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REGULAR PAPER

An Emotional-based Methodology to Detect Preferences in a Decision-making Process Applied to a Virtual Service Robot

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Abstract
In a multi-objective problem, no single solution optimally satisfies all objectives. Thus, the challenge is to find a balance between conflicting objectives. The decision-making necessarily requires human intervention. The person responsible for selecting the most appropriate solution among all the trade-off solutions is the decision maker (DM). The DM seeks to approach only the solutions that best suit her/his preferences. Since there is plenty of specialized literature showing that emotions play a critical role in decision-making, we aim to incorporate them into the decision-making process. To elicit emotions that can be quantifiable, we propose the Emotional Assessment Method. The method presents a simulation of the objectives to be optimized that represents the consequences of each decision. Using this methodology, the decision maker assesses the emotions evoked by each presented simulation to guide his/her search for solutions that satisfy his/her preferences. As a case study, we aim to identify subjects' preferences towards robot behaviors. Seventy-two subjects with varying levels of familiarity with robots (divided into two datasets) participated in the experiments. We concluded that the method elicits subjects' emotions while observing the consequences of the robot's performance. Also, we found out that it is possible to identify subjects' preferences based on both the context and the emotions to select the robot's behavior.

Keywords Emotions towards robots · Affective computing · Service robots · Multi-objective problem

1 Introduction

Imagine you are a traffic engineer responsible for designing a new traffic signal system for a highly congested intersection in a city. Your goal is to improve traffic flow and reduce wait times, which appears to be a straightforward task. However, as you begin analyzing the situation, you realize that there are multiple objectives that conflict with each other: minimize waiting times for cars, maximize pedestrian safety when crossing the intersection, minimize fuel consumption and emissions of polluting gases from vehicles, and maximize the efficiency of public transportation. These objectives are all important and desirable, but they conflict with each other. For example, if you adjust the traffic signal to reduce car wait times, it might increase pedestrian wait times, which could compromise safety. If you prioritize public transportation efficiency, it could slow down overall traffic and increase fuel consumption.

This scenario illustrates a *multi-objective problem*, where no single solution optimally satisfies all objectives. Instead of seeking a single solution, your challenge is to find a balance between these conflicting objectives. This involves optimizing a set of solutions that represent different trade-offs between the objectives. These solutions form a set known as the *Pareto optimal front* in the field of optimization.

While we can analyze this set to learn about the traffic signal problem, the ultimate goal is to implement a single design for the city. For instance, if the street intersection is highly crowded, we might opt for a solution near the best value for pedestrian safety in exchange for average performance in other objectives. The person who has the task of selecting the most appropriate solution among all the trade-off solutions is decision maker (DM). The DM is interested not in discovering the entire Pareto optimal front but in approaching the part

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that best suits their preferences. The process of analyzing and choosing this solution is known as *decision-making*.

As the selection depends on the final user and her/his particular needs, there is no automated method for determining the appropriate solution for her/him. Thus, decision-making necessarily requires human intervention.

Several methodologies have been proposed in the specialized literature (see, e.g., [1–3]) to assist the DM to find her/his most preferred solution. Many decision-making methods require the DM to provide preference information through a preference model. However, quantifying preferences can be quite challenging for the DM as it can increase the cognitive load during the decision-making process. For instance, a preference model requires a trade-off ratio (see, e.g. [4, 5]) for each pair of objectives. To illustrate, suppose we have to buy a house and have two candidates to consider. With this method, we are asked to specify how much additional money we are willing to offer in exchange for more square feet of space. This is not an easy task, and we may need to see some examples. In this regard, Larichev [6] questions whether these parameter values are psychologically meaningful to the DMs.

From the point of view of Neurosciences and Psychology, there is plenty of specialized literature showing that emotions play a critical role in decision-making. For instance, Damasio [7] presented a series of case studies of impairment of decision-making capabilities in patients with prefrontal lobe damage, suggesting that rationality actually requires emotions. Panksepp and Wilson [8] provided evidence of the role of dopamine-energized arousal of the medial forebrain bundle in enthusiasm-guiding decision-making. Also, Eagleman [9] described the Tammy Myers' case. She damaged her orbitofrontal cortex in an accident and lost the ability to make an emotional summary of her state. Thus, she was unable to make decisions, although she could describe the pros and cons of each possible choice. This situation paralyzed her, and she could spend the whole day lying on the couch without being able to move.

Based on these studies, we aim to incorporate emotions into the decision-making process. To elicit emotions that can be quantifiable, they need to be induced by stimulating the subject in a controlled manner. Stimulation methods to elicit emotions are divided into two groups: active and passive [10]. Active methods may involve *i)* social or dyadic interactions with others or *ii)* behavioral manipulation where an individual is instructed to adopt facial expressions, postures, or other emotionally relevant behaviors [10]. Passive methods include presenting emotional images, film or music video segments, narrative, and virtual reality [11–14].

Even though passive methods only partially capture the effect of users' emotions, we chose them because they are easier to control. This feature would eventually allow them to be incorporated into software to automatically articulate DM's preferences information to be used for decision-making. In this regard, when designing a passive method, it is critical to ensure that the simulation accurately represents the consequences of each decision. According to Fred Wenstøp [15, 16], decision-making centers on a consequentialist frame. That is, when we need to select a course of action, the value of an action derives from the value of its consequences. In other words, healthy decision-makers feel emotions when they are assessing the available courses of action, and after evaluating the consequences of their choice, they select the one that produces the best feeling. In this sense, some researchers (e.g., [17–19], aware of the importance of emotions and consequences, have proposed decision-making methodologies that evoke emotions by proposing scenarios that make consequences more vivid. For example, Wright and Goodwin [17] recommend decision simulation as a means to make consequences vivid, and this should take place before value elicitation. Similarly, Belton [20] proposed a decision-making method presenting scenarios in a structured and vivid way.

Our hypothesis is that presenting a simulation of the possible scenario associated with each alternative solution will help the DM visualize their advantages and disadvantages instead of just imagining them. In addition, it will help the DM to experience quantifiable emotions to guide the search for solutions that satisfy his/her preferences in multi-objective optimization problems.

As a case study, we aim to identify subjects' preferences based on emotions towards robot behaviors. The reason for adopting this problem is that, according to the World Robotics 2021 - Service Robots report presented by the International Federation of Robotics [21], there was an increase in the demand for service robots in 2020 due to the COVID-19 pandemic compared to 2019. For instance, autonomous mobile robots and delivery robots grew by 11%, cleaning robots grew by 92%, medical robotics accounted for 55%, and hospitality robots for food and drink preparation grew by 196%. Additionally, it reported an increasing demand for social robots "since they help residents of nursing homes to keep in contact with friends and family members in times of social distancing." In particular, robots for domestic tasks are the largest group of consumer robots.

These numbers show the increasing interaction between robots and humans. As a result, more attention has been paid to understanding subjects' responses to service robots. For instance, some employees and residents in retirement facilities have reported being concerned about possible damage from robot accidents due to navigational difficulties [22]. Also, interviews have been conducted with people in a Japanese mall to analyze their interaction with a service robot. They reported that people based their judgments mainly on the appearance of the robot and the way it moved [23]. On the other hand, closer correspondence between the subject's personality (extroverted or introverted) and the robot's behavior increases the time people spend interacting with robots [24].

For these reasons, we suggest that each robot should have a behavior according to the needs it satisfies, the context in which it operates, and, more importantly, the subject with which it interacts. Therefore, we propose a multicriteria optimization problem to design a controller for a virtual robotic platform with no human or animal characteristics, and that does not exhibit affective expressions or proximity behavior.

A robot controller is a reactive system that avoids collisions with obstacles by recognizing the environment based on the information obtained by the robot's sensors and reacts by modifying the robot's actuators [25]. Technically, the best controller would be the one that can reach a target in the shortest time possible, without colliding, and with the least amount of energy invested. However, from an end users's point of view, it might not be the best choice since the robot could be perceived as dangerous. Therefore, the chosen controller will depend on the context in which the service robot develops.

Consequently, we pose the following research questions:

1. Is it possible to elicit subjects' emotions while observing the consequences of a chosen solution?
2. Is it possible to identify subjects' preferences based on the context?
3. How important are elements of the simulated scenarios to elicit emotions?
4. Is it possible to identify subjects' preferences based on emotions to select solutions?

In order to answer them, we propose the Emotional Assessment Method (EAM), which is the main contribution of this paper. The method applied to our case study works as follows: we prepare simulations showing the performance of a wheeled robot in a domestic environment with the goal of reaching a specific point. The objectives of the optimization problem to be minimized are the following: *i)* time to reach the goal, *ii)* number of collisions, and *iii)* battery usage. Using this methodology, the decision maker assesses the emotions evoked by each presented robot simulation. Once all simulations have been assessed, a preference hierarchy is calculated.

As far as we know, the closest work is the one presented by Su et al. [26], in which they used emotions in the development of a learning model. However, unlike ours, in their approach, the decision maker only had access to the numerical values of the optimization problem and had to adjust the parameters for a PID controller (proportional-integral-derivative controller). In doing so, the facial expressions of the person responsible were recorded to recognize the affective states.

