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Using subgroup discovery to relate odor pleasantness and intensity to peripheral nervous system reactions

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Abstract—Activation of the autonomic nervous system is a primary characteristic of human hedonic responses to sensory stimuli. For smells, general tendencies of physiological reactions have been described using classical statistics. However, these physiological variations are generally not quantified precisely; each psychophysiological parameter has very often been studied separately and individual variability was not systematically considered. The current study presents an innovative approach based on data mining, whose goal is to extract knowledge from a dataset. This approach uses a subgroup discovery algorithm which allows extraction of rules that apply to as many olfactory stimuli and individuals as possible. These rules are described by intervals on a set of physiological attributes. Results allowed both quantifying how each physiological parameter relates to odor pleasantness and perceived intensity but also describing the participation of each individual to these rules. This approach can be applied to other fields of affective sciences characterized by complex and heterogeneous datasets.

Index Terms— Mining methods and algorithms, Pattern analysis, Physiological measures

1 Introduction

A prominent property of olfaction, the sense of smell, is its affective component [1]. This level of processing is primal to humans and determines if a stimulus is edible or poisonous, pleasant or not, arousing or not. Affective responses to smells can be expressed verbally (i.e. subjective component), and are always accompanied by peripheral nervous system reactivity (i.e. physiological component) [2], [3], [4], [5]. The main function of these physiological responses is to provide somatic signals to the brain in order to guide important behaviors, namely approaching or avoiding the odor source [6].

An important question in the field is how these affective responses to odors relate to physiological activity. Beyond the olfactory sphere, and in a general way, there are two main theories on the topic. The first considers simple affective dimensions characterized by approach and withdrawal behaviors [7], [8]. Affects in this case, are categorized along axes of pleasantness, arousal and dominance. It has been shown that each of these dimensions varies according to specific physiological channels [9]. This is the dimensional or biphasic theory of emotion. The other theory postulates a limited number of discrete basic emotions (e.g. sadness, fear, joy, surprise, anger, disgust) characterized by distinct physiological events [10]. Note that whatever the theory, these affective states or basic emotions involve neural networks belonging to the limbic system (in particular the amygdala), regions such as the insula, but also associative systems located in the prefrontal and orbitofrontal cortex [11].

If we come back to the sense of smell itself, some researchers postulate an organization of the affects induced by smells in terms of approach and withdrawal systems [12], while others consider that affects provoked by odors can be distinguished according to basic emotions such as sadness, fear, joy, surprise, anger or disgust [4] [13], [14], [15]. The truth is probably at the crossroads of these two theories insofar as odors can induce pleasant hedonic responses, pleasure, and the basic emotion of joy, or unpleasant hedonic responses, displeasure and the basic emotion of disgust [3]. Whatever the point of view or theory, the vast majority of psychophysical studies in olfaction shows that the subjective experience of odors is often characterized by a pervasive pleasantness dimension (e.g. "this odor smells very good or is bad") as well as descriptions related to the intensity of the odor (e.g. "this odor is very strong"). (see [16][17]).

As mentioned above, one prominent issue in the field concerns the relation between such perceptual and affective attributes of odors and physiological responses: how does the pleasant tone of a smell, and its perceived intensity, relate to peripheral physiological activity? Although past studies have revealed some relationship between physiological responses and odor pleasantness, and odor intensity, the directionality and the nature of these relationships varied from one study to another, and within individuals as a function of the ongoing task. For example, whereas for some, the electrodermal response increases with odor intensity [18], for others it varies according to the unpleasantness [19] or olfactory quality [20]. Such relationships between odor pleasantness and physiology have also been investigated using heart rate variability [21] and results showed that it is possible to discriminate between pleasant and unpleasant odors. Furthermore, whereas passively smelling odors or judging their pleasant tone induces similar heart rate activity patterns, familiarity judgment performed on the same smells overwrites this autonomic response [22]. These differences between studies and tasks may be a reflection of both methodological differences across studies but also of the large intra- and inter-individual variability in odor pleasantness and odor

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intensity [5], [23], [24]. This variability across people makes it difficult to examine the relationship between smell pleasantness and intensity, and physiology and it is therefore necessary and important to consider it. To do so, it becomes essential to imagine the relationship between subjective experience of smells (pleasantness, intensity), and physiology no longer as a bijective relationship with a single rule that will link the 2 entities, but as a relationship that can be diverse: here, each subjective experience can be associated with multiple forms of physiological patterns in different individuals depending on biological factors but also on the developmental trajectories of each and everyone.

It is important to note that, in general, the data collected in psychophysiological studies are characterized by their heterogeneity and complexity at different levels: i/ in terms of stimuli, past protocols can range from a few to several dozens of items, ii/ in terms of human participants, a great interindividual variability characterizes the subjective judgments reflected by a very large diversity in the evoked hedonic response for a large range of smells, iii/ in terms of physiological responses, multiple parameters and variables are measured in the same individual. In addition to this physiological variability, there is a variability in olfactory perception linked to factors such as age [25], gender [26] or the menstrual cycle [24]. However, to arrive at a thoroughgoing model of odor pleasantness and intensity and their physiological basis requires having some means of i/ assessing these physiological responses in their diversity and heterogeneity across people and in their complexity, and ii/ describing in an intelligible manner the rules linking these physiological parameters to the individual subjective odor-driven affective experience: in fact, manually generating multiple rules linking the subjective experience (in its diversity) and physiological responses is not manageable.

Standard statistical approaches enable tackling the problem of the relationship between the subjective affective experience of odors and their physiological underpinnings very often on a single parameter basis (e.g. by comparing mean responses for pleasant vs. unpleasant for each individual physiological parameter). Furthermore, whereas predicting modeling approaches (e.g. classification algorithm) enable considering multiple physiological parameters in a single analysis, their explanatory power remains rather low. The aim of the present study is therefore **to better understand the relationship between the subjective experience of odor pleasantness and of odor intensity, and their physiological foundations by using a computational exploratory approach that we intend to apply to the field of affective sciences.**

To achieve this aim, we propose to use a data mining approach based on a subgroup discovery (SD) algorithm. SD enables to find population subgroups that are statistically "most interesting" from a population of individuals (or items) and a property on individuals of interest. In that respect, we aim to obtain the largest possible subpopulations which present the most unusual distributional statistical characteristics, and which respect the property of interest. The dataset used in the current study was previously published [17] and involves 22 individuals who smelled a total of 109 stimuli (varying in olfactory quality - *chemical, medicinal, floral, etc.* - and in chemical families - *alcohols, aldehydes, esters etc.*.). Each odorant was rated along two main dimensions of interest, namely pleasantness and intensity. Finally, a total of 4 physiological channels were recorded: finger pulse frequency (FP), skin conductance (SC), skin surface temperature (ST) and abdominal respiration (AR). These physiological data are described by 7 numeric attributes: one attribute for FP, AR and ST and four attributes for the SC (latency, rise time, amplitude and number of events).

Although the present study did not have the choice of physiological parameters to use (the data come from a previous study), some methodological choices should be clarified. Indeed, considering the duration of the experiment, Licon et al [17] privileged physiological sensors easy to install (belt positioned on the clothes for the breathing and sensors on the hand for the other parameters). Although less sensitive than the electrocardiogram for measuring cardiac activity and in particular its variability, the finger pulse was chosen here because its placement on the volunteers' thumb is extremely simple. Finally, note that the current analysis further explored 3 other subjective dimensions that are rarely studied and for which we intend to examine their physiological underpinnings: odor-evoked relaxation, anxiety and stress.

Our population is therefore obtained from subjective descriptions (pleasantness and intensity) of 109 flasks by different individuals. The property of interest concerns the search for subgroups identified by conditions on physiological attributes (e.g. FP> 1.0) for which a subjective experience (e.g. unpleasant) is significantly more present than in the rest of the data set. Note that the discovery of the best subgroups is NP-Complete (see Theorem 4 in [27]). Therefore, tackling this problem with a correct and complete algorithm is not feasible in practice. Indeed, we started by using an exact algorithm named *FSSD* (Fast and efficient algorithm for Subgroup Set Discovery)[28]; in several days it does not converge towards the first best solution and therefore never calculates the following solutions. To circumvent this issue, we therefore used an SD algorithm called *monteclopi* [29] (Monte Carlo Tree Search type, MCTS). MCTS is a heuristic that provides a fast and not necessarily optimal response by randomly exploring the dataset and improving the most promising results found by building a tree accordingly. In this way, it gives us the best intervals found for a given target attribute (e.g. pleasant, neutral, unpleasant).

2 Related work

Up to now, the understanding of the physiological foundation of the subjective experience of odor pleasantness and odor intensity has been explored using classical statistics and supervised classification. According to our knowledge, exploratory subgroup discovery methods were very few, or not yet applied in this field of olfactory affective sciences. For classical standard statistical approaches, in the very large majority of studies, hedonic responses are compared across conditions (e.g. pleasant vs.

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unpleasant) by considering statistics such as the average or the amplitude of the signal in a given time interval. Here, complexity and heterogeneity of the data (e.g., heterogeneity in perceptual and physiological responses) is not well considered. These statistical methods used include mainly non parametric tests (e.g. Wilcoxon, Kruskal Wallis) [30] and parametrical tests (Analysis of Variance, ANOVA [31], [32],[33], [34], [35], [36], [37] or even MANOVA [38], [39], [40], [41], [42]) depending on the study design, normality of data and/or sample size. The main message of these studies is that pleasant and unpleasant odors act differently on the activity of the peripheral nervous system, and that certain parameters such as skin conductance, respiration, heart rate and its variability, or skin temperature may be of interest to discriminate these hedonic classes [3], [18], [19], [20], [21], [43], [44]. or basic emotions evoked by odors [4], [13], [14], [15].

Machine learning methods have been successfully applied in the field of olfaction for specific research questions. For example, there has been a rapid rise in the use of machine learning methods for predicting the relationship between a molecule's structure (e.g., the physico-chemical space) and its odor (e.g., fruity, musky, the perceptual space) [45]. Following this line of research, the most recent deep learning methods have been applied to tackle this challenge. GoogleAI [46] proposed the use of graph neural networks for studying the structure-odor relationship. They showed that these graph neural models outperform methods on tasks such as random forest model and k-nearest neighbor model on tasks of relating odor perception to odorant chemistry. Despite these recent successes, some research questions remain challenging: studying the relationship between two spaces that are not stable as the chemical space, and are characterized by their variability is much more difficult. This is the case when the core of our research question is investigating the link between the physiological space and the hedonic space which are characterized by their diversity and could be qualified as non stable. In that context, data science approaches were used in past physiological studies using a large variety of machine learning algorithms such as artificial neural networks (ANN) [47], [48], [49], [50], [51], [52], support vector machine (SVM) [49], [50], [53], [54], [55], multivariate pattern classification analysis (MVPA)[56], k-nearest neighbor [57], decision trees [58], random forest [50] and linear discriminant analysis (LDA) [59], [60], [61]. These approaches enable predicting subjective affective responses from autonomic activity. However, in most cases, these algorithms are qualified as black box classifiers (e.g. SVM or ANN) since their interpretability power is rather low which is not ideal for affective scientists who seek to explain and understand the physiological underpinnings of affective responses. Note that contrary to standard statistical approaches, only few of these data sciences studies were applied to the field of olfaction [61].

