove the background.

Facial images were captured throughout the seminar; however, only frames extracted within five to 10 minutes of the start were considered relevant to the research. In fact, we hypothesized that five minutes might be sufficient to disregard any initial emotional biases, while emotions after the first ten minutes would be strongly influenced by the content of the seminar itself rather than the target contest. This choice proved strategic for our purposes since the use of emotions not closely related to the contest would have risked distorting the measure of resonance.

Prior to the seminar, the students were divided into four groups based on their value clusters previously detected by the questionnaire, and each group was made to sit in front of a strategically placed camera. After the recording it was possible to extract a very large number of face frames (about 600.000 in total) for each of the value clusters and to analyse the resulting emotions with an overall accuracy close to 89%. Similar to the questionnaire, the results of emotion detection were displayed through the use of the radar graphs in Fig. 3. In this case Ekman's six emotions [25] appear on the axes, since for each of the frames belonging to a specific value cluster the dominant emotion detected by the classification algorithm was plotted.

It can be seen that the representations of each of the clusters, while not perfectly overlapping, are quite similar to each other. This demonstrates a certain alignment, due to a resonance effect, whereby individuals influenced by different value categories (and thus by a visibly different initial level of consonance) ended up smoothing out their divergences as a function of the context characterized by a common purpose of interest. Such a result certifies the theoretical studies carried out within the VSA, according to which the initial level of consonance can vary as a function of context.

IV. Conclusions

The main objective of our research was to offer a robust methodology to obtain an estimate of the level of consonance within a group of people and to assess its change due to the effect of context-mediated resonance. The main difficulty associated with the implementation of our work stood in the identification of a metric, based on objective criteria, that would allow the detection of the abstract constructs proposed by the ASV. On the other hand, the study of emotional space is a rather widespread topic in AI community, but the connection between emotions and the value categories that determine people's behavior in decision-making is still completely unexplored territory from a computer science perspective.

The two-fold approach chosen in the experimental phase proved decisive in establishing a metric to detect the initial level of consonance and its subsequent variation through statistical and ML methods that would guarantee objective and robust results [26]. Our study demonstrated how the use of a hybrid approach can enable the measurement of the distance between the interpretive and decision-making patterns of different individuals and how it varies according to a specific interaction context. Ultimately, consonance and resonance have been shown to be measurable entities through the use of AI: The radar graphs reported for both phases of the experiment demonstrated how they are fully observable from a qualitative point of view; moreover, the composition of the value clusters obtained through statistical analysis also showed how the initial level of consonance is to some extent quantifiable.

In conclusion, the synergy between ASV and AI demonstrated in this research reaffirms the application possibilities of the study of consonance in fields such as HCI and organizational management. The ability to understand and replicate human dynamics through the study of emotions opens the door to the creation of more intuitive and personalized interfaces. As the field of emotional AI continues to evolve, future research efforts could explore the implications of these findings in different contexts, further advancing our understanding of the intricate interplay between human dynamics and intelligent systems.

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