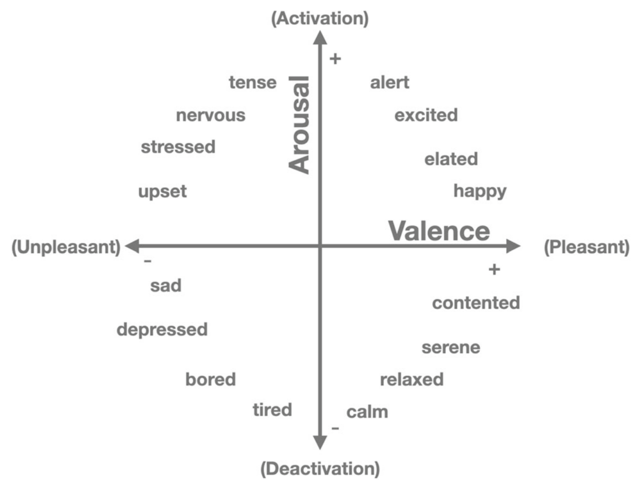


Fig. 1 Russell's Circumplex model of affect (adapted)

The remainder of this paper is organized as follows. In Section 2, we present some background concepts to understand the manuscript better. Next, in Section 3, we describe the proposed Emotional Assessment Method. In Section 4, we present the case study. Later, in Section 5, we present the experimental protocol and the implementation details. In Section 6, we show and discuss the experimental results. Finally, Section 7 concludes this paper and proposes future work.

2 Background Concepts

2.1 Emotional Assessment

The goal of this section is to introduce emotional assessment since we quantify emotions to incorporate them into the decision-making process.

Emotions emphasizes subjective experiences that people express in semantic terms. Therefore, unifying the language that defines and categorizes emotions has been a topic of debate [27]. Accordingly, different models have been developed to recognize an individual's emotions. In fact, two types of models have been proposed to categorize them: discrete and dimensional [13]. The discrete model postulates the existence of a small set of basic emotions, and that complex emotions arise from a combination of these [28–30]. In contrast, dimensional models consider a multidimensional space where each dimension represents a fundamental characteristic common to all emotions [31, 32]. To conduct the experiments, we rely on a dimensional model because discrete models have shown less effectiveness in qualifying ambiguous emotions [33].

The most widely used dimensional model for expressing emotions in written form is Russell's Circumplex affect

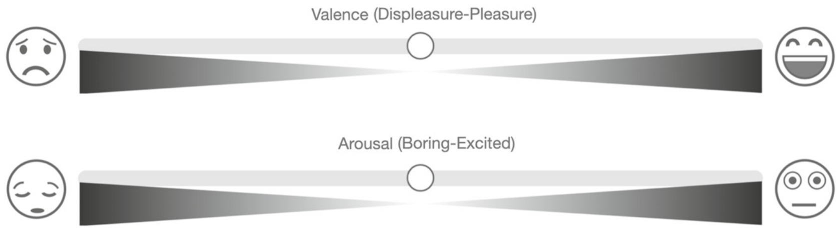


Fig. 2 Affective Slider. On the left side of the valence slider, a disappointing face is shown, indicating the lowest value of that category, while on the right side, a happy face is shown, indicating the highest value. Similarly, on the left side of the arousal slider, a sleepy face is shown, indicating that the subject is bored (i.e., the lowest arousal value), while on the right side, an excited face is shown, indicating the highest value

model [31]. The model proposes that emotions can be expressed in terms of two dimensions (see Figure 1): *arousal* and *valence*. Positive arousal values indicate activation (e.g., alert, excited), and negative values indicate deactivation (e.g., uninterested, bored). Whereas positive values of valence indicate pleasure (e.g., happy, elated) and negative values indicate displeasure (e.g., sad, stressed). In the context of our case study, we interpret valence as satisfaction and disappointment, respectively.

On the other hand, it has been proven that 27 distinct categories of emotion models can be applied to measure emotions in videos [27]; even more, they capture better reports of subjective experience than affective dimensions.

Given that one of our proposed scenarios is based on music to elicit stronger emotions, we used the Circumplex model of affect because: "the comparison between different dimensional models revealed that two dimensions are sufficient to describe emotions in music" [33]. Russell's Circumplex model of affect relies on language to represent emotions. However, there is a risk of cultural bias that limits a proper description of emotions. For this reason, Bradley and Lang [34] presented the Self-Assessment Manikin (SAM). SAM is a non-verbal pictorial evaluation technique that measures the arousal and valence associated with a person's affective reaction to a stimulus. Its most modern version is the *Affective Slider* [35], which applies principles of updated subject interface designs and metacommunicative representations. This interface[1] displays sliders for arousal and valence, which makes the self-assessment a continuous scale. Both ends of each slider show a pictorial representation of a facial expression according to each category (see Figure 2).

2.2 Multi-criteria Optimization

In Section 1, we introduce the traffic signal design problem, which is characterized by having several objectives that need to be optimized, but they are in conflict with each other. This is an example of a multi-criteria optimization problem, which is formally defined as follows.

Definition 2.1 (Multi-criteria Optimization Problem) A Multi-criteria Optimization Problem (MOP) is defined as:

$$\begin{aligned} &\text{Minimize} \quad \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})]^T \\ &\text{subject to} \quad \mathbf{x} \in \mathcal{X}. \end{aligned} \tag{1}$$

The vector function $\mathbf{f} : \mathcal{X} \to \mathbb{R}^k$ is composed by $k \geq 2$ scalar *objective functions* $f_i : \mathbb{R}^n \to \mathbb{R}$ $(i = 1, \ldots, k)$. The vector $\mathbf{x} \in \mathbb{R}^n$ represents the *n design variables* whose values we can manipulate to obtain different values of our k objectives. The *feasible set* $\mathcal{X} \subseteq \mathbb{R}^n$ is implicitly determined by a set of equality and inequality constraints.

For the traffic signal design problem, let's assume that we have only two objectives: minimizing vehicle waiting times and maximizing pedestrian safety. In MOPs, it is common for the objectives to be in conflict with each other. This means we cannot obtain a single solution that optimizes all the objectives at once. Improving one objective will lead to a deterioration of another objective. For example, in the traffic signal design problem, reducing vehicle waiting times increases the risk for pedestrians. In other words, it is not possible to have a solution that improves both objectives. Therefore, in multi-criteria optimization, we aim to obtain a set of optimal solutions that represent a trade-off between the objectives.

In our problem, we can identify several trade-off solutions. One solution has the shortest vehicle waiting times but poses a significant risk for pedestrians (solution $\mathbf{p}_1$ in Figure 3). On the other hand, a solution provides maximum pedestrian safety but results in long waiting times for cars (solution $\mathbf{p}_2$ in Figure 3). However, by allowing some increase in waiting time for solution $\mathbf{p}_1$ in exchange for improving safety, we find several optimal designs in the middle of the extremal designs, as shown in Figure 3. The set of all these trade-off solutions is called the *Pareto front*.

From a practical perspective, what does it mean to have several alternative designs? Without additional context,

[1] https://github.com/albertobeta/AffectiveSlider

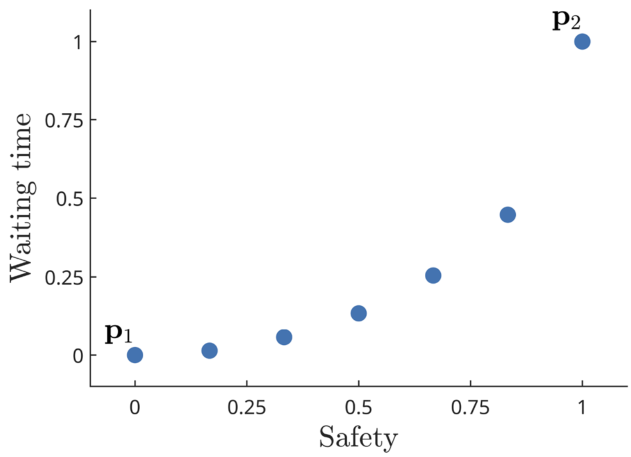


Fig. 3 Illustration of the Pareto front for the traffic design problem where we want to minimize vehicle waiting times and maximize pedestrian safety

which is the best traffic signal design? The answer to this question falls to a traffic engineer who is familiar with the specific demands of the street intersection, whether it's a busy pedestrian area like Tokyo's Shibuya crosswalk or an arterial intersection with high vehicle volumes. The Pareto front represents all the reasonable alternatives for any person with no specific scenario in mind. However, we must select a single design once we have a particular situation.

This final step in solving our multi-criteria optimization problem is known as *decision-making* or *preference incorporation*. Since the choice depends on the specific needs of the final user, no method can automatically determine the optimal solution. Thus, decision-making necessarily requires human intervention.

2.3 Robots

As explained in Section 1, our case study aims to identify DM's preferences based on emotional responses to the robot's behavior rather than its appearance. For this reason, this section discusses the rationale behind designing the virtual robotic platform without human or animal characteristics, avoiding affective expressions or proximity behavior.

Norman [36] described perspectives on intimacy, suggesting strong human-technology engagements. This intimacy represents a range of human responses: subjective feelings, physiological activation, and motor expressions. Moreover, Masahiro Mori coined the term *Uncanny Valley* [37], which suggests that the more anthropomorphic a robot is, the more unsettling it can be for people. Conversely, robots with fewer anthropomorphic features tend to evoke indifference. This concept implies that DM's emotions towards the service robot might focus on its anthropomorphic characteristics. For example, evidence indicates that emotional narratives, virtual reality, movie segments, or music videos featuring people, animals, or objects can evoke emotions [11–14], particularly when they display affective expressions or proximity behavior [38], regardless of whether they are real, virtual, or represented by inanimate objects like robots.

Nevertheless, Hoenen [39] argued that social actions towards a non-anthropomorphic or non-zoomorphic robot are sufficient to establish it as a social entity. For instance, Oberman and colleagues [40] demonstrated that aggressive behavior towards a non-anthropomorphic robot (emotional priming) can alter the activity of the mirror-neuron system, with a stronger response when participants are primed with a sad story about the observed actor. Also, people tend to develop an intimate connection with robots by assigning them names, personal traits, intentions, feelings, and unique characteristics [41, 42].