In summary, whereas some classifiers such as decision trees or regressions can provide a better explanatory power, they are still not relevant to achieve our aim because these methods attempt to predict classes of items in the entire dataset whereas our objective is to determine whether there are subsets of items in the entire dataset that are characterized by exceptional physiological properties. Thus, the present article proposes a data mining method (subgroup discovery) that will attempt to search for such knowledge in the data by extracting, in the whole dataset, subgroups of items (odor pleasantness and odor intensity) characterized by exceptional rules (patterns of specific physiological responses).

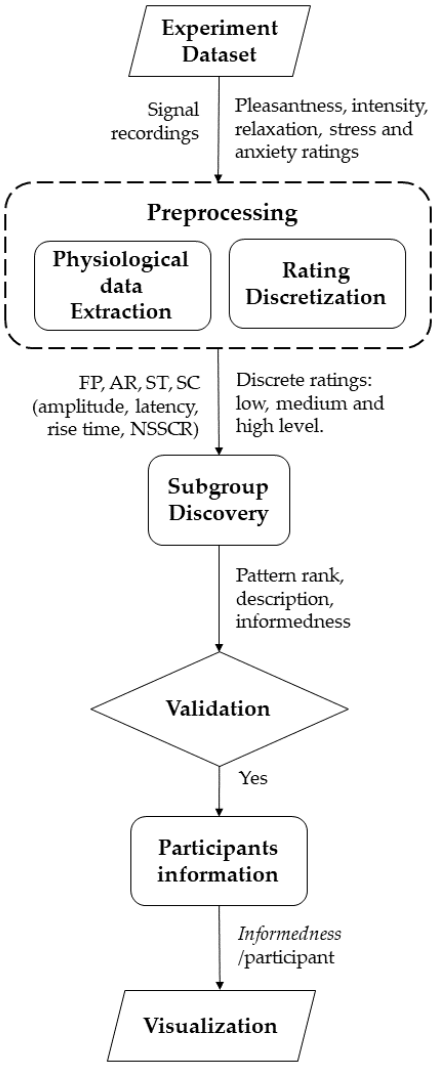

Fig. 1. Steps of the workflow. The raw data of the experiment are preprocessed (filtering, normalization, subtraction of the baseline) and the subjective ratings are discretized into 3 categories for each individual. Once the data is clean, the subgroup search describing the different perceptual dimension is performed. Then a statistical validation of the generated patterns is performed: the pattern is validated if its informedness is outside the confidence interval of the distribution of a bootstrapping of 1000 random draws. Finally, the extraction of information concerning the individual involvement of the subjects for each pattern is made and the visualization of all the results is accessible in different ways.

3 Material and Methods

In this section, we first present the psycho-physiological experiment from which the data was obtained. Secondly, we describe the preprocessing of physiological data, and that of perceptual data. Then, we present the process of

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data analysis (from pattern generation using data mining algorithms, validation of these results by bootstrapping) to visualization of each individual in the observed patterns. An overview of the whole analytical process is shown in Fig. 1.

3.1 Experiment

The dataset comes from a previous study [17] which consisted in recording physiological responses to odorant molecules, together with psychophysical ratings. For a better understanding, we will summarize this experiment. Twenty-two subjects (11 men and 11 women) between the ages of 19 and 46 years (mean±SD, 32±10 years) participated in the study and each of them inhaled 109 different stimuli (105 odorants and 4 odorless trials containing only mineral oil). These odorant molecules were chosen so as to cover a large series of chemical families with different molecular weights and olfactory perceptual qualities. The odorants were presented in 15ml vials. These vials contained 5ml of odorants diluted in deodorized mineral oil and a scentless polypropylene fabric that absorbs stimuli to optimize evaporation and air/oil sharing.

During the experiments, participants were comfortably installed in a 7×7×4m room (room temperature of about 22°C), in a semi-reclined seated position. This room was dedicated to the study of the sense of smell in that it was equipped with a ventilation system allowing a renewal of the ambient air. The Autonomic Nervous System (ANS) recording equipment included a total of four physiological parameters which were simultaneously and continuously recorded and displayed during the experiment: finger pulse (FP) frequency, skin conductance (SC), skin surface temperature (ST) and abdominal respiration (AR).

FP frequency was measured using a photoplethysmographic probe (3.2 cm/1.8 cm, LED photodetector) placed on the thumb of the non-dominant hand. Data were reduced to pulse rate, in beats per minute (bpm).

SC amplitude (in microsiemens: µS) was recorded by two circular Ag/AgCl electrodes (diameter one cm) placed on the third phalanx of the forefinger and of the middle finger of the non-dominant hand. Data were reduced to latency (ms), rise time (ms), amplitude (µS) and number of events.

ST was measured using a small ceramic-encapsulated metal-oxide semiconductor (9.5 mm length, two mm diameter). The thermistor, designed to operate from 0°C to 50°C, was placed directly on the first phalanx of the fourth finger. Data were reduced to skin temperature mean.

Changes in AR circumference were measured using a respiratory belt transducer (100 cm rest length, ten cm maximum elongation, 3.5 cm width), responding linearly to changes in length. Data were reduced to respiratory frequency, in cycles per minute (cpm).

Once ANS measures had stabilized, odorant trials were initiated. Each trial began with a white screen (for five seconds) followed by a written instruction, "Please prepare to smell", followed by a countdown, "3, 2, 1" (for five seconds).

Then, the investigator presented odorant stimuli about one cm below the participant's nose for three seconds. Participants were instructed to sniff each flask for as long as it was presented, not to move and to focus their attention on the white screen in front of them during 30 seconds. Afterwards, they were asked to rate the odorant molecule along 5 dimensions: pleasantness, intensity, relaxation, stress and anxiety induced by the odorants, on a scale from 1 (not at all) to 9 (extremely). Participants could complete their ratings within a time window of 25 seconds. The 109 trials were divided in four sub-sessions or blocks (27 or 28 odorants/session), presented in random order. The duration of each block was around 30 minutes. Total session duration was around three hours.

It should be noted that in the original study by Licon et al [17], the same participants returned to the laboratory one day later for a second session. During this second session, participants were presented with the same series of 109 flasks, and their tasks were to rate, among others, each stimulus for the following 6 basic emotional states: joy, sadness, fear, anger, disgust, and surprise; neutral state and pleasure were also added. For more details, refer to the second session in Licon et al [17].

3.2 Physiological data and parameters

Physiological data were sampled and recorded at 256 Hz, then converted and amplified via an 8-channel PROCOMP+ system (Thought Technology, Montreal, Canada) and displayed, stored, reduced and analyzed off-line. This device has already been used in several studies related to the senses and emotions in various fields such as psychiatry [62], food sciences [63] or neuroscience [6]. All physiological parameters were analyzed in the 30-s window after stimulus onset (using the ten seconds before odor presentation as baseline). Abdominal respiration (AR, cycle per minute or cpm), skin temperature (ST, mean temperature in C°) and finger pulse frequency (FP, in beats per minute or bpm) were normalized by subtracting baseline values (in the 10-sec period preceding stimulus onset) from the values in the 30-s window after stimulus onset. Note that for AR and FP, baseline values were multiplied by a factor

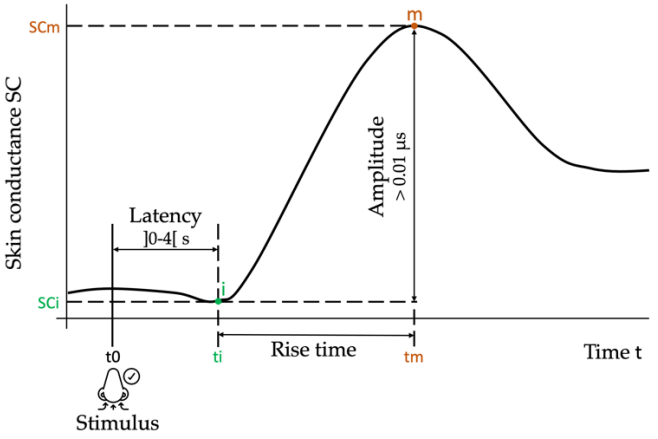

Fig. 2. Physiological attributes of the electrodermal response following stimulus presentation: latency (ms), rise time (ms), amplitude (µS). t0 corresponds to the time-point of odor presentation, i is the initiation point of the SC response and m is the maximum point of the SC response. The amplitude minimum is 0.01 μs and the initiation point is sought within the first 4 seconds. The calculation of the 3 variables is as follows: Latency = t0-ti, Rise Time = tm-ti, Amplitude = SCm-Sci.

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of 3 in order to be in the same time scale as that of the post-stimulus period (30 sec).

For Skin conductance (SC), in terms of signal analysis, SC has been smoothed by a Gaussian filter and analyzed through 4 variables. It should be noted that multiple SC responses can appear in the time between two trials. These multiple responses were considered by computing the number of skin conductance event (NSSCR) before and after the signal (as AR and FP), during baseline and after stimulus onset. We then focused on the first SC event following the olfactory stimulation by computing SC amplitude, latency and rise time, which are the most common SC parameters used in emotion and olfaction studies [19], [17], [49], [50], [64]. These SC parameters are depicted in Fig. 2. Note that the SC response begins in a time window of 4 seconds (maximum) after stimulus onset. In the case whereby no peak has been identified, the 3 attributes (latency, amplitude and rise time) are equal to 0.

3.3 Perceptual data and discretization

The ratings of each subjective scale were discretized using k-means [65] clustering (k = 3 classes; low, medium and high for pleasantness, intensity, relaxation, stress and relaxation). This discretization method has been chosen because it takes into account individual's valuation strategy which is not the case with more standard methods based on equi-depth and equi-width technics (see Fig. 3). This discretization has been applied to each participant independently. K-Means enable partitioning into k clusters so that the distance between intra-cluster points is minimized and the inter-cluster distance is maximized allowing partitioning the subjective data in three categories as different as possible. Note that if an individual did use less than 3 different ratings on all odorants for a given subjective dimension, then a discretization into 3 classes was not possible. In such cases, the individual was not included in the analysis for this specific subjective judgment (this case only happens for anxiety ratings of 2 individuals).

