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## Modeling emotion to enable intelligent behavior in robots

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### Abstract

Over the past decades, research in cognitive and affective neuroscience has emphasized that emotion is crucial for human intelligence and in fact inseparable from cognition. Concurrently, there has been growing interest in simulating and modeling emotion-related processes in robots and artificial agents. In this opinion paper, our goal is to provide a snapshot of the present landscape in emotion modeling and to show how neuroscience can help advance the current state of the art. We start with an overview of the existing literature on emotion modeling in three areas of research: affective computing, social robotics, and neurorobotics. Briefly summarizing the current state of knowledge on natural emotion, we then highlight how existing proposals in artificial emotion do not make sufficient contact with neuroscientific evidence. We conclude by providing a set of principles to help guide future research in artificial emotion and intelligent robotics. Overall, we argue that a stronger integration of emotion-related processes in robot models is critical for the design of intelligent, human-like behavior. Such integration not only will contribute to the development of autonomous social machines capable of tackling real-world problems but would contribute to advancing understanding of natural emotion.

### Résumé

Au cours des dernières décennies, la recherche en neurosciences cognitives et affectives a souligné que l'émotion est cruciale pour l'intelligence humaine, et qu'elle est en réalité inséparable de la cognition. Parallèlement, il y a eu un intérêt croissant pour la simulation et la modélisation des

processus liés aux émotions dans les robots et les agents artificiels. Dans cet article d'opinion, notre objectif est de donner un aperçu du paysage actuel dans la modélisation des émotions et de montrer comment les neurosciences peuvent contribuer à faire progresser l'état de l'art en la matière. Nous commençons par un aperçu de la littérature existante sur la modélisation des émotions dans trois domaines de recherche : l'informatique affective, la robotique sociale et la neurorobotique. Après un bref résumé de l'état actuel des connaissances sur les émotions naturelles, nous montrons que les propositions existantes en matière d'émotions artificielles ne tiennent pas suffisamment compte des données neuroscientifiques. Nous concluons en proposant un ensemble de principes pour guider les futures recherches sur les émotions artificielles et la robotique intelligente. Dans l'ensemble, nous soutenons qu'une meilleure intégration des processus liés aux émotions dans les modèles de robots est essentielle pour la conception d'un comportement intelligent, semblable à celui de l'humain. Une telle intégration contribuera non seulement au développement de machines sociales et autonomes capables de s'attaquer à des problèmes du monde réel, mais aussi à faire progresser la compréhension des émotions naturelles.

## 1. INTRODUCTION

In recent decades there has been increased interest in modeling *emotion* or *affect*<sup>1</sup> in robots and artificial agents (Marsella et al., 2010; Kowalczyk & Czubenko, 2016; Moerland et al., 2018; Ojha et al., 2021; and Smith & Carette, 2022). This may include the recognition of human emotions, the generation of emotion expressions, but also the study and modeling of the link between emotion and certain brain processes (e.g. neuromodulation), physiological processes (e.g. hormones), mental/cognitive processes (e.g. attention, decision, memory), or behavioral processes (e.g. navigation, social interaction). Proposed attempts at tackling this challenge stem from diverse fields, including social robotics, neurorobotics, and affective computing, which differ in terms of their theoretical foundations, engineering approaches, and research goals (see Section 2). As such, existing approaches are largely disconnected from one another. However, progress in the field requires identifying common threads so that the strengths and weaknesses of different proposals and frameworks can be evaluated. A key goal of the present opinion paper is to outline such a synthesis so as to identify fruitful research directions in the development of emotion in intelligent machines.

But why should machines be concerned with emotion in the first place? In a nutshell, because flexible, intelligent behaviors in animals (including humans) critically rely on emotion. The definition of “emotion” is broad and subject to debate. Here we focus on *affective processes* defined as the mental and physiological processes which determine the valence of an object or event, its significance and/or

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1 In the literature, the term “emotion” usually refers to a bounded episode in response to a specific event or object. The term “affect” generally encompasses what pertains to emotional responses but also feelings, mood, and so on. This distinction is particularly useful when specialists need to be precise about their object of study. Yet, “emotion” continues to be used to refer to emotional/affective mechanisms and phenomena in general terms, as is typically the case when researchers discuss the distinction or connection between “cognition” and “emotion”. Unless stated otherwise, in this paper we use “emotion” and “affect” interchangeably. Likewise, we use “emotion modeling” and “affective modeling” interchangeably to refer to attempts to model emotion- and affect-related processes in machines (see Hudlicka (2011) for a proposed classification of emotion modeling).

relevance for one's survival, well-being and goals, as well as the responses that ensue. These processes are ubiquitous in our mental activities and contribute to how we perceive the world, how we learn and remember past experiences, how we make decisions, how we adapt to new situations, and how we communicate with each other. Thus, the focus of this paper is about whether and how modeling affective processes could enable the design of intelligent behavior in the sense of animal- or human-like ability to interact with their physical and social environment. The question of whether machines can experience "feelings" or show "empathy" is, however, beyond the scope of the paper.