3 Emotional Assessment Method

The objective of the EAM is to provide a simulated representation of potential scenarios linked to each alternative solution. This aims to assist the DM in visualizing the merits and drawbacks of these solutions, moving beyond mere imagination. Moreover, it facilitates the experience of quantifiable emotions, aiding the DM in navigating a search for solutions that align with their preferences in the context of multi-objective optimization problems.

The method can be summarized in the Algorithm 1. First, we need to identify whether this method may be suitable for the problem at hand (see line 1, Section 3.1). If this is the case, we identify the objectives, $\mathbf{f}$, to be optimized (see line 2, Section 3.2). Then, we select a subset of solutions, $\mathbf{P}$, from the Pareto front (see line 3, Section 3.3); such solutions are the events to be simulated. For each event, we generate the simulations, $\mathcal{S}$, based on the functions to be optimized (lines 4-6, Section 3.4). Then, we ask the DM to self-assess his/her emotions, after watching every simulation (lines 7-10, Section 3.5). Once all the simulations have been evaluated, $\mathbf{V}$, we can obtain the subject's preference hierarchy, $\mathbf{V}'$ (line 11, Section 3.6). In what follows, we present every step of the method in more detail.

3.1 Suitability of the Problem

The proposed methodology focuses on evaluating a design or solution based on the user's emotional response, rather than just analyzing the performance values of the design. Therefore, this approach aims to provide a more holistic evaluation that considers the emotional effect of the solution on the user. Thus, the elicitation of emotions is a key element in our methodology when the decision-maker is evaluating a solution to an engineering problem.

Algorithm 1 Emotional Assessment Method.

if the problem is suitable **then**
  $\mathbf{f} \leftarrow$ SELECTOBJECTIVES
  $\mathbf{P} \leftarrow$ SELECTEVENTS($\mathbf{f}$)
  for each solution $\mathbf{p}_i$ in $\mathbf{P}$ **do**
    $\mathcal{S}_i \leftarrow$ GENERATESIMULATION($\mathbf{p}_i$)
  end for
  for each simulation $\mathcal{S}_i$ **do**
    SHOWSIMULATION($\mathcal{S}_i$)
    $\mathbf{v}_i \leftarrow$ EVALUATEEMOTION($\mathcal{S}_i$) ▷ $\mathbf{v}_i$ = (valence,arousal)
  end for
  $\mathbf{V}' \leftarrow$ GETSPREFERENCEHIERARCHY($\mathbf{V}$)
end if

Decisions related to personal and social matters are undoubtedly influenced by our emotions. However, according to Damasio [7], emotional somatic markers are also activated when individuals face problems that require analytic reasoning. This means that emotions also play a role in tasks such as creating a motor, solving math problems, composing music, and even designing a service robot.

On the other hand, according to Wright and Goodwin [17], decision-making is difficult when the user is unable to mentally picture the resulting experience of selecting a particular course of action. Therefore, an important element for decision-making based on emotions is to provide vivid scenarios to enable the user to experience the consequences of each available option. They also found that decision simulation can be effective in providing this experience.

In our proposal, we suggest the use of computer simulations to help visualize the effect of each of the designs or solutions to be evaluated.

The proposed methodology can be effectively applied to various types of problems. Nonetheless, it is best suited for problems where the performance of the objectives to be optimized can be represented through a computer simulation. This makes it easier to assess the consequences of each design. To summarize, the problem must meet the following desirable properties:

1. The performance of the objectives related to a problem must have an effect on the personal concerns of the decision-maker.
2. It is important that the simulation includes a visual representation of each objective's performance.
3. Distinguishable levels of objective performance, including low, medium, and high, should be represented in the simulation.

Consider the case of minimizing the travel time of a car's trajectory. First, the travel time could mean that the decision-maker will arrive late or early for an important appointment. Second, the user would be able to perceive the course of time in the simulation easily. Third, a computer simulation can effectively represent both short and long travel times. In contrast, in the protein folding problem, energy needs to be minimized. Regardless, it is unclear whether low or high energy impacts the personal concerns of the user. Moreover, while it is possible to represent energy in a quantitative manner, it is challenging to depict the practical consequences of that value.

Another excellent example in which our methodology can be applied is the design of robot arm trajectories intended for human interaction. In a survey, Takagi [43] presents two studies in which a robot arm cooperates with a human to handle goods. In such applications, the goal is not only the efficiency of movement but also to ensure that the robot arm is not frightening to the human. In some recent studies, some authors have proposed robots for serving drinks (e.g., [44–46]).

For instance, we may need to design the trajectory of a robot arm to prepare and serve tea. In this case, the objectives for optimizing the arm trajectory would be: *i*) to minimize the time to reach the items, *ii*) to minimize the length of the trajectory, and *iii*) to maximize the user's sense of security.

These three objectives, particularly the last one, are closely linked to the user's concerns noted in the aforementioned desirability properties. Consequently, they can elicit emotions that we can use to guide the optimization of the objectives.

The second and third properties are related to the simulated scenario presented to the user. This simulation should display the arm's performance in a carefully designed scenario. For example, we can depict a tray with several items: a loose tea canister, a crystal teapot, and a ceramic cup. The material of the items emphasizes the importance of handling them properly.

It is essential to represent each objective performance. For instance, for objective *iii*, we can indirectly assess the user's sense of security based on the speed and smoothness of the robotic arm's movements. While time and trajectory length are important factors, if the robotic arm accidentally spills hot water, it can make the user feel unsafe.

To accurately simulate different performance levels, the simulation should include scenarios where items are moved slowly and carefully, as well as scenarios where the teapot can be dropped or even broken by the robotic arm.

3.2 Multiple Objectives for Decision Making

When dealing with optimization problems that have only one objective to optimize, there is a single optimal solution available[2]. This means that we can use a systematic approach to

[2] In some single-objective problems, we may obtain two solutions in terms of the parameters of the design. However, they have the same optimal value for the objective.

solve our problem without any need for human intervention. For instance, if we only want to minimize the car waiting time in the traffic signal design problem, we will get only one solution, which is the one with the lowest waiting time. Therefore, we do not need to make any decisions since the optimization method finds the optimal solution we need.

As we have previously discussed, in multi-criteria optimization problems, there are several optimal solutions available. In this case, we have to choose the appropriate trade-off solution that suits our specific situation. In Figure 3, we have only shown a representative sample of the Pareto front. However, most problems have an infinite number of trade-off solutions. In order to make a decision, we have to select a small sample of trade-off solutions.

For instance, with two objectives, we can visualize the performance of each solution by plotting the data on a two-dimensional graph, like the one shown in Figure 3. However, when dealing with three or more objectives, it becomes challenging to evaluate the solutions' performances because there is no standard method to visualize all the solutions in four or more dimensions.

An additional challenge in multi-criteria decision problems is that the objectives to be optimized are usually expressed in different units. For instance, waiting times may be measured in minutes, while pollution levels could be measured in grams of carbon monoxide per cubic meter. As a result, it becomes difficult to compare different alternatives.

3.3 Selection of Events

When faced with too many options, people often struggle to choose at all. Even for problems with only two options, it is impossible to keep in mind all the relevant information about the potential advantages and disadvantages of each option. It creates a state of paralysis. We postpone the decision-making to the next day, and the day after that, and so on. Even if we manage to overcome this paralysis and actually make a choice, we end up less satisfied with our final choice than if we have had fewer options. When there are a lot of alternatives to consider, it's easy to imagine having made the wrong choice or have made another decision that would have been better. This phenomenon is often referred to as "buyer fatigue" or "decision overload". As people are overwhelmed by the choices they face daily, they lose the ability to decide and resist making further decisions. Simon [47] asserted that the number of alternatives the DM must explore is so great, the information she/he would need to evaluate is so vast, that even an approximation to objective rationality is hard to conceive. Additionally, Miller [48] and Migliore et al. [49] explained that the average person can hold about 7 ± 2 items in their short-term memory. To overcome the cognitive overload, we recommend selecting a subset of the Pareto optimal front, $\mathbf{P}$, such that $\mathbf{P} = \{\mathbf{p}_1, \ldots, \mathbf{p}_j\}$, where $j = 7 \pm 2$.