Fig. 3 illustrates an example of the different discretizations based on subjective ratings of a participant judging 6 different odorant molecules. A visualization of the discretization of each subject for each perceptual attribute is available in Fig. S1 (Supplementary file).

Note that to validate the classes generated by the k-means clustering, we ran the algorithm 100 times with different initializations for the same individual and a given subjective dimension. Results revealed a relative stability of the generated clusters (95.1% in average for all subjects for pleasantness, 95.9% for intensity, 95.8% for relaxation, 97.3% for stress and 96.3% for anxiety). We further validated these clusters using silhouette analyses in each individual and showed that for all dimensions, silhouette coefficient values were relatively high, which validate the consistency of clusters: pleasantness: [0.61-0.81], intensity: [0.64-0.88], relaxation: [0.66-0.93], stress: [0.67-1], anxiety: [0.63-1].

3.4 Subgroup discovery analysis

The above listed pre-processing ended in a dataset D analyzed through a subgroup discovery method described below. The dataset D consists of the set O of m odorant molecules, the set S of n individuals, a set P of physiological attributes and a set E of subjective evaluations.

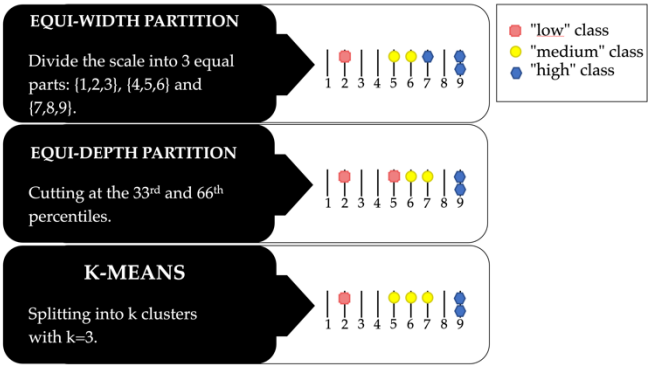

Fig. 3. Example of classical discretizations and the k-means discretization (k=3) in 3 discrete variables: low, medium and high based on subjective ratings of a participant evaluating 6 odorants (ratings: 2,5,6,7,9,9). In literature, self-reported ratings are usually discretized by dividing the ratings in k groups with k=2 or 3. The methods used are generally equi-depth (division into k equal size intervals) [58], [66], [67] or equi-width (quantile division: k groups with the same number of values) [3].

By convention, we denote by x_i, the ith attribute of the set of attributes X:

$$O = \{o_1, \dots, o_m\}$$
$$S = \{s_1, \dots, s_n\}$$
$$P = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7\}$$
$$= \{FP, AR, ST, SC\ amplitude, SC\ latency, SC\ rise\ time, SC\ NSSCR\}$$
$$E = \{e_1, e_2, e_3, e_4, e_5\}$$
$$= \{Pleasantness, Intensity, Relaxation, Stress, Anxiety\}$$

A pair of a given odorant and a given individual uniquely identifies a tuple in dataset D:

$$D: (o, s) \rightarrow P \times E$$

The value of the attribute $p \in P$ is denoted by $p(o, s)$. Similarly, the value (aka class) of the attribute $e \in E$ is denoted by $e(o, s)$. Note that for these attributes, there are 3 classes generated by the discretization process: low, medium, high. The set of tuples for an attribute e of class label c, are as follows:

$$D^{(e,c)} = \{(o, s) \in D \mid e(o, s) = c\}$$

An example of dataset is presented in Table 1a with only one perceptual attribute (pleasantness). In this example, $D^{(Pleasantness,\ medium)}$ corresponds to the "medium" class lines represented in bold in Table 1b. The other classes represented in italics are noted: $D^{(Pleasantness,\ \neg medium)}$. So, in terms of support: $|D^{(Pleasantness,\ medium)}| = 5$ and $|D^{(Pleasantness,\ \neg medium)}| = 4$.

We used a subgroup discovery approach to find a set of pairs, of individuals and odors that characterizes the specific class c against the other classes ($\neg c$) for a targeted perceptual attribute e. These subgroups are identified by an intent, i.e., a description. For this, we seek to identify the conditions on some physiological attributes strongly associated with a given subjective class (ex. Medium, Low, High). This can be formalized by a descriptive rule related to a subgroup.

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TABLE 1
EXAMPLE OF DATASET

a.

		Descriptive attributes							Target
Subject	**Odor**	**FP (bpm[a])**	**AR (cpm[b])**	**ST (°C)**	**SC Latency (ms)**	**SC Rise_Time (ms)**	**SC Amplitude (µs)**	**SC NSSCR (nb events)**	**Class : Pleasantness**
s_1	o_1	0.34	-0.34	-0.04	2.98	3.02	0.2	1.0	Medium
s_1	o_2	-1.67	-0.34	-0.03	0.80	3.44	0.08	0.0	Low
s_1	o_3	2.0	0.0	0.020	0.0	0.0	0.0	1.0	Medium
s_2	o_1	-1.0	-1.0	-0.021	0.0	0.0	0.0	0.0	Medium
s_2	o_2	-0.33	-0.33	-0.05	0.0	0.0	0.0	0.0	Medium
s_2	o_3	-1.0	-0.33	-0.023	1.81	3.05	0.15	5.0	High
s_3	o_1	1.0	0.33	-0.05	1.81	3.36	0.11	0.0	High
s_3	o_2	3.67	0.67	0.06	2.46	1.81	0.03	4.0	Low
s_3	o_4	-6.33	0.33	-0.68	2.49	1.79	0.06	2.0	Medium

Example :
e = Pleasantness
c = Medium
r = SC_NSCCR∈ [0,1]

Legend :
$cov(r)$
Bold $D^{(e,c)}$
Italics $D^{(e,\neg c)}$

b.

Subject	**Odor**	**SC NSSCR**	**Class : Pleasantness**
s_1	o_1	1.0	**Medium**
s_1	o_2	0.0	*Low*
s_1	o_3	1.0	**Medium**
s_2	o_1	0.0	**Medium**
s_2	o_2	0.0	**Medium**
s_2	o_3	5.0	*High*
s_3	o_1	0.0	*High*
s_3	o_2	4.0	*Low*
s_3	o_4	2.0	**Medium**

c.

Subject	**Odor**	**SC NSSCR**	**Class : Pleasantness**
s_1	o_1	1.0	Medium
s_1	o_2	0.0	Low
s_1	o_3	1.0	Medium
s_2	o_1	0.0	Medium
s_2	o_2	0.0	Medium
s_2	o_3	5.0	High
s_3	o_1	0.0	High
s_3	o_2	4.0	Low
s_3	o_4	2.0	Medium

d.

Subject	**Odor**	**SC NSSCR**	**Class : Pleasantness**
s_1	o_1	1.0	**Medium**
s_1	o_2	0.0	*Low*
s_1	o_3	1.0	**Medium**
s_2	o_1	0.0	**Medium**
s_2	o_2	0.0	**Medium**
s_2	o_3	5.0	*High*
s_3	o_1	0.0	*High*
s_3	o_2	4.0	*Low*
s_3	o_4	2.0	**Medium**

a) Example of dataset for the subjective ratings of pleasantness (note that for FP, AR, ST and SC-NSSCR, each value is calculated by substracting a baseline value from the physiological signal following odor presentation - see section 3.2; bpm means beats per minute and cpm means cycles per minute). b) Support for the "medium class". c) Support for the pattern r=SC_NSSCR∈[0,1]. d) Explanation of informedness with the true positives in bold and highlighted and the false positives in italics and highlighted for the pattern r and the class c.

A descriptive rule r, denoted $r: d \rightarrow (e, c)$, is defined by a physiological description strongly associated to the class c of a targeted perceptual attribute e. The description is a set of intervals $r = \{[x_1, y_1], [x_2, y_2], \ldots, [x_k, y_k]\}$, each being a restriction on the value of physiological attributes. The pairs (o, s) whose physiological attribute values belong to the intervals of description D are members of the coverage of D:

$$cov(r) = \{(o, s) \ \forall i = 1 \ldots k, x_i \leq p_i(o, s) \leq y_i\}$$

Let's consider the following pattern r = "SC_NSSCR ∈ [0,1]" and the previous dataset this time illustrated in the Table 1c. $cov(r)$ corresponds to the gray lines, that means all the lines with the number of events is 0 or 1 (see underlined values).

We aim to discover subgroups where one target class for a given perceptual attribute is over-represented, the other entities being under-represented. For that, we are interested in the subgroups that maximize a quality measure. There are several quality measures [68], [69]. In this study, we focused on the *informedness* [70] which corresponds to the difference between the true positive rate and false positive rate of the pattern. This quality measure allows to identify subgroups that maximize coverage for one class target and minimize coverage for other classes. It is a trade-off between recall and precision.

$$informedness(r, e, c) = \frac{|cov(r) \wedge D^{(e,c)}|}{|D^{(e,c)}|} - \frac{|cov(r) \wedge D^{(e,\neg c)}|}{|D^{(e,\neg c)}|}$$

Let us take again the examples of the Table 1b and 1c: let us consider, for the target "medium", the subjective evaluation of the "pleasantness", and the pattern: r = "SC_NSSCR ∈ [0,1]".

A new annotation of the dataset is depicted in Table 1d. Here, the lines in grey correspond to $cov(r)$, those in bold to $D^{(e,c)}$ and those in italics to $D^{(e,\neg c)}$. The lines in bold and highlighted illustrate the true positive, namely $cov(r) \wedge (D^{(e,c)})$ and the bold and highlighted lines the false positives, namely $cov(r) \wedge (D^{(e,\neg c)})$.

We therefore have the following quality score:

$$Informedness(r, pleasantness, medium) = 4/5 - 2/4 = 0.3$$

The objective of a subgroup discovery algorithm is therefore looking for physiological intervals which optimize *informedness*. Because the search space is huge, generating all the solutions is not possible, extremely time consuming and actually not feasible. We therefore opted for heuristic approaches which return the best solutions found for a given time budget. We use the *monteclopi* algorithm [29], which is based on Monte Carlo Tree Search (MCTS) [71] to explore the search space. Especially, *monteclopi* builds a search tree, which is expanded and updated at each iteration. Each path of the tree is described by a score determined by a quality measure. This algorithm is a combination of classic tree search implementations that uses exploration and exploitation. Exploration consists of randomly searching for new paths in order to find another solution. Exploitation allows the improvement of the most promising paths so as to maximize the measure of quality.