Considerable effort has been devoted to developing systems that detect emotions in human users and display simulated emotional expressions in response. However, the brain and behavior literature shows that emotion is involved in nearly all mental processes underlying intelligent behavior, including perception, attention, decision-making, and action (Pessoa, 2017; Lindquist & Barrett, 2012). Accordingly, we ask how to go beyond the recognition/production of emotional expressions so as to allow robots to tackle real-world problems, such as navigating an unknown environment or handling an uncontrolled social interaction. For machines to deal intelligently with such problems, much like in humans, affective processing should be integrated across the computational processes that determine their behavior. Our aim is to bridge the gap between computational models of intelligent behaviors and the neuroscience of emotion, while providing a set of recommendations for future research.

## 2. VIRTUAL AND ROBOTIC MODELS OF EMOTION

The past two decades have witnessed the development of a variety of computational and robotic models of emotion, mostly stemming from three research fields: *affective computing*, *social robotics*, and *neurorobotics*. Affective computing involves “the design of systems that can recognize, interpret, and simulate human emotions and related affective phenomena”<sup>2</sup>. Thus, emotion and affective processes are at the core of the field (it is worth noting that it also covers systems aimed at sensing and analyzing human emotion, for instance, with no interest in modeling or simulating emotion). Second, social robotics involves “the study of robots that are able to interact and communicate among themselves, with humans, and with the environment, within the social and cultural structure attached to its role”<sup>3</sup>. This notion encompasses modeling socio-affective capabilities but also other research topics ranging from measuring humans’ attitude toward robots to speech generation, for instance. Last, neurorobotics investigates “embodied systems built on the basis of brain-inspired algorithms, computational models of biological neural networks, or actual biological systems”<sup>4</sup>. Thus, it covers a wide range of brain functions and mechanisms, many (if not all) of which involve affective processes as we argue in Section 3 (though emotion is far from being considered at the core of neurorobotics). Overall, despite considerable overlap, research in these fields typically rely on different theories, methods, and approaches.

To characterize the range of work related to emotion modeling in these fields (Figure 1), we propose the following set of criteria: Is the model virtually or physically embodied? Is the focus on social or non-social behavior? Is the architecture modular or integrative? Is the model defined by a theory of emotion or in a more bottom-up approach? Is the end goal to develop a specific application and to better understand natural emotion? In some cases, these criteria clearly distinguish the above-mentioned fields. For instance, neurorobotics and social robotics study systems that are physically embodied, which is not necessarily the case in affective computing. Also, social robotics focuses on social behavior while the other two may also address non-social behavior. However, more generally, the distinction between fields is less straightforward and one has to consider each proposal individually. Thus, to describe the current state of the art, we selected representative examples from the literature which we sought to discuss through the prism of these criteria (see summary in Table 1). Rather than a comprehensive review<sup>5</sup> of computational and robotic models of emotion, this overview aims to provide a snapshot of the present landscape so as to identify common research threads, different approaches and potential weaknesses.

### 2.1. Snapshot of the existing literature

#### *Embodiment: virtual vs. physical*

The first, and most straightforward, criterion that can be used to distinguish existing emotion models is embodiment. Several computational models of emotion have been implemented on 3-D animated agents (Gratch & Marsella, 2004; Courgeon et al., 2011). Such virtual avatars can exhibit rich non-