In particular, for three objectives, we might select the four trade-off solutions shown in Figure 4. The illustration shows hypothetical alternatives for the traffic design problem with three objectives: maximize pedestrian safety, minimize car waiting time, and maximize public transportation efficiency. A useful sample must show a diverse trade-off among the alternatives for different situations that can be of interest to the decision-maker. For instance, $\mathbf{p}_1$ represents a balanced trade-off among the three objectives. Although this solution is the closest solution to the ideal solution, point [1, 0, 1], is not necessarily the best for all situations. If safety is a primary concern, then the decision-maker will be more interested in a solution near the best value for safety, such as $\mathbf{p}_2$. In a similar way, we can provide the decision-maker with alternatives like $\mathbf{p}_3$ and $\mathbf{p}_4$ which are the solutions that are closer to the

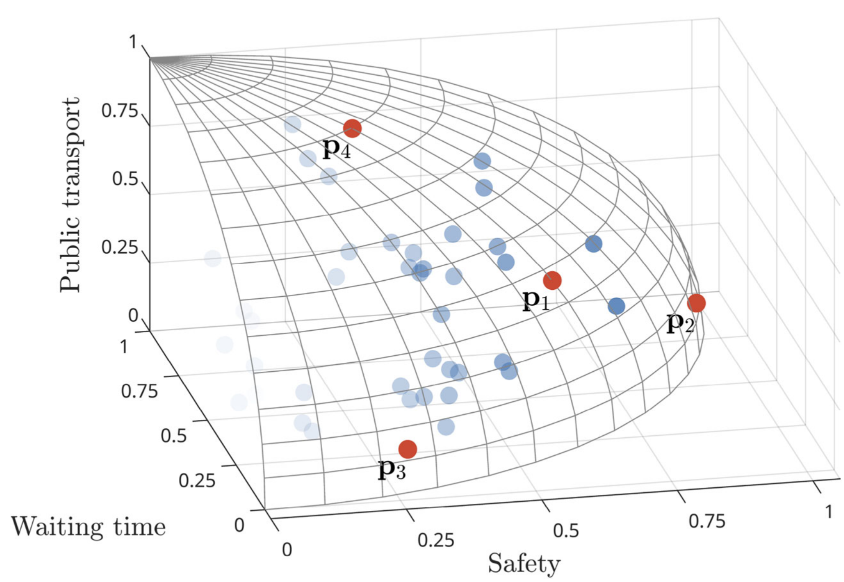


Fig. 4 Illustration showing trade-off alternatives for traffic design: maximize pedestrian safety, minimize car waiting time, and optimize public transportation efficiency. The four red points, labeled as $\mathbf{p}_1$–$\mathbf{p}_4$, represent a selection that the decision-maker should choose from. The solid blue points show other possible solutions. The transparent blue points show non-optimal solutions

best performance of waiting time and public transportation efficiency, respectively.

3.4 Stimulation Through the Simulation

Core Affect is a neurophysiological state that is consciously accessible as a simple feeling [50]. It can be expressed in terms of valence and arousal or activation. The Core Affect can be modified by stimuli, this feature is known as *Quality Affect* [31, 50]. All objects, places, and events enter the consciousness being interpreted affectively and cause a *Perception of affective quality*. That is, the individual perception identified by a subject of the stimulus' ability to change the Core Affect. In other words, perception of affective quality indicates how pleasant, unpleasant, exciting, boring, annoying, or soothing the stimuli are. These emotions influence people's subsequent reactions in response to stimuli [50], such as decision-making. Thus, the proposed scenarios should provide adequate stimuli for the subject to develop a sufficiently differentiated perception of affective quality.

In the approach we propose, we aim to analyze emotions not associated with the object but with its actions or performance in relation to the task based on the context. In other words, we aim to analyze how the values of the specific targets to be enhanced (i.e., safety, speed, and battery) affect the subject.

On the other hand, since musical characteristics such as tempo, mode, and loudness have been proven to influence emotional states during music listening [51], we include soundtracks in the simulations. For instance, the rhythm of music synchronizes to an internal biological rhythm (heart rate or respiration) [52, 53]. Consequently, the mechanism of rhythm entertainment causes increased arousal during visual stimulation [53, 54]. In [55], the authors provided evidence that music tempo can influence human action pace. They use tempi variations to vary the difficulty in gaming situations based on the synchronization of events. A faster tempo has been associated with happiness, whereas sadness has been associated with a slow tempo [56–59]. However, it does not mean that we are directing the subject's emotions towards a biased decision: tempo manipulation affects arousal but not mood [60, 61].

Finally, emotion can be induced by a piece of music if it is repeatedly paired with positive or negative stimuli; this mechanism is known as evaluative conditioning [62].

3.5 Subject's Emotional Self-assessment

In order to evaluate the subject's emotions elicited by a simulation, we use the Affective Slider. As previously explained in Section 2.1, the Affective Slider displays sliders for arousal and valence. Each emotional self-assessment value is in the range [0, 1]. Thus, the two emotional self-assessment values are represented as points in the two-dimensional space defined as the following set $\mathbf{V} = \left\{\mathbf{v}_1, \ldots, \mathbf{v}_j, \ldots, \mathbf{v}_n\right\} = \left\{(x, y)_1, \ldots, (x, y)_j, \ldots, (x, y)_n\right\}$, where point $(x, y)_j$ is associated to the j-th simulation to be evaluated, $x \in [0, 1]$ is the value of valence, and $y \in [0, 1]$ is the value of arousal (see Figure 8).

3.6 Preference Hierarchy Detection

In order to identify the subject's preference hierarchy, we arrange $\mathbf{V}$ in descending order using the following relation:

Definition 3.1 (Preference order) We say that vector $\mathbf{v}_1$ is preferred to $\mathbf{v}_2$, denoted by $\mathbf{v}_1 \geq \mathbf{v}_2$, if and only if $\|\mathbf{v}_1\| \geq \|\mathbf{v}_2\|$, where $\|\cdot\|$ is the Euclidean norm.

In Algorithm 1, the list of vectors, where each pair of elements follows this preference order, is denoted by $\mathbf{V}'$. Thus, $\mathbf{V}'$ has a total order of the solutions presented to the decision-maker. Therefore, even though the user expresses their preferences through two values (valence and arousal), we can identify the most preferred solution based on this ordering.

4 Case Study

As a case study, we selected the problem of designing a controller for a virtual robot. The robot should navigate in a domestic environment to reach a specific destination. In the following paragraphs, we present more details of this problem and discuss how it can be adapted for decision-making based on emotions.

1. **Suitability of the problem**
   In Section 3, we outlined the desirable properties of problems in which our methodology is more appropriate. Next, we describe how the design of a service robot possesses these properties:

   (a) The three objectives can be linked to the personal or social concerns of the decision-maker in order to promote the activation of somatic markers. For example, objective (*i*) could be associated with the speed at which the service robot retrieves a medication bottle from another room. Objective (*ii*) focuses on the longevity of the battery, which implies how often the user or a caretaker needs to recharge the robot. Finally, objective (*iii*) is crucial to the user as it ensures that fragile furniture, pets, or kids are not damaged during its trajectory.

Table 1 Description of the events carried out by the simulated robot in each video while navigating through both the austere and fragile scenarios

Type of event	Objective description						Video number	
	Speed		Safety		Goal		Scenarios	
	High	Low	Yes	No	Yes	No	Austere	Fragile
1	✓		✓		✓		1	2
2	✓			✓		✓	3	4
3	✓		✓			✓	5	6
4		✓		✓		✓	7	8
5		✓	✓		✓		9	10
6		✓		✓	✓		11	12

Watch videos in the following link: https://drive.google.com/drive/folders/1yANuIoCLXBQxL4HCcpWCWszIGHCMg27N?usp=share_link

(b) All the objectives can be conveyed through multimedia resources, such as images, animations, or sounds. Simulations can be reproduced in real time so that the user can naturally perceive the course of the time. Similarly, the battery usage can be illustrated using a battery-level indicator, similar to the one found in cell phones. For objective (*iii*), the simulation can depict a robot colliding with furniture or people.

(c) Finally, the simulation can display a robot design along various levels of performance, ranging from a reasonable design to a deficient design. We can show a robot moving fast or slow, colliding several times, or perfectly avoiding obstacles. Regarding battery usage, the simulation can represent a robot that follows a long trajectory, causing the battery to drain quickly and displaying a red battery alert indicator. Conversely, we can present the user with a robot that follows a more direct trajectory, thus enabling it to conserve battery power.

2. **Multiple objectives for decision making**
We define three objectives to be minimized:

(a) time to reach the goal,
(b) battery usage, and
(c) risk of collisions.

3. **Selection of events**
Although the three objectives that determine the robot's performance can have continuous values, in order to have distinguishable behaviors, we select the opposite values for each objective, i.e., the worst and best values. This determines a set of events described next.
As we have three objectives, and each one has two values, the total number of robot alternatives is eight. However, to prevent decision overload (as explained in Section 3), we decided to limit the number of events to six. Our goal was to include behaviors whose performance might be easily differentiated by the decision-maker. Therefore, we included the worst and best behaviors. In the first one, the robot moves slowly, collides frequently, and its battery runs out before reaching the goal. The second behavior is a fast-moving robot that perfectly avoids obstacles and reaches the goal with plenty of battery charge. The other events in the set comprise robot behaviors with mixed performances, meaning that there is a tradeoff among objectives. Table 1 shows the settings of each of the six events according to the robot's performance.

4. **Stimulation through the simulation**
We prepare simulations showing the performance of a non-anthropomorphic/non-zoomorphic wheeled robot navigating in a domestic environment. The details of both the robot's and the environment's simulations are described as follows:

(a) **Simulated robot**. The simulated robot is a replica of the Parallax Arlo robot[3], an indoor mobile platform that has the following components (as shown in Figure 5). A top and a bottom round-plates: the top round-plate is sustained by four aluminum-like cylinders placed on the bottom round-plate. Two side wheels are placed on opposite sides of the base, each with an actuator. Two caster wheels are positioned perpendicular to the side wheels. Finally, it has four ultrasonic sensors to detect obstacles; fixing the right wheel at 0° as a reference, the sensors are located in the following positions: 40°, 90°, 140°, and 270°. Since the main goal of this paper is to analyze the subject's emotions, the virtual robot is remotely operated. Thus, it was implemented as a Wizard of Oz design.