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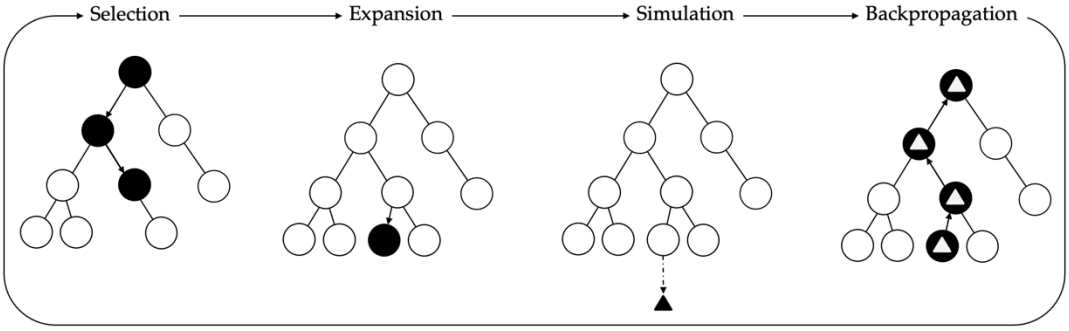

Fig. 4. Steps of the MCTS algorithm.

Monteclopi thus allows us to look for other good solutions while validating the quality of the current best. For that, at each iteration, the algorithm goes through four phases: selection, expansion, simulation (aka roll-out) and back propagation (aka update). These four steps are illustrated in Fig. 4. Selection consists in selecting the unexplored child of a node from the tree already constructed. This node is developed in the expansion step and a new transition is added to the construct tree. The tree then simulates the value of this state: it successively performs random transitions from the extended node, until it reaches a terminal node. Then the backpropagation state allows to update the tree by adding the value of the new state and by correcting the value of each state upstream in the tree. These four steps are executed successively, until there is no more time budget or all the search space has been explored. At this point, the nodes with the best *informedness* are returned.

Monteclopi is given a time budget as a parameter (here 200 seconds) and it returns the 10 best patterns found at the end of the allotted time.

3.5 Validation of patterns

In order to validate the quality of a pattern, we performed bootstrapping by calculating the *informedness* of 10,000 groups for each pattern discovered, with the same support as the current pattern, drawn at random (with replacement between each draw). The aim is to validate the pattern if its *informedness* is outside the 95% of the random distribution. For this, we calculate the interval between the 100.α and 100.(1-α) percentiles of the bootstrap distribution with $\alpha = 0.025$. Only patterns with an *informedness* above the 97.5th percentile are kept, the others are rejected. An example of pattern validation is illustrated in Fig. 5. This interval-based validation makes it possible to avoid reporting subgroups indicating an *informedness* likely to be observed by a random subset of entities.

3.6 Participation of individuals in the generated patterns

Here, we calculated the number of individuals participating in a given pattern and we quantified how much they participate in it. To this end, we considered only the data of an individual when the *informedness* is positive. Let us consider s_i an individual, the data for this individual are noted:

$$D_{s_i} : (o, s_i) \rightarrow P \times E$$

For example, in Table 1, D_{s_1} corresponds to the first three rows in the table.

The *informedness* computed for a participant s for the rule r and the target (e, c) is:

$$informedness(r, e, c, s) = \frac{|cov(r) \wedge D_s^{(e,c)}|}{|D_s^{(e,c)}|} - \frac{|cov(r) \wedge D_s^{(e,\neg c)}|}{|D_s^{(e,\neg c)}|}$$

The higher the *informedness* for an individual, the more the individual participates.

The number of participants to the pattern r and the target c is:

$$Nb_{participants(r,e,c,S)} = |\{s \; \forall s \in S, informedness(r, e, c, s) > 0 \; is \; True\}$$

Let us consider the previous example and always the target "medium" for the "pleasantness" and the pattern: r = "SC_NSSCR ∈ [0,1]". The number of participants for this rule and this target is computing from the *informedness* of each individual:

$$Informedness(r, pleasantness, medium, s_1) = \mathbf{2}/\mathbf{2} - 1/1 = 0$$
$$Informedness(r, pleasantness, medium, s_2) = \mathbf{2}/\mathbf{2} - 0/1 = 1$$
$$Informedness(r, pleasantness, medium, s_3) = \mathbf{0}/\mathbf{1} - 1/2 = -0.5$$
$$Nb_{participants(r,pleasantness,medium)} = \{s_2\} = 1$$

Thus, whereas Subject 1 and Subject 3 do not participate in the pattern and Subject 2 participates to the pattern at 100%.

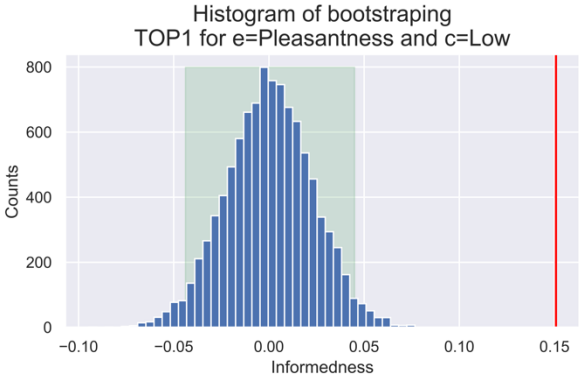

Fig. 5. Example of validation. In blue: the bootstrapping distribution. The rectangle around the distribution: the 95% percentile interval. The vertical bar: the informedness of the TOP1 pattern of the target "low" for pleasantness.

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4 Results

4.1 Overall description of results and quality

All 10 best descriptive rules of each perceptual attribute are presented in Tables S1-5 (Supplementary file). The set contains 150 patterns (top 10 descriptive rules, 3 classes, 5 perceptual attributes). The *informedness* of these patterns is between 0.042 and 0.151, which may be seen as not high but still outside the 95% confidence interval (for a better understanding of the bootstrapping procedure, see section 3.5 and especially Figure 5). As can be seen in Figure S2 (which shows the Top 1 validations of each category), for each pattern, the quality measure (vertical bar) is located beyond the upper limit of the confidence interval (rectangle around the distribution). These patterns are therefore significant.

The number of individuals participating in the patterns varies between 20% and 86.36%. Finally, whereas 83,33% of the rules contain only one interval ($\neq [-\infty; +\infty]$) (named as *Simple descriptive rules*; aggregated result shown in the Fig. 6, Fig. S8 and section 4.2), 16,66% of the rules contain multiple intervals (named as *Multidimensional descriptive rules*; presented in section 4.3).

For descriptive purposes, a specific terminology will be used to describe the different classes within each subjective dimension. For odor pleasantness, we will use the terms "unpleasant", "neutral", and "pleasant" for the respective classes "low", "medium", and "high". For odor intensity, we will use the following notations: we will use the terms "not at all intense", "midly intense", and "very intense" for the respective classes "low", "medium", and "high". Note that for the 3 other subjective ratings, the same notation as that for intensity will be used: "Not at all" + relaxing/stressful/anxiety-inducing for the "low" class, "Mildly" + relaxing /stressful/anxiety-inducing for the "medium" class, "Very" + relaxing/stressful/anxiety-inducing for the "high" class.

4.2 Simple descriptive rules

Fig. 6 depicts the *simple descriptive rules*. These rules are represented in a combined visualization for odor pleasantness and odor intensity. For the same class (low, medium, high), one can have several rules whose interval concerns the same physiological attribute. For visualization purposes we presented the rule with the best *informedness*. All these selected rules are displayed on axes for each physiological attribute.

For pleasantness (Fig. 6a), it can be seen that pleasant odors are associated with a decrease in FP activity, and very small variations in skin temperature; combined with neutral odors, they decrease activity in most SC attributes. For neutral odors, they decrease SC activity (number of events) and skin temperature. For unpleasant odors, the activity is mainly focused on one parameter, namely SC which increases for 3 attributes (amplitude, latency and rise time). For intensity (Fig. 6b), not at all intense odors decrease AR, increase ST and decrease SC (number of events). Moreover, there is a gradual increase of SC activity from mildly intense to very intense for 3 attributes (amplitude, latency and rise time). Finally, very intense odors induced an increase in SC activity for the attribute number of events.

Mixed results were observed for relaxation, stress and anxiety (Fig. S7a-c). Not at all relaxing odors induced few variations in AR, a decrease in ST and an increase in SC latency and rise time. Mildly relaxing odors induced a decrease in FP and AR activities and small increases in SC amplitude and rise time. Very relaxing odors induced an

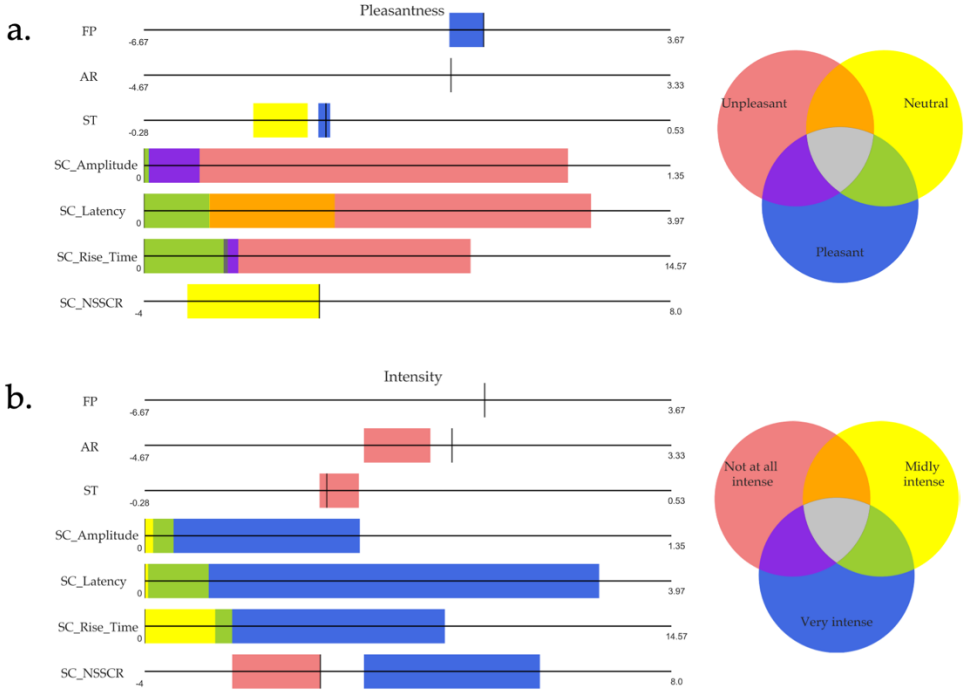

Fig. 6. Visualization of simple rules for odor pleasantness (a) and odor intensity (b). Each vertical line corresponds to the value zero (0).