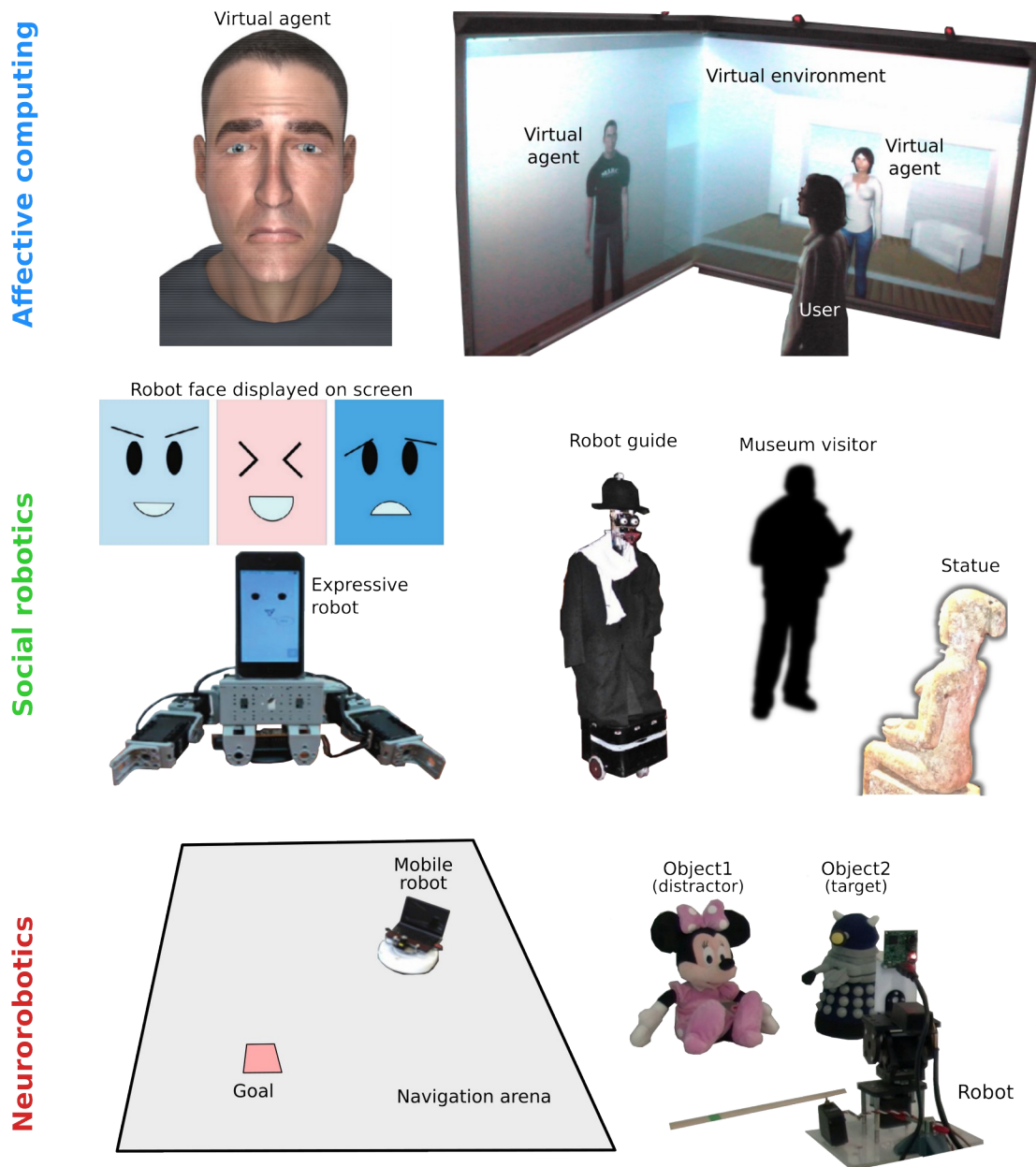
2 Taken from the website of the journal *IEEE Transactions on Affective Computing*: <https://www.computer.org/csdl/journal/ta>, last visited on September 7, 2023

3 Taken from the website of the *International Journal of Social Robotics*: <https://www.springer.com/journal/12369>, last visited on September 7, 2023

4 Taken from the website of the journal *Frontiers in Neurobotics*: <https://www.frontiersin.org/journals/neurobotics/about>, last visited on September 7, 2023

5 For further examples of computational models and architectures of emotion, we invite the reader to refer to Marsella and colleagues (2010), Kowalczyk and Czubenko (2016), Moerland and colleagues (2018), Ojha and colleagues (2021), and Smith and Carrette (2022).

verbal behaviors (gestures, postures, and facial expressions), in addition to verbal utterances to convey socio-emotional cues to human users (Pelachaud, 2009; Courgeon et al., 2011; Sagar et al., 2016). To increase the feeling of immersion and give a sense of situated interaction, they can be integrated in virtual reality (Ochs et al., 2016). Nevertheless, these models suffer from limitations due to the absence of physical interaction with the real world. Robots, on the other hand, are embodied and situated in the real world. In this category, there are expressive robots equipped with actuators controlling eye and mouth movements with enough degrees of freedom to mimic stereotypical emotional facial expressions (Breazeal, 2003; Karaouzene et al., 2013; Correira et al., 2016). Some platforms are based on more anthropomorphic robot faces (e.g. Wu et al., 2009), while simpler ones display facial expressions on a screen (e.g. Masuyama et al., 2018). Moreover, physically embodied yet non-expressive robots have also been used to model aspects of affective processes related to *behavior regulation* during task performance (e.g. Avila-Garcia & Cañamero 2004; Krichmar, 2013; Belkaid et al., 2018). While benefiting from real physical embodiment, robotic models suffer from limited behavioral repertoires due to the inherent difficulties of movement generation in mechanical systems, among other factors.