(b) **Simulated environment**. To evoke emotions, we simulate the virtual robot heading to a target position (a small table holding a soda) while evading obstacles. The robot navigates either in an austere or a fragile scenario. The aim of proposing different scenarios of domestic environments is to identify which can generate emotions with greater intensity. The proposed scenarios have the following elements in common: a dining table, two sofas, a small table

[3] https://www.parallax.com/product/arlo-complete-robot-system/

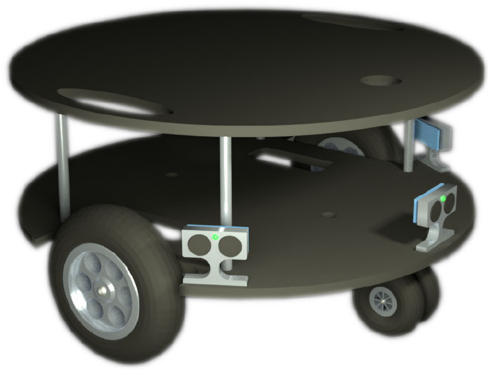


Fig. 5 Indoor mobile simulated robot platform that will navigate through the proposed scenarios to elicit participants' emotions

that holds a soda, a dining room buffet, a console table, a battery indicator, and people. In what follows, we will describe both scenarios in detail:

(i) **Austere scenario**. In the austere scenario (see Figure 6), both the dining table and the small table simulate being made of wood. Additionally, there are two static adults: one of them is standing between the dining table and the living room, whereas the other one is standing close to the small table that holds a soda. In preliminary experiments, we simulated people moving through the whole scenario. However, we replaced them with static people because the results showed the participants were distracted from the main objective to be evaluated, which is the robot's behavior.

(ii) **Fragile scenario**. In the fragile scenario (see Figure 7), we added two side tables, a coffee table, and lamps of different sizes placed on the dining room buffet and on most of the tables. In contrast to the austere scenario, the dining table and the small table simulate being made of glass, as well as the added tables.

Additionally, there are three adults and two children. As in the austere scenario, one of the adults is standing between the dining table and the living room; another one is standing between a sofa and the coffee table, whereas the last one is standing close to the dining room buffet. The two children are sitting side by side, next to the small table that holds a soda.

In order to induce evaluative conditioning, we have added different sound effects to highlight special events. Thus, the subject hears: *i)* cheerings if the robot achieves its goal; *ii)* booings if the robot runs out of battery; *iii)* screams and cries if the robot hurts someone; and *iv)* the sound of a collision if the robot crashes into the furniture.

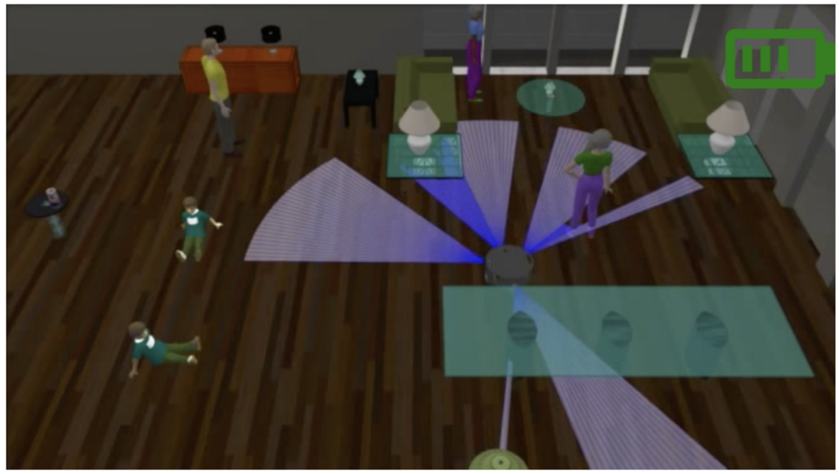
Also, we use music with a fast tempo to indicate the simulated robot is navigating at high speed. In contrast, we use music with a slow tempo to indicate a lower speed.

In Table 1, we enumerate the videos of both scenarios. For example, videos 1 and 2 show the robot navigating quickly, while avoiding collisions, and reaching the goal (i.e., type of event = 1). The difference between them is that in video 1, the virtual robot runs through the austere scenario, whereas in video 2, it does it in the fragile scenario. Thus, odd-numbered videos are associated with austere scenarios and even-numbered videos are associated with fragile scenarios.

5. **Subject's emotional self-assessment**
The emotional self-assessment values $\mathbf{V} = [\mathbf{v}_1, \ldots, \mathbf{v}_n]$ are associated with videos $1, \ldots, n$; where the pair of videos $(2k-1, 2k)$ simulate the type of event $k = 1, \ldots, 6$. For example, videos 1 and 2 simulate the type of event $k = 1$, videos 3 and 4 simulate the type of event 2, and so

Fig. 6 Austere scenario

Fig. 7 Fragile scenario



on (see Table 1). At this stage, the subject should assign an emotional self-assessment value for each video according to Russell's adapted Circumplex model of affect. This results in a vector $\mathbf{v}_i = (\text{valence}, \text{arousal})$ for each video $i = 1, \ldots, n$.

6. **Preference hierarchy detection**
   Figure 8 shows an example of the preference hierarchy detection method. For instance, it can be seen that $\mathbf{v}_2 = (0.72, 0.7)$ and $\mathbf{v}_{10} = (0.79, 0.6)$ have the two largest magnitudes, 1.0084 and 0.9841 (red dotted line and green dotted line), respectively. Since $\mathbf{v}_2$ is associated with video 2, it can be concluded that the subject prefers the robot to reach its destination at high speed, without colliding (see Table 1). Additionally, since $\mathbf{v}_{10}$ is associated with video 10, the second subject's preference is the robot reaching its destination at low speed, without colliding. Finally, the total preference order, from the most preferred robot to least preferred, is the following: $\mathbf{V}' = [\mathbf{v}_2, \mathbf{v}_{10}, \mathbf{v}_4, \mathbf{v}_{12}, \mathbf{v}_8, \mathbf{v}_6]$.

5 Experimental Design

The experiments proposed in this section aim: *i)* to analyze the possibility of eliciting the subject's emotions given the elements of the simulated scenarios, and *ii)* to identify the subject's preferences based on emotions to select neurocontrollers.

5.1 Participants

In the first set of experiments, a total of thirty subjects took part, including three females and twenty-seven males. All of them were college students majoring in Computer Engineering at the Universidad Autónoma Metropolitana, Cuajimalpa Campus. The students' ages ranged from 18 to 25 years old, and they had some degree of familiarity with robots. For instance, 56.67% of them completed 7 out of 12 trimesters, 23.33% completed 9 out of 12, and 20% completed 2 out of 12.

Since most of the Computer Engineering students are male, we conducted additional experiments to incorporate more women with different levels of experience with robots. Thus, forty-two subjects participated in a second set of experiments, comprising thirty-three females and nine males. Of these, 18 participants had never seen a virtual or physical service robot, and the remaining 24 had either seen or used one

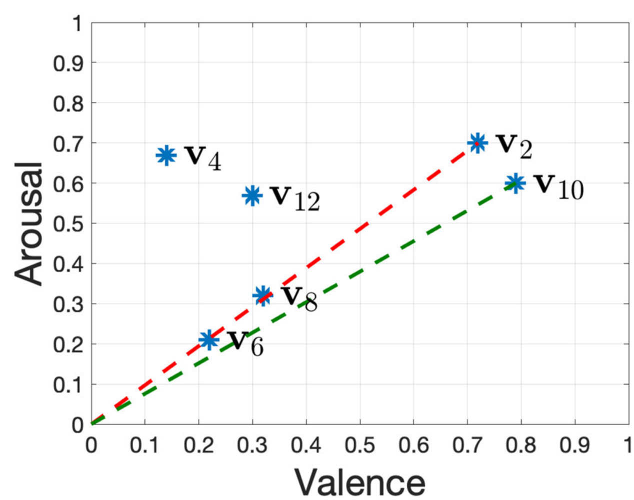


Fig. 8 Example of the preference hierarchy detection: $\mathbf{v}_2$ and $\mathbf{v}_{10}$ are associated with the highest preference (i.e., the magnitude represented with the red dotted line) and the second preference (i.e., the magnitude represented with the green dotted line), respectively

before. The participants had an average age of 36±8 years old.

5.2 Experimental Protocol

The participants performed the experiments through an online platform within a thirty-minute session. Each subject was provided with the following link: https://cerebral.cua.uam.mx/tests/app/. When entering the website, the subjects were prompted to provide their name, and after clicking the start button, the following experimental protocol started.

First, the subjects were presented with a video explaining the experiment, including the meaning of the scales used for self-assessment. In preliminary experiments, a person provided the protocol description; however, the subjects soon lost attention and forgot the instructions. Consequently, we replaced the person with an animation, improving the retention of instructions (see Figure 9).

After the informative video, the subjects of the second set of experiments were presented with a questionnaire in which they should indicate their age, gender, level of knowledge of programming robots, level of familiarity with robots, and reasons for believing they have this familiarity.

Then, all subjects were presented with a sequence consisting of the following steps started for each video:

Step 1: A two-second screen showing the current video number to inform the subject about its progress.

Step 2: One of the twelve videos was presented.

Step 3: At the end of each video, subjects evaluate their emotions with the Affective Slider by sliding both the arousal and valence bars in a horizontal motion.

Step 4: The subjects of the second set of experiments were asked to include comments regarding their arousal and valence self-assessments.

Fig. 9 A snapshot of the animated presenter explaining the experimental protocol

Table 2 Soundtracks used in the fragile scenario

Video number	Song	Artist	Reference
2	New Day	Ikson	[67]
4	Luminance	Nightdrive	[68]
6	Cyberpunk	Delirix	[69]
8	Perfect time	Svyat Ilin	[70]
10	Perfect time	Svyat Ilin	[70]
12	Tre-grazie	Ilya Truhanov	[71]

5.3 Implementation details

To generate the simulations, we used ROS Noetic Ninjemys and Gazebo 11.5.1 installed on a computer with Ubuntu 20.04.3 LTS, running on a CPU Intel i7-1165G7 with four cores, and a GPU Intel Iris Xe MAX. Additionally, we used the package *teleop_twist_ joy* for tele-operating the Twist-based ROS robot with a standard joystick. Also, some videos were edited with KDEnlive 21.08.1 and others with iMovie 10.2.3.