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TABLE 2
PERCENTAGE OF MULTIDIMENSIONAL RULES FOR EACH AFFECTIVE DIMENSION AND CLASS

Classes	Pleasantness (%)	Intensity (%)	Relaxation (%)	Stress (%)	Anxiety (%)
Low	0	0	0	0	0
Medium	50	60	0	60	70
High	20	0	0	0	0

The other rules are one-dimensional, they are called simple rules and are described in section 4.2.

increase in AR and ST and a mild increase in SC latency. For stress, not at all stressful odors induced an increase in SC amplitude, latency and rise time. Mildly stressful odors induced a very small increase in SC amplitude, latency and rise time, and very stressful odors decreased FP activity, changed in both directions AR activity, increase mildly SC amplitude and induced an increase in SC number of events. Finally, for anxiety, not at all anxious-inducing odors decreased ST and increased SC activity (amplitude, rise time and to a lesser degree latency). Mildly anxious-inducing odors increased very slightly SC amplitude and rise time. Very anxious-inducing odors induced a change in both directions of AR, increased slightly SC amplitude and increased strongly SC latency.

4.3 Multidimensional descriptive rules

The rules with multiple intervals are depicted in Fig. S3 (Supplementary file). Each interval is represented by a colored bar on the axis of the corresponding physiological attributes. A first result of interest is that 92.3% of these multidimensional rules concern the "medium" class (Table 2) of four perceptual dimensions (Pleasantness, Intensity, Stress and Anxiety). The relaxation dimension did not contain any *multidimensional descriptive rules* and therefore contains only simple rules. A second result of interest is that none of the extreme ratings ("low", "high") for the dimensions of intensity, relaxation, stress and anxiety was described by any multiple physiological rules. The only exception was the state "High" pleasantness which was characterized by 20% of multiple rules. In summary, these data suggest that simple physiological rules are in place when the olfactory system is confronted with chemicals evaluated with extreme subjective hedonic scores: odors evaluated as "high" and "low" in terms of pleasantness were associated with no or very few multiple rules. However, it should be kept in mind that these descriptive rules are not systematically the same across individuals. This variability is discussed in Section 4.4.

4.4 Variability in the generated descriptive rules

The number of individuals participating in a given pattern was calculated from the *informedness* of each individual for that pattern. A first visualization in a standardized frame, allowed us to visualize which individuals participate in the pattern and how much they participate to the pattern. The graph of patterns classified as TOP 1 can be viewed in Fig. S4 (Supplementary file). One such example is displayed in Fig. 7 whereby each point depicts a participant labelled with his/her number. The two axes of the figure correspond to the false positive and true positive rate. Note that *informedness* is the number of true positive ratio minus the false positive ratio and it must be positive for the individual to be noted as a participant in the pattern. In sum, each subject positioned above the unit slope line participates to the pattern (symbolized in white). The more a white point is distant from the unit slope line, the greater the number of true positives compared to false positives and therefore the more the subject participates in the pattern.

A second visualization was carried out in the form of a Venn diagram (see Fig. S5 and S6, Supplementary file) created with Interativenn [72]. Fig. 8a illustrates such data for pleasantness ratings. For each target, we selected the same patterns as those visualized in Fig. 6 and calculated the overlap in terms of individuals for each pattern of the same class. The Venn diagrams thus allow us to illustrate whether it is the same individuals who participate in the different patterns or not. For example, in the 15 individuals who participate in the "1. SC_Latency" pattern of the unpleasant in fig. 8a: 13 are also present in the other two patterns, 1 individual is common only with the pattern "4. Sc_Rise_Time" and 1 individual is not present in the other patterns. In order to be able to compare these 3 diagrams, we reconstructed these diagrams retaining only physiological attributes common to the unpleasant, neutral and pleasant odors (Fig. 8b). An important result to extract from this analysis is that the more unpleasant the subjective emotional experience, the greater the number of individuals participating in the physiological pattern. In other words, the physiological response to aversive stimuli appears to be more invariant than the physiological response to appetitive stimuli.

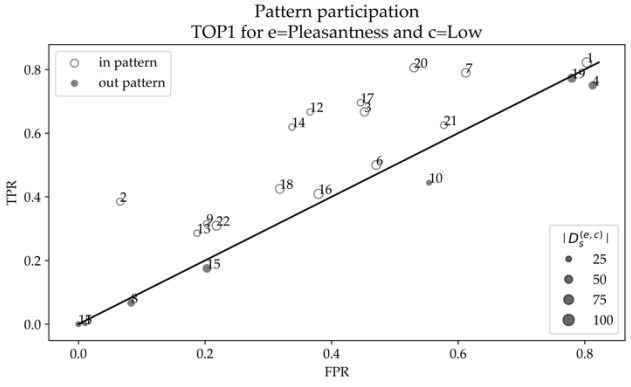

Fig. 7. Participation of each subject in the best pattern found for unpleasant odors. The number displayed on each point corresponds to the subject's identification number. The size of the dot indicates the number of odors classified as unpleasant to that individual.

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5 Discussion

The present study was aimed at exploring the physiological underpinnings of odor pleasantness and odor intensity by considering inter-individual diversity. To this end, we used a computational exploratory approach and generated a series of descriptive rules for different subjective experiences. A first result of interest was that our approach provided a set of descriptive rules linking the dimensions of intensity and pleasantness with a number of physiological parameters. For example, for the dimension of olfactory intensity, we observed a gradual increase in the electrodermal response as a function of an increase in intensity. For odor pleasantness, while the perception of pleasant odors is associated with a decrease in cardiac activity, the perception of unpleasant odors is associated with a strong activation of the electrodermal response. These results are in line with previous studies [2], [3], [4], [18], [20] and support the hypothesis of a stronger somatic response for aversive (unpleasant and intense) olfactory stimuli.

A second result of interest concerns the invariance or diversity that characterizes physiological responses to both pleasant and unpleasant stimuli. While for the former we observed great diversity among individuals, the pattern observed for the latter was very consistent among participants. These data bring a new element of information to the study of subjective hedonic experience of smells by opening the door to the existence of universal somatic and physiological responses between individuals, responses that provide relevant information about our harmful environment [6]. On the other hand, beyond these responses to aversive stimuli, there would exist physiological patterns dedicated to appetitive stimuli, which are important for our well-being, and which would be more sensitive to individual development and trajectory of each and everyone. These results of greater inter-individual variability observed in responses to pleasant and neutral odors compared to unpleasant odors are in agreement with the study by Kroupi et al [61]. In the latter, a classifier discriminated with a high level of prediction the unpleasantness of an odor from EEG data. However, the algorithm struggled to predict the pleasantness and/or neutrality of an odor. Because the explanatory power of such a predictive approach is relatively poor, the explanation for these classification difficulties was not explicit. In another study [60], the authors improved the quality of the model by making predictions within a subject rather than from all subjects' data.

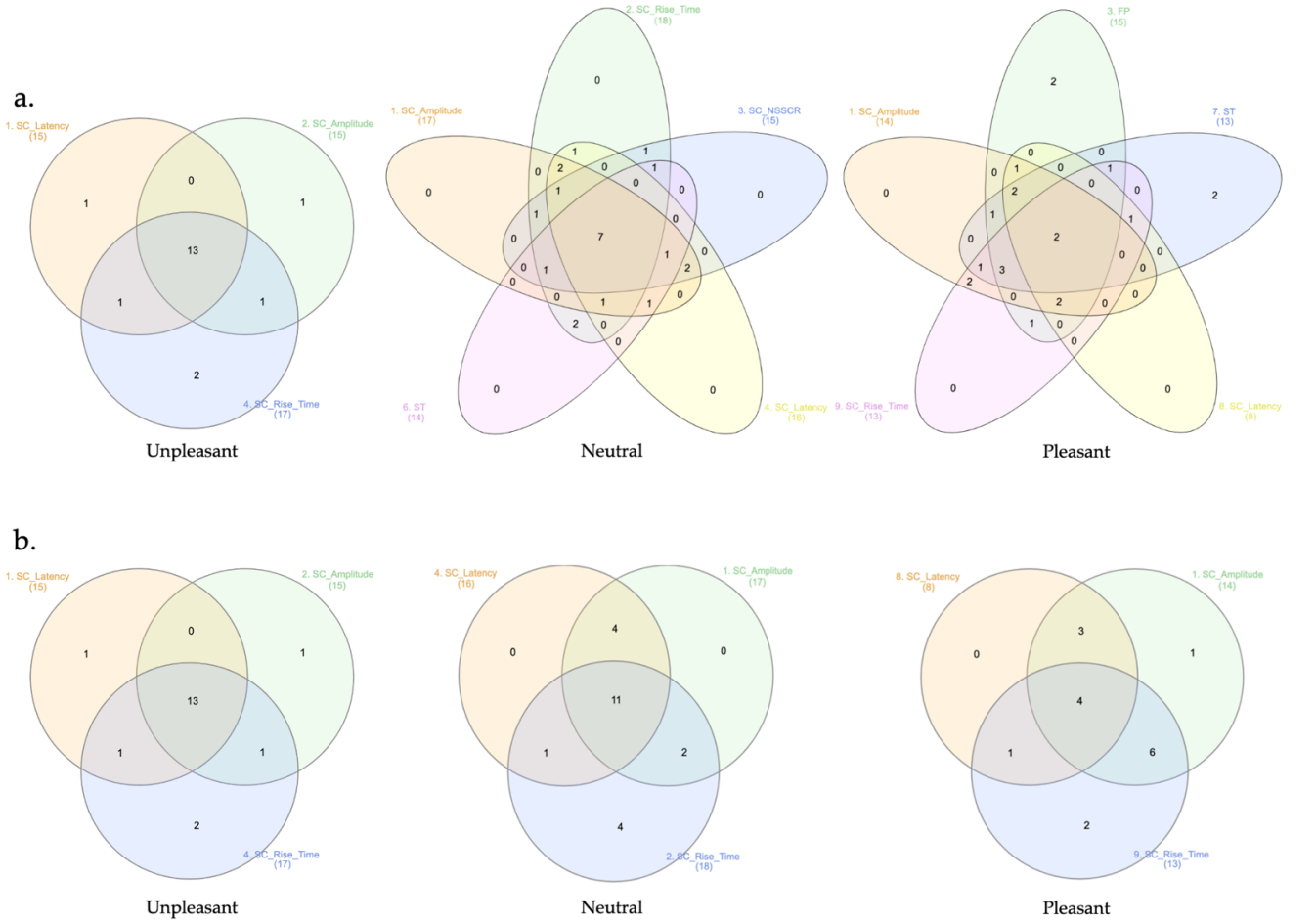

Fig. 8. Venn diagrams of the overlap of individuals in the different physiological patterns for each class of pleasantness by considering all physiological parameters (a) or only those common to the three classes (b). Each circle or ellipse corresponds to a pattern with a simple descriptive rule, it is labeled by its classification number in the TOP10 pattern followed by the physiological attribute concerned by the rule and then by the number of subjects participating in this pattern. The numbers in each diagram indicate both the number of subjects in each intersection and the relative complement in order to know the number of common participants in the overlapping patterns.