**Figure 1:** Emotion modeling approaches. In affective computing, virtual agents convey socio-emotional signals through facial expression and postures (top, left; Courgeon et al., 2011), such as in professional training applications (top, right; Ochs et al., 2016). In social robotics, expressive robots, which may have robotic appearances (middle, left; Masuyama et al., 2018) or anthropomorphic characteristics mimicking human features such as a face with eyes and mouth (middle, right; Karaouzene et al., 2013) are used for situated interactions with humans in applications such as museum guides (middle, right; Karaouzene et al., 2013). In neurorobotics, affective processing helps robots navigate their environments (bottom, left; Krichmar, 2013) and visually explore objects in the visual scene (bottom, right; Belkaid et al., 2017). Pictures are adapted from Courgeon (2011; top row), Masuyama (2016; middle, left), Karaouzene (2017; middle, right), Krichmar (2013; bottom,

*left*) and Belkaid et al. (2018; *bottom, right*).

#### *Behavior socialness: social vs. non-social*

Another distinction can be made in terms of the nature of the behavior exhibited by the machine. Indeed, the majority of artificial emotion models focus on social behavior for the purpose of facilitating human-machine interactions: selecting verbal utterances for customer service chatbots (Yacoubi & Sabouret, 2018), interacting with and learning from museum visitors (Karaouzene et al., 2013), or enriching socio-affective behaviors in companion robots (Correia et al., 2016) or virtual trainers (Gratch & Marsella, 2004). On the other hand, we mentioned above that another family of models examines emotion in non-social behaviors, including foraging (Avila-Garcia & Cañamero, 2004, Krichmar, 2013) and visual search (Belkaid et al., 2017). Such models emphasize the role of emotion in organizing and motivating behavior. Notably, few models address both social and non-social behaviors simultaneously (for an exception related to action selection balancing the need for food and the need for social interaction, see Khan & Cañamero, 2018).

#### *Architecture design: modular vs. integrative*

In cognitive science, *modularity* refers to the notion that the mind is composed of independent processing modules – typical modules would be attention, memory, decision, emotion<sup>6</sup>, and so on. Similarly, modularity is an engineering design principle and an important aspect to take into account in system's architecture. In the context of emotion modeling, a modular design means that emotion is simply *added* to the overall system architecture as a separate module which communicates with other components; for example, to activate certain expressive behaviors (e.g. facial expression, posture) in an action module (Breazeal, 2003; Courgeon et al., 2011; Correia et al., 2016). In contrast, integrative approaches highlight the interdependence between emotion and cognition by distributing emotional processing across the system (Krichmar, 2013; Belkaid et al., 2018).

#### *Theoretical approach: top-down vs. bottom-up*

Theories of emotion in psychology generally pertain to one of the following three classes (Coppin & Sander, 2012): theories of basic emotions, appraisal theories of emotion, and constructivist emotion theories (including dimensional theories). Some computational models of emotion take direct inspiration from emotion theories developed by psychologists (Smith & Carette, 2022), and explicitly instantiate theoretical principles in what can be referred to as a *top-down* fashion. For example, the EMA model (Gratch & Marsella, 2004) implements the appraisal and coping theory proposed by Lazarus (1991), and TEATIME (Yacoubi & Sabouret, 2018) implements the action-tendency theory proposed by Frijda (1986). In contrast, affective modeling can be approached in a more *bottom-up* fashion by focusing on the implementation of specific brain mechanisms related to natural emotion. For example, deriving robot affect (e.g. joy, frustration, boredom) from internal signals such as prediction errors, novelty, and progress in task performance (Belkaid et al., 2017; Broekens & Chetouani, 2019).

<sup>6</sup> As will be highlighted later on, a growing literature in neuroscience provides evidence for the integration of emotion and cognition in the brain (Phelps and LeDoux, 2005; Pessoa, 2008; 2013; Grossberg, 2018).



Importantly, such bottom-up approaches can complement and inform existing emotion theories by providing concrete implementations of processes that are otherwise outlined descriptively.