To simulate furniture and people in both scenarios in Gazebo, we used the following categories of the 3D models of the dataset[4] developed by Rasouli and Tsotsos [63]: Decoration, Furniture, and Miscellaneous.

Additionally, for the fragile scenario, we selected royalty-free music based on their tempi (see Table 2). Also, we included free sound effects like crowd booing, applauding, and groaning [64, 65], and a car crashing [66].

Finally, we mapped the range of values of the Affective Slider (i.e., [0,1]), to that of the Circumplex model of affect (i.e., [-0.5,0.5]) in order to visualize the results in the two-dimensional plane proposed by Russell.

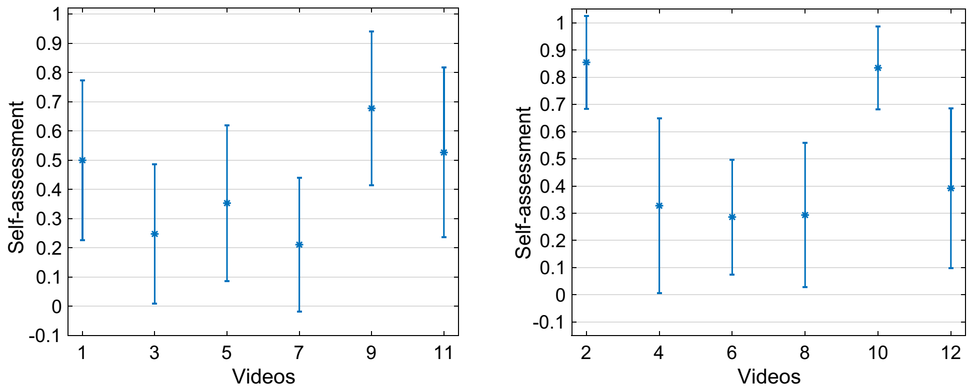
6 Results and Discussions

Note that, on the one hand, subjects may have different emotions throughout the video. On the other hand, subjects "may experience both sad and happy feelings at the same time depending on the stimulus" [72]. Thus, to analyze the results, we assume that the subject reflected in the Affective Slider the most outstanding or lasting emotion experienced during the simulation.

6.1 Emotion Detection

Figures 10 and 11 show the mean and standard deviation of affective self-assessments (valence and arousal, respectively), performed by subjects during the experiments.

[4] http://data.nvision2.eecs.yorku.ca/3DGEMS/



(a) Austere scenario (b) Fragile scenario

Fig. 10 Valence self-assessment comparison. Low valence values indicate disappointment, while high valence values indicate satisfaction. The emotion is evaluated after watching videos of the virtual robot navigating through the proposed scenarios

Sub-figures (a) and (b) show the results of evaluating the videos of the simulated robot navigating through the austere and fragile scenarios, respectively.

It can be observed that, in all cases, the mean is greater than zero. These results evidence that it is possible for subjects to associate certain emotions with the actions performed by the simulated robotic platform without human or animal characteristics that do not exhibit affective expressions or proximity behavior.

6.2 Emotions Elicited Between Scenarios

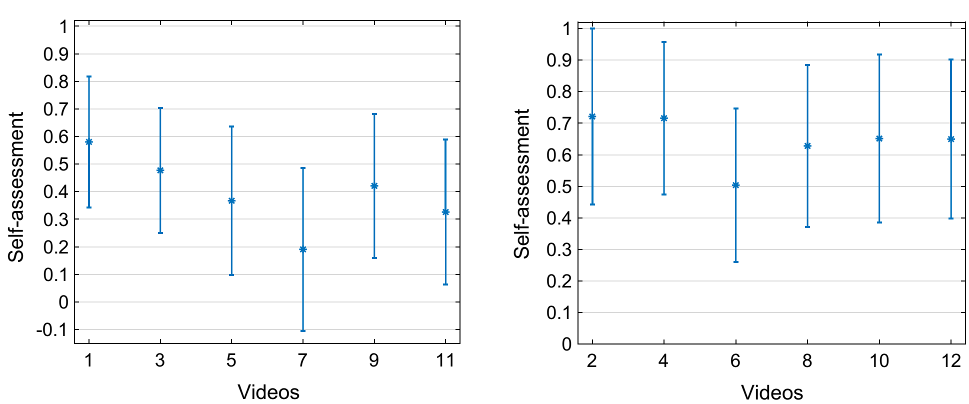
In order to identify if there is a statistically significant difference between the intensity of the emotions evoked by the proposed scenarios, a t-test was applied with $\alpha = 0.05$ for both valence and arousal. The results show that the null hypothesis is rejected in both measures of emotions, such that in valence $p = 9.4925\text{e-}04$ and in arousal $p = 1.7638\text{e-}21$. In other words, the subjects' emotions are different while observing the robot's performance based on the context in which it develops (i.e., austere scenario vs. fragile scenario).

6.3 Emotions Based on Educated Decisions

Subjects' backgrounds are important for making an educated decision. To determine whether background is also important when assigning a subjective emotion, we analyzed if subjects familiarized with robots assign higher self-assessment values.

In Figure 12, we present the valence and arousal self-assessment values for both familiarized and no-familiarized subjects. It can be seen that, in most cases, familiarized subjects assign higher self-assessment values. However, the differences are not statistically significant, except for the following cases.

The results show that familiarized subjects assign higher valence self-assessment values of safety and speed when the robot reaches the goal, even in austere environments, see



(a) Austere scenario (b) Fragile scenario

Fig. 11 Arousal self-assessment comparison. Low arousal values indicate deactivation (e.g., uninterested, bored), while high arousal values indicate activation (e.g., alert, excited). The emotion is evaluated after watching videos of the virtual robot navigating through the proposed scenarios

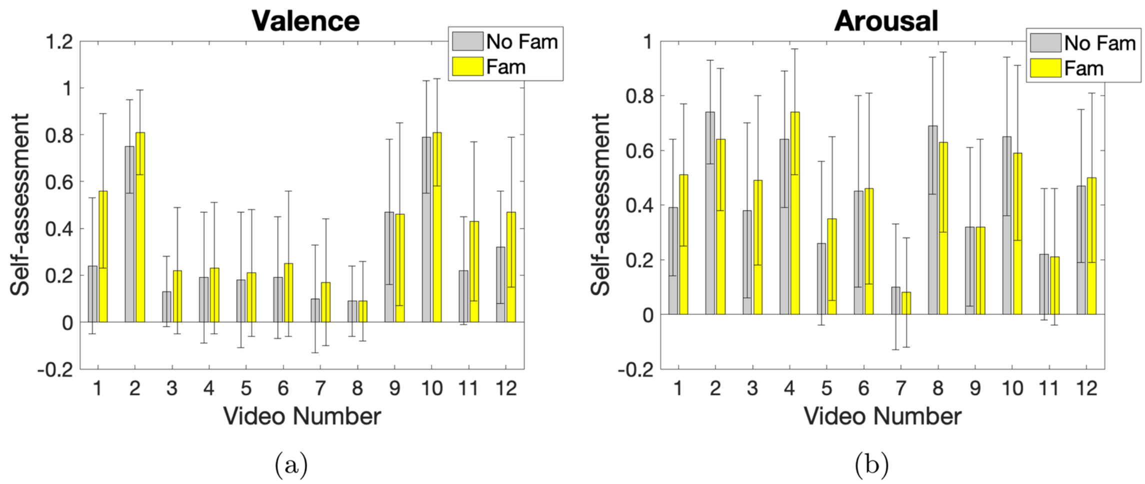


Fig. 12 Comparison between (a) valence and (b) arousal self-assessment values of subjects familiarized and no-familiarized with robots

Figure 12(a) videos 1, 11, and 12. These results are confirmed in statistical tests indicating significant differences in each video, such that $p = 0.0323$, $p = 0.0213$, and $p = 0.0101$, respectively.

6.4 Stimulation to Elicit Emotions

In what follows, we analyze whether the video components (i.e., furniture materials, ages of the simulated people, music, and sound effects) generate a difference in the subjects' emotional responses. To that end, we perform a t-test with $\alpha = 0.05$ for each pair of videos, austere and fragile (see Table 3).

Figure 13(a) displays the average valence for the six types of events, revealing that most of them have higher mean values in the fragile scenario.

On the other hand, as Table 3 shows, in terms of valence, there are statistically significant differences in the types of events: 1, 5, and 6. If we look into the details of these three events (Table 1), the robot reaches the goal, and, in the case of types of events 1 and 5, it evades obstacles. As a result, subjects may find them more satisfactory to watch than the rest of the videos.

Additionally, there is no statistically significant difference between types of events 1 and 5. In other words, the null hypothesis was not rejected, given that p-value = 0.1681 and 0.09, respectively. In both cases, the robot reaches the goal and does not collide. However, there is a difference in navigation speed, indicating that it is not evident or important to the subjects.

On the other hand, the standard deviation of the type of event 6 shows a lack of consensus in subjects' emotions. After all, the robot manages to reach the goal but collides at some point. Also, the austere scenario has a greater valence mean than the fragile one.

Furthermore, in types of events 2, 3, and 4, the valence reflects unpleasant emotions because the robot does not reach the goal and collides with objects.