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This reinforces the idea that inter-individual variability hinders the correct classification of emotions at the population level and that it is important to put the individual at the center of the analysis.

As a secondary objective, we asked the question of whether subjective dimensions such as perceived and reported stress, relaxation or anxiety could have a physiological correlate in the manner already studied for the dimensions of intensity and especially pleasantness. The rules generated for these dimensions do not seem to fit the hypothesis of a decrease in sympathetic activity (decrease in AR, FP, SC and increase in ST) in response to relaxing, non-stressful and non-anxiety-inducing stimuli. This observation leads us to make different hypotheses. The first is that the generated rules do not correspond to a physiological reality and that they depend on the data set or are generated at random. The second is that not all smells have the potential of inducing strong states of anxiety, stress and/or relaxation, and therefore the data distribution within each of these dimensions was not ideal to perform our analysis. Indeed, it may be the case that most of the participants declared to perceive most odorants as not at all (or very) relaxing, stressful and anxiety-inducing stimuli leading to strong disparities in the classes low, medium and high for these dimensions. The third hypothesis is that the participants from the current study exhibited difficulties in understanding the meaning of these dimensions of relaxation, stress and anxiety and thus/or showed difficulties in describing their own feelings about these emotional dimensions when applied to olfaction. Even if it is difficult to provide a definitive answer regarding the acceptance or rejection of one of these hypotheses, we think that the first hypothesis is the less plausible since if it was validated, this would have to apply to all subjective judgements including judgements of pleasantness and intensity. The results for these dimensions of pleasantness and intensity are - however - in good agreement with the literature. Moreover, the second hypothesis is strengthened by the fact that the 3 classes of these 3 affective dimensions were very clearly unbalanced, the rating "1" (not at all) was used widely more (between 33.5 and 45.7%) than the others (see Fig. S7, Supplementary file) (aggregate means and standard deviations in a scale from 1 to 9 across all subjects and all stimuli: 3.36+/-2.32 for relaxation, 2.87+/-2.32 for stress, 2.61+/-2.00 for anxiety). As such, our study cannot conclude whether the second hypothesis and/or the third hypothesis (misunderstanding of the dimensions of relaxation, stress, and anxiety as applied to the universe of smells) is the most plausible. In both cases, and to clarify this limitation, it will be important for future studies in this area to consider i/ the ability of odors to induce these subjective experiences in humans, and ii/ the development of appropriate measurement scales to assess the subjective nature of these dimensions. In particular, it would be relevant to combine within the same scale, different states that may belong to the same subjective dimension. This is the case of the state of relaxation which can be opposed on the same continuum to perceived stress. It is possible that with such a scale, participants can describe their subjective experience more easily. Nevertheless, we note that the results observed for these dimensions do not compromise our approach in any way, since it proved to be effective for our dimensions of interest, namely pleasantness and intensity.

When such a scientific approach of linking perceptual dimensions (pleasantness and intensity) with a physiological space is undertaken, one question that may be asked is how the data mining approach is positioned in relation to other approaches in artificial intelligence such as machine learning. In fact, these two approaches complement each other. Whereas machine learning allows us to validate predictive models, the data mining approach is more focused on knowledge extraction by providing descriptive and especially explanatory modeling. When datasets are characterized by a large inter-individual variability (which is the case of our data), it sometimes happens that the machine learning approach does not allow to put forward a solid predictive model. To illustrate this with our data, we tested a series of classifiers (e.g., Decision trees (DT), Random Forest (RF), Logistic regression (Log. Reg.), K-nearest neighbors (KNN), Support vector machine (SVM), Multilayer perceptron (MLP)), all available in the scikit-learn Python library [73] using tuning in k-fold cross-validation. Note that the higher the value of k, the higher the accuracy should be, and it is common to use k-values of 5 or 10. Here, the performance was very similar to different k-values (3, 5 and 10; accuracy difference less than 2%), and a value of k=10 was chosen. The tuning allows to choose a set of optimal hyperparameters for the learning algorithm. The mean cross-validated accuracies of the best estimators are shown in Table 3 for pleasantness and intensity; the other affective dimensions and details on the parameters selected by tuning are available in Table S6 (Sup-plementary file). Note that the accuracy is never better than the size of the largest class. Indeed, for relaxation, stress and anxiety, DT, RF, Log. Reg, SVM and MLP classify in more than 90% of cases the most frequent class. As mentioned in the Section 2 (Related works), the classification scores are not high suggesting that these different algorithms have not been able to manage the diversity of human perception inherent in this dataset. In this case, the data mining approach can be interesting to implement because it allows to extract a certain number of rules linking olfactory perception and physiology and in fine to open the door to the validation of new hypotheses that we would not necessarily have thought of when analyzing the data manually. It should also be noted that this data mining approach has different objectives than machine learning methods such as feature extraction. Whereas feature selection allows to extract the most relevant predictive variables in order to define the most robust predictive model, in data mining, the extraction is not about feature extraction but about the rules that will link features from two different spaces. In data mining, the generated knowledge is characterized by a high level of interpretability. In our study, these rules are computed by mathematically well-funded measures and consist in conjunctions of conditions on physiological attributes that conclude on particular subjective experiences of odors. The generated rules are easy to assimilate for a domain expert such as psychologists or neuroscientists in our case. Because it enables modeling that extracts

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TABLE 3
MEAN 5-FOLD CROSS-VALIDATION ACCURACY (%) OF THE BEST PREDICTORS FOUND BY TUNING

	DT	RF	Log. Reg.	KNN	SVM	MLP	Size of the largest class (%)
Pleasantness	39.3	39.8	39.5	34.4	40.3	41.2	40.1
Intensity	38.7	40.7	40.6	38	41.5	40.8	38.2

descriptive rules from the data that link subgroups belonging to both perceptual and physiological spaces, such approach is positioned upstream of predictive modeling and therefore allows developing new hypotheses in the field. In sum, the rules generated may allow scientists to start a hypothetical-deductive approach, to formulate new scientific assumptions, then to set up new experiments and lastly to test new predictive models using machine learning approaches.

Although the present study provides interesting results linking physiology and odor pleasantness and intensity, some limitations are to be noted and should be discussed. A first limitation concerns the size of the sample studied (n=22). Is it sufficient to extract knowledge linking odor pleasantness or odor intensity with physiological responses with such a number of participants? When using conventional statistics, power analysis is used to answer this question. For example, in Licon's original study with these 22 subjects, a significant relationship was observed between physiological responses to odors and odor pleasantness (Licon et al., 2018, page 5). The statistical power associated with this correlation was adequate and exceeded the 80% threshold (83% in this case). In our case, the minimum number of volunteers is actually the one that allows us to observe exceptional patterns that stand out from chance. Even though our analysis revealed a number of exceptional patterns, the fact that our findings are limited by our sample of participants cannot be ruled out. It will therefore be important in future studies to investigate a method for assessing a minimum sample size for such data mining approaches. For example, one could imagine data mining algorithms, that would discover rules on the basis of a first sample and that would set out to verify if these rules are still observed on another independent sample. These future algorithms should also be able to account for the variation that could exist between the rules generated by the 2 datasets (for instance using Jaccard-based measure [74]), and evaluate the optimal sample size capable of generating stable rules. Nevertheless, it should be kept in mind that a recurrent problem in this topic of the relations between perception and physiology in the field of odors concerns the data sets which are very few. The vast majority of studies use a limited number of odorants, unlike our study which is one of the few to include more than 100 molecules. Thus, beyond the development of new data mining algorithms, it will be necessary to accumulate more perceptual and physiological data sets by integrating more olfactory stimuli in the experimental designs.

A second point of improvement concerns the scales used to evaluate the different perceptual and affective dimensions. As mentioned above in this discussion, one can wonder whether the fact that participants over-represent or under-represent certain categories of the scales may have introduced a bias in our results. Although these patterns are very unfrequent for the main dimensions of pleasantness and intensity (see Figures S1 and S7), it happens for the dimensions of stress, relaxation and anxiety that participants do not have the same distribution of the "low", "medium", "high" categories. For these three dimensions, it is therefore possible that this non-uniform distribution may introduce bias into our data. Note however that subgroup discovery analysis considers in a way this bias by extracting invariant descriptions through both the score and the number of individuals who participate to the pattern. Nevertheless, it will be important in future work to further limit the polarized reactions of the participants by taking into account the intrinsic distribution of each individual by weighting individual's trials according to this distribution. This could be done by adding metrics such as subjective interestingness [75]. A third limitation of our study concerns other physiological parameters that can undoubtedly help to improve knowledge extraction. This will imply not only new signals and modalities, but also more complex features of selected physiological signals. Our protocol focused on physiological signals that were simple enough to measure and already collected in a previous study [17]. A possible perspective of our study would be to complete these measurements by parameters even more discriminating in the classification of affective responses. One can think for example of heart rate variability which can be measured using ECG sensors. The measurement of EEG is also an avenue to follow by considering signal amplitudes and latencies but also more complex features in the time-frequency domain for example. Finally, measurement of brain activity via fMRI should also be considered. For the latter, the problem will be the number of trials per hedonic condition (e.g. pleasant vs. unpleasant) which may be limited due to the temporal resolution of the method (which limits the study in time) and the habituation phenomena (which increases the duration of experiment). Taken as a whole, such an approach will enrich our knowledge of the perceived pleasantness and intensity of smells at different levels of processing (behavior, central nervous system, peripheral nervous system), a multimodal approach that is too rarely implemented.

6 CONCLUSIONS

The main aim of the present study was to set out to examine whether the use of subgroup discovery may help in improving our understanding of the relationship between perceptual dimensions of pleasantness and intensity of

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odors and their physiological underpinnings. The presented workflow enabled to relate autonomic nervous system activity patterns with specific odor perceptual responses. On specificity of this method is that it applies to a large amount of data, which is not always the case with all datasets from affective sciences. To circumvent this issue, and generate pertinent hypotheses in the field, one could combine different datasets from different studies with similar protocols since our approach can be used on experiments whose stimuli (olfactory and non-olfactory) are not necessarily the same for all participants. Last but not least, this approach can be applied to other fields of affective sciences characterized by large, complex and heterogeneous datasets.