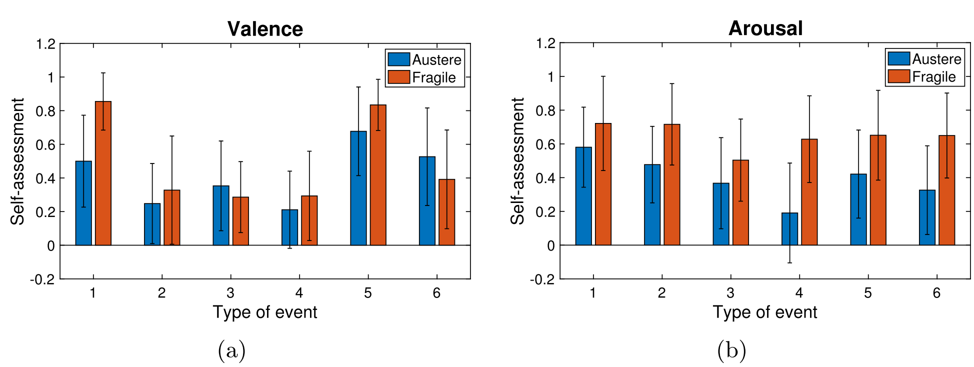


Fig. 13 Comparison between the values of (a) valence and (b) arousal self-assessment after watching videos of the virtual robot navigating through the austere and fragile scenarios (see Table 3)

Table 3 Statistical testing to analyze the difference between the intensity of the emotions evoked by the proposed scenarios: t-test with alpha=0.05

Type of event	Video number A vs. F	Valence H	Valence *p*	Arousal H	Arousal *p*
1	1 vs. 2	1	9.96e-09	1	0.0052
2	3 vs. 4	0	0.1910	1	1.86e-05
3	5 vs. 6	0	0.1745	1	0.0251
4	7 vs. 8	0	0.1471	1	0.0251
5	9 vs. 10	1	0.0023	1	0.0001
6	11 vs. 12	1	0.0058	1	06.54e-06

Where A = Austere, F = Fragile, H = null hypothesis (where 1 means the null hypothesis is rejected), and *p*=*p*-value

Finally, in Table 3, we can also observe that statistically significant differences were found among all the arousal means. As expected, for the reasons explained in Section 3.4, in all cases, there is an increase in the arousal self-assessment after watching videos of the virtual robot navigating through the fragile scenario by adding music and different sound effects to highlight special events. In particular, in the type of event 4, the damages caused by crashing were more evident in the fragile scenario since the robot ran over a child. This observation is supported by the fact that some subjects mentioned that the emotions generated were not pleasant and that they felt stressed because the children's cries, the shattering glass, or the sound effects were shocking.

It is important to recall that, in general, pleasant emotions have a valence greater than 0.5, whereas unpleasant emotions have a valence less than 0.5. In this sense, it is interesting to point out another effect of the additional elements in fragile scenarios. In most of the types of events (Figure 13(a)), valence values below 0.5 (event types 3 and 6) become smaller for fragile scenarios, and valence values above 0.5 (event types 1 and 5) become more extensive for the fragile counterpart. This effect suggests that additional elements of the fragile scenarios contribute to intensifying either negative or positive emotions. Type of event 4 is a particular case since its valence (negative emotion) increases in the fragile scenario. That is, the video produces a less unpleasant emotion. A possible explanation for this effect is that some subjects, besides evaluating the robot's performance, positively appraise the music and sound effects. For instance, regarding the fragile scenario, a participant commented that ambient sound and music make a difference.

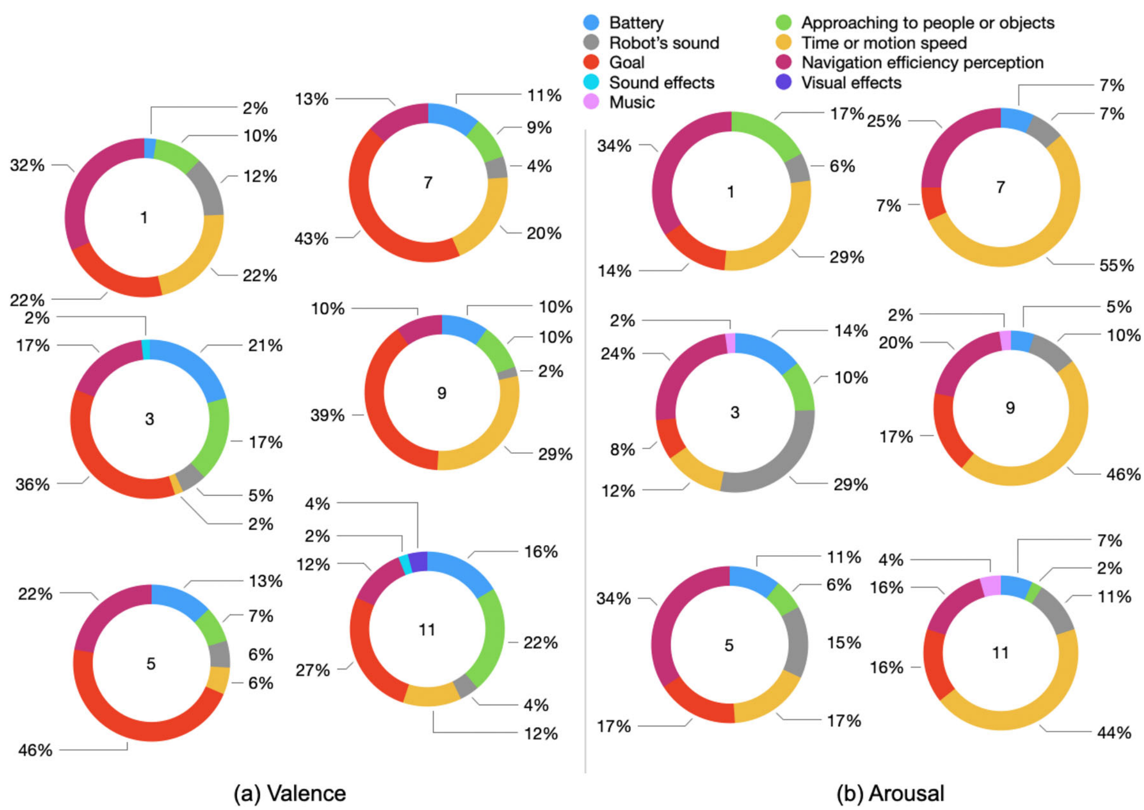


Fig. 14 Percentages of mentions the subjects explicitly made on components and objectives, after watching videos of the virtual robot navigating through austere scenarios. The percentages are rounded to the nearest integer

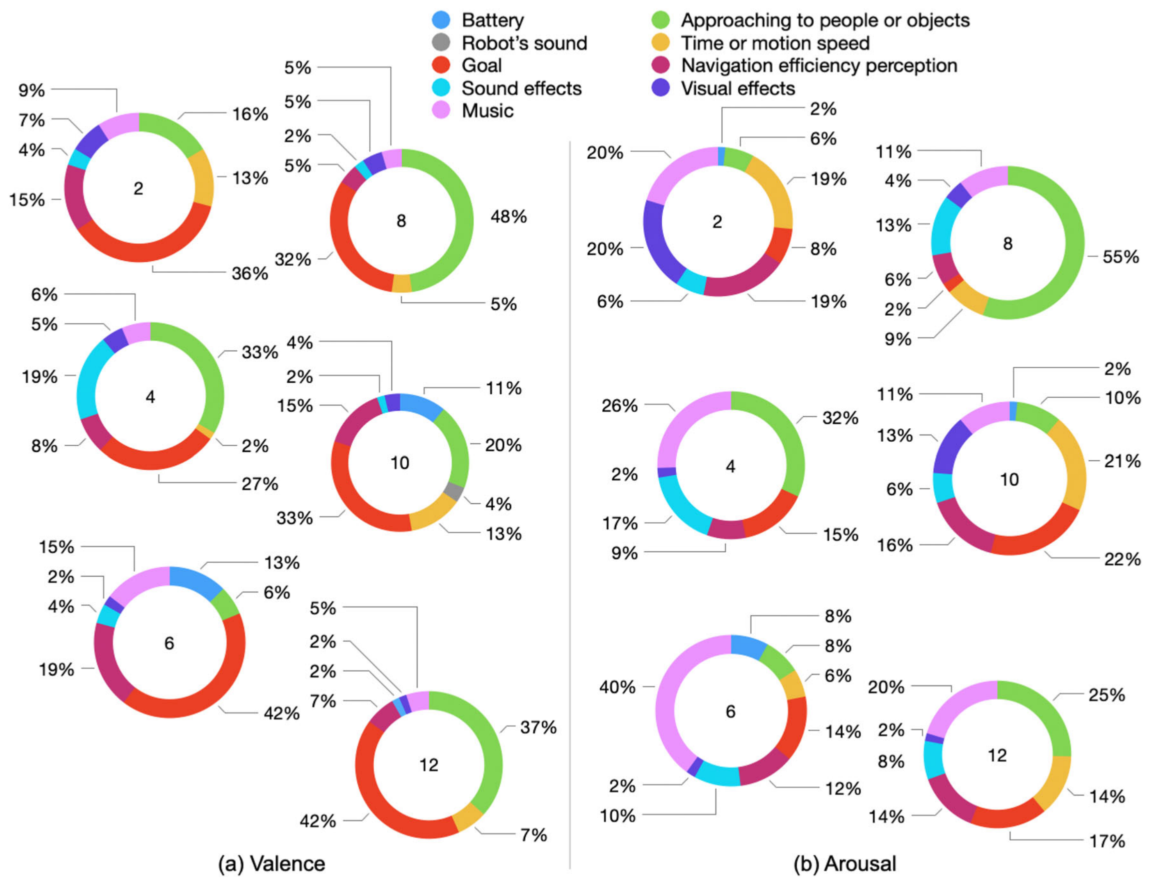


Fig. 15 Percentages of mentions the subjects explicitly made on components and objectives, after watching videos of the virtual robot navigating through fragile scenarios. The percentages are rounded to the nearest integer

In order to understand the above results, we summarize the number of mentions the subjects explicitly made about the following video components and objectives (based on the second set of experiments): battery life, approach towards people or objects, robot's sound, time or motion speed, goal, navigation efficiency perception, sound effects, visual effects, and music. In Figures 14 and 15, we present the graphics associated with the comments given about the austere and fragile scenarios, respectively.