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REFERENCES

[1] Y. Yeshurun and N. Sobel, "An Odor is Not Worth a Thousand Words: From Multidimensional Odors to Unidimensional Odor Objects," *Annu. Rev. Psychol.*, vol. 61, no. 1, pp. 219–241, Jan. 2010, doi: 10.1146/annurev.psych.60.110707.163639.

[2] J. Djordjevic, J. N. Lundstrom, F. Clément, J. A. Boyle, S. Pouliot, and M. Jones-Gotman, "A Rose by Any Other Name: Would it Smell as Sweet?," *J. Neurophysiol.*, vol. 99, no. 1, pp. 386–393, Jan. 2008, doi: 10.1152/jn.00896.2007.

[3] M. Bensafi, C. Rouby, V. Farget, B. Bertrand, M. Vigouroux, and A. Holley, "Psychophysiological correlates of affects in human olfaction," *Neurophysiol. Clin. Neurophysiol.*, vol. 32, no. 5, pp. 326–332, Nov. 2002, doi: 10.1016/S0987-7053(02)00339-8.

[4] O. Robin, O. Alaoui-Ismaïli, A. Dittmar, and E. Vernet-Maury, "Basic Emotions Evoked by Eugenol Odor Differ According to the Dental Experience. A Neurovegetative Analysis," *Chem. Senses*, vol. 24, no. 3, pp. 327–335, Jan. 1999, doi: 10.1093/chemse/24.3.327.

[5] C. Ferdenzi *et al.*, "Variability of Affective Responses to Odors: Culture, Gender, and Olfactory Knowledge," *Chem. Senses*, vol. 38, no. 2, pp. 175–186, Feb. 2013, doi: 10.1093/chemse/bjs083.

[6] P. Joussain, C. Ferdenzi, J. Djordjevic, and M. Bensafi, "Relationship Between Psychophysiological Responses to Aversive Odors and Nutritional Status During Normal Aging," *Chem. Senses*, vol. 42, no. 6, pp. 465–472, Jul. 2017, doi: 10.1093/chemse/bjx027.

[7] R. J. Davidson, "Anterior cerebral asymmetry and the nature of emotion," *Brain Cogn.*, vol. 20, no. 1, pp. 125–151, Sep. 1992, doi: 10.1016/0278-2626(92)90065-T.

[8] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm, "Looking at pictures: Affective, facial, visceral, and behavioral reactions," *Psychophysiology*, vol. 30, no. 3, pp. 261–273, 1993, doi: 10.1111/j.1469-8986.1993.tb03352.x.

[9] A. J. Gerber *et al.*, "An affective circumplex model of neural systems subserving valence, arousal, and cognitive overlay during the appraisal of emotional faces," *Neuropsychologia*, vol. 46, no. 8, pp. 2129–2139, Jul. 2008, doi: 10.1016/j.neuropsychologia.2008.02.032.

[10] P. Ekman, "Are there basic emotions?," *Psychol. Rev.*, vol. 99, no. 3, pp. 550–553, 1992, doi: 10.1037/0033-295X.99.3.550.

[11] R. J. Dolan, "Emotion, Cognition, and Behavior," *Science*, vol. 298, no. 5596, pp. 1191–1194, Nov. 2002, doi: 10.1126/science.1076358.

[12] E. T. Rolls, "Taste and smell processing in the brain," in *Handbook of Clinical Neurology*, vol. 164, Elsevier, 2019, pp. 97–118. doi: 10.1016/B978-0-444-63855-7.00007-1.

[13] O. Alaoui-Ismaïli, O. Robin, H. Rada, A. Dittmar, and E. Vernet-Maury, "Basic Emotions Evoked by Odorants: Comparison Between Autonomic Responses and Self-Evaluation," *Physiol. Behav.*, vol. 62, no. 4, pp. 713–720, Oct. 1997, doi: 10.1016/S0031-9384(97)90016-0.

[14] O. Alaoui-Ismaïli, E. Vernet-Maury, A. Dittmar, G. Delhomme, and J. Chanel, "Odor Hedonics: Connection With Emotional Response Estimated by Autonomic Parameters," *Chem. Senses*, vol. 22, no. 3, pp. 237–248, 1997, doi: 10.1093/chemse/22.3.237.

[15] E. Vernet-Maury, O. Alaoui-Ismaïli, A. Dittmar, G. Delhomme, and J. Chanel, "Basic emotions induced by odorants: a new approach based on autonomic pattern results," *J. Auton. Nerv. Syst.*, vol. 75, no. 2, pp. 176–183, Feb. 1999, doi: 10.1016/S0165-1838(98)00168-4.

[16] R. M. Khan *et al.*, "Predicting Odor Pleasantness from Odorant Structure: Pleasantness as a Reflection of the Physical World," *J. Neurosci.*, vol. 27, no. 37, pp. 10015–10023, Sep. 2007, doi: 10.1523/JNEUROSCI.1158-07.2007.

[17] C. C. Licon, C. Manesse, M. Dantec, A. Fournel, and M. Bensafi, "Pleasantness and trigeminal sensations as salient dimensions in organizing the semantic and physiological spaces of odors," *Sci. Rep.*, vol. 8, no. 1, Art. no. 1, May 2018, doi: 10.1038/s41598-018-26510-5.

[18] M. Bensafi, C. Rouby, V. Farget, B. Bertrand, M. Vigouroux, and A. Holley, "Autonomic Nervous System Responses to Odours: the Role of Pleasantness and Arousal," *Chem. Senses*, vol. 27, no. 8, pp. 703–709, Oct. 2002, doi: 10.1093/chemse/27.8.703.

[19] P. Brauchli, P. B. Rüegg, F. Etzweiler, and H. Zeier, "Electrocortical and Autonomic Alteration by Administration of a Pleasant and an Unpleasant Odor," *Chem. Senses*, vol. 20, no. 5, pp. 505–515, 1995, doi: 10.1093/chemse/20.5.505.

[20] P. Møller and G. Dijksterhuis, "Differential human electrodermal responses to odours," *Neurosci. Lett.*, vol. 346, no. 3, pp. 129–132, Aug. 2003, doi: 10.1016/S0304-3940(03)00498-1.

[21] M. Nardelli, G. Valenza, A. Greco, A. Lanatá, E. P. Scilingo, and R. Bailón, "Quantifying the lagged Poincaré plot geometry of ultrashort heart rate variability series: automatic recognition of odor hedonic tone," *Med. Biol. Eng. Comput.*, vol. 58, no. 5, pp. 1099–1112, May 2020, doi: 10.1007/s11517-019-02095-7.

[22] M. Bensafi, C. Rouby, V. Farget, B. Bertrand, M. Vigouroux, and A. Holley, "Influence of affective and cognitive judgments on autonomic parameters during inhalation of pleasant and unpleasant odors in humans," *Neurosci. Lett.*, vol. 319, no. 3, pp. 162–166, Feb. 2002, doi: 10.1016/S0304-3940(01)02572-1.

[23] M. Mantel, J.-M. Roy, and M. Bensafi, "Accounting

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For Subjectivity In Experimental Research On Human Olfaction," *Chem. Senses*, no. bjaa082, Jan. 2021, doi: 10.1093/chemse/bjaa082.

[24] C. Rouby, S. Pouliot, and M. Bensafi, "Odor hedonics and their modulators," *Food Qual. Prefer.*, vol. 20, no. 8, pp. 545–549, Dec. 2009, doi: 10.1016/j.foodqual.2009.05.004.

[25] R. Doty and V. Kamath, "The influences of age on olfaction: a review," *Front. Psychol.*, vol. 5, 2014, Accessed: Apr. 15, 2022. [Online]. Available: https://www.frontiersin.org/article/10.3389/fpsyg.2014.00020

[26] P. Sorokowski *et al.*, "Sex Differences in Human Olfaction: A Meta-Analysis," *Front. Psychol.*, vol. 10, 2019, Accessed: Apr. 15, 2022. [Online]. Available: https://www.frontiersin.org/article/10.3389/fpsyg.2019.00242

[27] D. Angluin and P. Laird, "Learning from noisy examples," *Mach. Learn.*, vol. 2, no. 4, pp. 343–370, 1988.

[28] A. Belfodil *et al.*, "FSSD - A Fast and Efficient Algorithm for Subgroup Set Discovery," Washington DC, United States, Oct. 2019. Accessed: Jan. 07, 2022. [Online]. Available: https://hal.archives-ouvertes.fr/hal-02355503

[29] R. Mathonat, "Rule discovery in labeled sequential data: application to game analytics.," University of Lyon, France, 2020.

[30] C. Collet, E. Vernet-Maury, G. Delhomme, and A. Dittmar, "Autonomic nervous system response patterns specificity to basic emotions," *J. Auton. Nerv. Syst.*, vol. 62, no. 1, pp. 45–57, Jan. 1997, doi: 10.1016/S0165-1838(96)00108-7.

[31] W. He, S. Boesveldt, C. de Graaf, and R. A. de Wijk, "Dynamics of autonomic nervous system responses and facial expressions to odors," *Front. Psychol.*, vol. 5, 2014, doi: 10.3389/fpsyg.2014.00110.

[32] S. A. Neumann and S. R. Waldstein, "Similar patterns of cardiovascular response during emotional activation as a function of affective valence and arousal and gender," *J. Psychosom. Res.*, vol. 50, no. 5, pp. 245–253, May 2001, doi: 10.1016/S0022-3999(01)00198-2.

[33] D. Palomba, M. Sarlo, A. Angrilli, A. Mini, and L. Stegagno, "Cardiac responses associated with affective processing of unpleasant film stimuli," *Int. J. Psychophysiol.*, vol. 36, no. 1, pp. 45–57, Apr. 2000, doi: 10.1016/S0167-8760(99)00099-9.

[34] T. Ritz, M. Thöns, S. Fahrenkrug, and B. Dahme, "Airways, respiration, and respiratory sinus arrhythmia during picture viewing," *Psychophysiology*, vol. 42, no. 5, pp. 568–578, 2005, doi: 10.1111/j.1469-8986.2005.00312.x.

[35] E. P. M. Vianna and D. Tranel, "Gastric myoelectrical activity as an index of emotional arousal," *Int. J. Psychophysiol.*, vol. 61, no. 1, pp. 70–76, Jul. 2006, doi: 10.1016/j.ijpsycho.2005.10.019.

[36] S. R. Vrana, "The psychophysiology of disgust: Differentiating negative emotional contexts with facial EMG," *Psychophysiology*, vol. 30, no. 3, pp. 279–286, 1993, doi: 10.1111/j.1469-8986.1993.tb03354.x.