6.5 Preference Hierarchy Detection

As a result of the analysis shown in the previous sections, it can be concluded that the values of arousal provide information that allows discriminating more clearly the advantages of including visual and sound elements in the stimulation videos. On the other hand, valence is more suitable to identify subjects' preferences, in this case, to select robot controllers that could be applied to the custom configuration of robots. Therefore, the combination of both emotions could define subjects' preferences more clearly. For this reason, in this section, we analyze the subjects' preferences by computing the preference hierarchy detection proposed in Section 3.6.

Table 4 details the order of preferences of each subject based on the first experiment. Figure 16 summarizes these results and shows the following. Most subjects, 57%, selected video 2 (i.e., type of event 1). According to the objectives

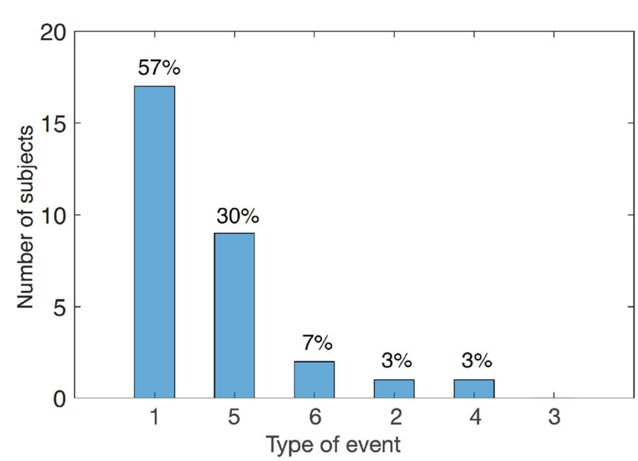


Fig. 16 Order of preferences arranged in descending order. See Table 4

described in Table 1, subjects prefer the robot to reach its destination at high speed without colliding. It is followed by video 10 (i.e., type of event 5), selected by 30% of the subjects. That is, the second preference is for the robot to reach its destination at a low speed. In other words, 87% of the subjects prefer the robot not to collide and to reach the goal, regardless of the speed. It is followed by video 12 (i.e., type of event 6), selected by 7% of the subjects. In this video, the robot reaches its destination at high speed but collides. That is, 94% of the subjects prefer the robot to reach the destination, regardless of whether it collides or its speed. These results coincide with the interpretation given to the observations in the previous section. The same applies to types of events 2 (videos 3 and 4) and 4 (videos 7 and 8), which were evaluated with a valence value that reflects unpleasant emotions because the robot does not reach the goal and collides with objects.

7 Conclusions

In this paper, we proposed the Emotional Assessment Method (EAM). The method involves generating a simulation depicting the optimization objectives and illustrating the repercussions of each decision. Through this method, the decision-maker evaluates the emotions elicited by each simulation, directing their exploration for solutions that align with their preferences. As a case study, our focus is on discerning individuals' preferences regarding robot behaviors.

The virtual robotic platform had no human or animal characteristics and did not exhibit affective expressions or proximity behavior. We prepared simulations showing the performance of the robot in a home environment whose goal was to reach a certain point while avoiding obstacles. Regarding the optimization problem, the objectives to be minimized were time to reach the goal, battery usage, and risk of collisions.

In the experiments proposed, we designed six different controllers presented in separate videos. In order to evaluate the possibility of identifying subjects' preferences based on the context, we developed two different scenarios, one of them with more fragile elements and people than the other, but also with music and different sound effects to highlight special events. Seventy-two subjects with different degrees of familiarity with robots participated in the experiments. They used the Affective Slider to evaluate their emotions in terms of arousal and valence.

We concluded that it is possible to elicit subjects' emotions while observing the consequences of a robotic platform – without human or animal characteristics, that does not exhibit affective expressions or proximity behavior – navigating throughout a domestic environment (see Section 6.1). Moreover, subjects' emotions are different while observing the robot's performance based on the context in which it develops (see Section 6.2). Additionally, we have identified that familiarized subjects assign higher valence self-assessment values on safety and speed when the robot reaches the goal, even in austere environments (see Section 6.3).

Also, we identified that associating sounds and visual effects with the robot's development in videos increases the valence and arousal of subjects' self-assessments (see Section 6.4).

Finally, we identified that subjects' emotions could be used explicitly in the decision-making process for the proposed case study (see Section 6). For instance, the values of valence self-assessment are more suitable to identify subjects' preferences, in this case, to select robot controllers that could be applied to the custom configuration of robots. For example, in the experiments, it was observed that participants preferred the robot to reach the goal without colliding, regardless of the speed. And that, although on average, they are unsatisfied if the robot crashes, even if it reaches the goal, many would be willing to tolerate that failure. However, they would not be willing for the robot to miss the target. Additionally, we found that arousal provides information that allows discriminating more clearly the advantages of including visual and sound elements in the stimulation videos.

8 Future Work

For future work, we suggest implementing the EAM in an Interactive Multiobjective Optimization (IMO) to incorporate preferences based on emotions. IMO is an optimization approach based on the active involvement of the decision-maker throughout the optimization process. In IMO, the decision-maker is presented with a set of alternative solutions or trade-off options. These solutions represent different combinations of objectives that need to be optimized. The decision-maker then provides feedback on their preferences, priorities, or trade-offs. Based on this feedback, the optimization algorithm adjusts its search strategy to generate a new set of solutions that better align with the decision-maker's preferences. This interactive process continues iteratively until a satisfactory solution or a set of Pareto-optimal solutions is reached. In addition, we propose different case studies, such as vessel design, bike design, and robotic arm movements when holding different objects.

Appendix

Table 4 Order of preferences: the norm values $\|v_1\|, \|v_2\|, \ldots, \|v_6\|$ are ordered in a descending order

	Order of preferences											
subjects	Video	$\|v_1\|$	Video	$\|v_2\|$	Video	$\|v_3\|$	Video	$\|v_4\|$	Video	$\|v_5\|$	Video	$\|v_6\|$
1	2	1	10	0.99	4	0.68	12	0.64	8	0.45	6	0
2	10	1.16	2	0.98	4	0.80	12	0.79	8	0.71	6	1
3	2	0.93	4	0.87	12	0.86	8	0.79	6	0.73	10	1
4	12	0.98	10	0.96	8	0.94	6	0.80	4	0.69	2	0
5	10	1.34	12	1.15	2	0.98	8	0.97	4	0.81	6	1
6	2	1.41	10	1.38	4	1	8	1	12	0.50	6	0
7	2	1.41	10	1.41	4	1.33	12	1.15	8	1.08	6	1
8	10	1.35	4	1.28	2	1.27	8	0.76	12	0.26	6	0
9	10	1.35	4	1.28	2	1.27	8	0.76	12	0.26	6	0
10	2	1.26	4	1.03	10	0.90	12	0.71	8	0.26	6	0
11	2	1.41	10	1.23	6	1.04	4	0.97	12	0.92	8	1
12	2	1.41	10	1.41	6	1	8	0.66	12	0.32	4	0
13	2	1.41	6	1.04	10	1.03	8	0.74	12	0.69	4	1
14	2	1.41	10	1.41	6	0.89	12	0.66	4	0.63	8	0
15	2	1.23	10	1.10	4	1.08	8	0.92	6	0.69	12	1
16	10	1.20	2	1.18	4	1.04	6	1.03	8	0.87	12	1
17	4	1.17	12	1.10	10	0.97	8	0.94	2	0.69	6	1
18	8	1.41	12	1.41	4	1.29	2	1.10	10	0.77	6	1
19	2	1.41	12	1	4	0.77	10	0.73	8	0.67	6	0
20	2	0.92	4	0.84	8	0.83	10	0.73	12	0.73	6	0
21	10	1.06	2	0.83	12	0.70	4	0.67	8	0.61	6	0
22	2	1.37	10	1.26	12	0.89	6	0.85	4	0.74	8	1
23	2	1.41	10	1.05	6	0.33	4	0.13	8	0	12	0
24	2	0.83	4	0.76	10	0.70	12	0.70	8	0.70	6	1
25	12	1.41	10	1.18	2	1.10	8	0.87	4	0.78	6	0
26	2	1.36	12	1.22	10	1.03	8	0.67	4	0.47	6	0
27	10	0.94	4	0.90	12	0.90	2	0.87	6	0.50	8	0
28	2	1.27	8	0.94	10	0.91	12	0.85	4	0.84	6	1
29	10	1.20	2	1.05	6	0.84	8	0.83	4	0.82	12	1
30	10	0.86	2	0.80	8	0.79	12	0.71	6	0.65	4	0

Higher values indicate the subjects' main preferences towards the objectives represented by the corresponding video

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Data Availability All data generated or analyzed during this study are included in this published article.

Declarations

Competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The volunteers were informed that they were free to choose whether they wanted to participate and that they could withdraw from the study at any time without any negative repercussions.

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