[37] R. A. de Wijk, V. Kooijman, R. H. G. Verhoeven, N. T. E. Holthuysen, and C. de Graaf, "Autonomic nervous system responses on and facial expressions to the sight, smell, and taste of liked and disliked foods," *Food Qual. Prefer.*, vol. 26, no. 2, pp. 196–203, Dec. 2012, doi: 10.1016/j.foodqual.2012.04.015.

[38] paul Ekman and R. W. Levenson, "Autonomic nervous system activity distinguishes between emotions. Science," *Science*, vol. 221, no. 86, pp. 1208–1210, 1983.

[39] R. W. Levenson, K. Heider, and P. Ekman, "Emotion and Autonomic Nervous System Activity in the Minangkabau of West Sumatra," p. 17.

[40] M. Shiota, S. Neufeld, W. Yeung, S. Moser, and E. Perea, "Feeling Good: Autonomic Nervous System Responding in Five Positive Emotions," *Emot. Wash. DC*, vol. 11, pp. 1368–78, Dec. 2011, doi: 10.1037/a0024278.

[41] I. Van Diest *et al.*, "Critical Conditions for Hyperventilation Responses: The Role of Autonomic Response Propositions During Emotional Imagery," *Behav. Modif.*, vol. 25, no. 4, pp. 621–639, Sep. 2001, doi: 10.1177/0145445501254008.

[42] U. Hess, A. Kappas, G. J. McHugo, J. T. Lanzetta, and R. E. Kleck, "The facilitative effect of facial expression on the self-generation of emotion," *Int. J. Psychophysiol.*, vol. 12, no. 3, pp. 251–265, May 1992, doi: 10.1016/0167-8760(92)90064-I.

[43] S. Delplanque *et al.*, "Sequential unfolding of novelty and pleasantness appraisals of odors: Evidence from facial electromyography and autonomic reactions," *Emotion*, vol. 9, no. 3, pp. 316–328, 2009, doi: 10.1037/a0015369.

[44] S. Watanuki and Y.-K. Kim, "Physiological Responses Induced by Pleasant Stimuli," *J. Physiol. Anthropol. Appl. Human Sci.*, vol. 24, no. 1, pp. 135–138, 2005, doi: 10.2114/jpa.24.135.

[45] C. C. Licon *et al.*, "Chemical features mining provides new descriptive structure-odor relationships," *PLOS Comput. Biol.*, vol. 15, no. 4, p. e1006945, Apr. 2019, doi: 10.1371/journal.pcbi.1006945.

[46] B. Sanchez-Lengeling, J. N. Wei, B. K. Lee, R. C. Gerkin, A. Aspuru-Guzik, and A. B. Wiltschko, "Machine Learning for Scent: Learning Generalizable Perceptual Representations of Small Molecules," *ArXiv191010685 Phys. Stat*, Oct. 2019, Accessed: Jul. 13, 2021. [Online]. Available: http://arxiv.org/abs/1910.10685

[47] A. Choi and W. Woo, "Physiological Sensing and Feature Extraction for Emotion Recognition by Exploiting Acupuncture Spots," in *Affective Computing and Intelligent Interaction*, Berlin, Heidelberg, 2005, pp. 590–597. doi: 10.1007/11573548_76.

[48] A. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion Recognition Using Bio-sensors: First Steps towards an Automatic System," in *Affective Dialogue Systems*, Berlin, Heidelberg, 2004, pp. 36–48. doi: 10.1007/978-3-540-24842-2_4.

[49] C. D. Katsis, N. Katertsidis, G. Ganiatsas, and D. I. Fotiadis, "Toward Emotion Recognition in Car-Racing Drivers: A Biosignal Processing Approach," *IEEE Trans. Syst. Man Cybern. - Part Syst. Hum.*, vol. 38, no. 3, pp. 502–512, May 2008, doi: 10.1109/TSMCA.2008.918624.

[50] C. D. Katsis, N. S. Katertsidis, and D. I. Fotiadis, "An integrated system based on physiological signals for the assessment of affective states in patients with anxiety disorders," *Biomed. Signal Process. Control*, vol. 6, no. 3, pp. 261–268, Jul. 2011, doi: 10.1016/j.bspc.2010.12.001.

[51] C. L. Lisetti and F. Nasoz, "Using Noninvasive Wearable Computers to Recognize Human Emotions from Physiological Signals," *EURASIP J. Adv. Signal Process.*, vol. 2004, no. 11, p. 929414, Dec. 2004, doi: 10.1155/S1110865704406192.

[52] S. Yoo, C. Lee, Y. Park, N. Kim, B. Lee, and K. Jeong, *Neural Network Based Emotion Estimation Using Heart Rate Variability and Skin Resistance*, vol. 3610. 2005, p. 824. doi:

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10.1007/11539087_110.
[53] P. A. Kragel and K. S. LaBar, "Multivariate Pattern Classification Reveals Autonomic and Experiential Representations of Discrete Emotions," *Emot. Wash. DC*, vol. 13, no. 4, pp. 681–690, Aug. 2013, doi: 10.1037/a0031820.
[54] C. Liu, K. Conn, N. Sarkar, and W. Stone, "Physiology-based affect recognition for computer-assisted intervention of children with Autism Spectrum Disorder," *Int. J. Hum.-Comput. Stud.*, vol. 66, no. 9, pp. 662–677, Sep. 2008, doi: 10.1016/j.ijhsc.2008.04.003.
[55] J. Zhai and A. Barreto, "Stress Detection in Computer Users Based on Digital Signal Processing of Noninvasive Physiological Variables," in *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug. 2006, pp. 1355–1358. doi: 10.1109/IEMBS.2006.259421.
[56] C. L. Stephens, I. C. Christie, and B. H. Friedman, "Autonomic specificity of basic emotions: Evidence from pattern classification and cluster analysis," *Biol. Psychol.*, vol. 84, no. 3, pp. 463–473, Jul. 2010, doi: 10.1016/j.biopsycho.2010.03.014.
[57] I. C. Christie and B. H. Friedman, "Autonomic specificity of discrete emotion and dimensions of affective space: a multivariate approach," *Int. J. Psychophysiol.*, vol. 51, no. 2, pp. 143–153, Jan. 2004, doi: 10.1016/j.ijpsycho.2003.08.002.
[58] C. A. Frantzidis *et al.*, "On the Classification of Emotional Biosignals Evoked While Viewing Affective Pictures: An Integrated Data-Mining-Based Approach for Healthcare Applications," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 309–318, Mar. 2010, doi: 10.1109/TITB.2009.2038481.
[59] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005, doi: 10.1109/TITS.2005.848368.
[60] J. Kim and E. André, "Emotion recognition based on physiological changes in music listening," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 12, pp. 2067–2083, Dec. 2008, doi: 10.1109/TPAMI.2008.26.
[61] E. Kroupi, J. Vesin, and T. Ebrahimi, "Subject-Independent Odor Pleasantness Classification Using Brain and Peripheral Signals," *IEEE Trans. Affect. Comput.*, vol. 7, no. 4, pp. 422–434, Oct. 2016, doi: 10.1109/TAFFC.2015.2496310.
[62] "Emotion perception and overconfidence in errors under stress in psychosis - ScienceDirect." https://www.sciencedirect.com/science/article/pii/S0165178117310818?casa_token=3TSACKgxaBkAAAAA:dU5e5UnBIKFt8DQy-wEx0XFKOm_dF2lKnIAKMOIi__PZo-bMi2mvco473Vt7JH6jSEbOdRDx5U6Q (accessed Apr. 19, 2022).
[63] L. X. Liao, A. M. Corsi, P. Chrysochou, and L. Lockshin, "Emotional responses towards food packaging: A joint application of self-report and physiological measures of emotion," *Food Qual. Prefer.*, vol. 42, pp. 48–55, Jun. 2015, doi: 10.1016/j.foodqual.2015.01.009.
[64] M. E. Dawson, A. M. Schell, and D. L. Filion, "The electrodermal system," in *Handbook of psychophysiology, 4th ed*, New York, NY, US: Cambridge University Press, 2017, pp. 217–243.
[65] J. Macqueen, "Some methods for classification and analysis of multivariate observations," *Proc. Fifth Berkeley Symp. Math. Stat. Probab.*, vol. 1, no. 14, pp. 281–297.
[66] A. K. Anderson *et al.*, "Dissociated neural representations of intensity and valence in human olfaction," *Nat. Neurosci.*, vol. 6, no. 2, pp. 196–202, Feb. 2003, doi: 10.1038/nn1001.
[67] H.-R. Hou, X.-N. Zhang, and Q.-H. Meng, "Odor-induced emotion recognition based on average frequency band division of EEG signals," *J. Neurosci. Methods*, vol. 334, p. 108599, Mar. 2020, doi: 10.1016/j.jneumeth.2020.108599.
[68] J. Fürnkranz, D. Gamberger, and N. Lavrač, *Foundations of Rule Learning*. Springer Science & Business Media, 2012.
[69] T. Abudawood and P. Flach, "Evaluation Measures for Multi-class Subgroup Discovery," in *Machine Learning and Knowledge Discovery in Databases*, Berlin, Heidelberg, 2009, pp. 35–50. doi: 10.1007/978-3-642-04180-8_20.
[70] D. M. Powers, "Recall & Precision versus The Bookmaker," *Int. Conf. Cogn. Sci.*, Jul. 2003, Accessed: Feb. 17, 2021. [Online]. Available: https://dspace.flinders.edu.au/xmlui/handle/2328/27159
[71] C. B. Browne *et al.*, "A Survey of Monte Carlo Tree Search Methods," *IEEE Trans. Comput. Intell. AI Games*, vol. 4, no. 1, pp. 1–43, Mar. 2012, doi: 10.1109/TCIAIG.2012.2186810.
[72] H. Heberle, G. V. Meirelles, F. R. da Silva, G. P. Telles, and R. Minghim, "InteractiVenn: a web-based tool for the analysis of sets through Venn diagrams," *BMC Bioinformatics*, vol. 16, no. 1, p. 169, May 2015, doi: 10.1186/s12859-015-0611-3.
[73] F. Pedregosa *et al.*, "Scikit-learn: Machine Learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, 2011.
[74] E. Galbrun and P. Miettinen, "What Is Redescription Mining," in *Redescription Mining*, E. Galbrun and P. Miettinen, Eds. Cham: Springer International Publishing, 2017, pp. 1–23. doi: 10.1007/978-3-319-72889-6_1.
[75] T. De Bie, "Maximum entropy models and subjective interestingness: an application to tiles in binary databases," *Data Min. Knowl. Discov.*, vol. 23, no. 3, pp. 407–446, Nov. 2011, doi: 10.1007/s10618-010-0209-3.

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