*Research goal: application-oriented vs. modeling-oriented*

One last aspect on which emotion models can greatly differ is the research goal. Indeed, a significant portion of the literature on emotion modeling has aimed to enrich human-machine interactions across multiple applications, such as elderly care (Correira et al., 2016) or training in the context of high-stakes decision-making (Gratch & Marsella, 2004). A complementary goal is to model mechanisms of natural emotion to advance the understanding of the neural systems involved (Balkenius et al., 2009; Krichmar, 2013; Belkaid et al., 2018; Khan & Cañamero, 2018; Lowe et al., 2019). In this context, it is worth noting that many neuroscience-informed models are implemented in simplified simulated environments, and are not embodied in virtual or robotic agents.

	Embodiment	Behavior	Design	Approach	Goal
(Avila-Garcia & Cañamero, 2004)	Robotic	Non-social	Integrative	Bottom-up	Modeling
(Balkenius et al., 2009)	Robotic	Non-social	Integrative	Bottom-up	Modeling
(Belkaid et al., 2017)	Robotic	Non-social	Integrative	Bottom-up	Modeling
(Breazeal, 2003)	Robotic	Social	Modular	Top-down	Application
(Broekens & Chetouani, 2019)	Undetermined	Undetermined	Undetermined	Bottom-up	Application
(Correira et al., 2016)	Robotic	Social	Modular	Top-down	Application
(Courgeon et al., 2011)	Virtual	Social	Undetermined	Top-down	Application
(Gratch & Marsella, 2004)	Virtual	Social	Modular	Top-down	Application
(Karaouzene et al., 2013)	Robotic	Social	Integrative	Bottom-up	Application
(Khan & Cañamero, 2018)	Robotic	Both	Integrative	Bottom-up	Modeling
(Krichmar, 2013)	Robotic	Non-social	Integrative	Bottom-up	Modeling
(Lowe et al., 2019)	Undetermined	Undetermined	Undetermined	Bottom-up	Modeling

(Masuyama et al., 2018)	Robotic	Social	Modular	Top-down	Application
(Ochs et al., 2016)	Virtual	Social	Undetermined	Undetermined	Application
(Pelachaud, 2009)	Virtual	Social	Undetermined	Undetermined	Application
(Sagar et al., 2016)	Virtual	Social	Integrative	Bottom-up	Application
(Yacoubi & Sabouret, 2018)	Undetermined	Social	Modular	Top-down	Application

**Table 1:** Summary of how representative examples of affective modeling from the areas of affective computing, social robotics, and neurorobotics can tentatively be characterized in terms of the five proposed criteria: embodiment (virtual vs. physical), behavior socialness (social vs. non-social), architecture design (modular vs. integrative), theoretical approach (top-down vs. bottom-up), and research goal (application-oriented vs. modeling-oriented).

## 2.2. Outlook

In our view, despite advances, the literature on affective modeling suffers from a number of shortcomings. In particular, existing models are often domain specific. For example, models of how emotion can improve communication in social contexts do not address how affective processes can guide environment exploration or behavior regulation when handling conflicting goals, and vice versa. Thus, adapting a model to a new context of application effectively amounts to designing a new model. More importantly, emotion-based architectures are seldom designed as more general-purpose architectures. Overall, the field lacks frameworks for integrating affective processing in intelligent systems that can scale up beyond controlled toy scenarios.

To develop such frameworks, we argue that stronger connections with the neuroscience of emotion is needed. While it is in theory possible to engineer intelligent machines without consideration of living organisms, we believe it is enormously beneficial to take cues from how biology gives rise to intelligent behaviors, as demonstrated by proposals inspired by biological cognition (e.g. Mnih et al, 2015; Cully et al., 2015; Moulin-Frier et al., 2017; Doncieux et al., 2018). As a model of autonomous learning and decision-making, reinforcement learning<sup>7</sup> is a good example of fruitful interaction between neuroscience and artificial intelligence (Neftci & Averbeck, 2019). Interestingly,

<sup>7</sup> The core idea in reinforcement learning is that autonomous behavior is driven by the process of learning and selecting actions that maximize the agent's rewards. The foundations of these models come from research in biology on associative learning, while more sophisticated models are constantly being developed in the field of artificial intelligence and machine learning.

reinforcement learning has been proposed as a possible framework to bridge the machine learning and emotion modeling communities (Moerland et al., 2018). Indeed, reinforcement learning models acknowledge the central role of affective processing by postulating that reward-seeking drives autonomous behavior. However, this framework primarily addresses processes related to specific forms of learning and decision-making. Notably, it does not encompass processes such as attention and executive control that we believe have strong potential to benefit from affective processing (see Section 3.1). More generally, how affective processes are modeled in robots and artificial agents often contrasts sharply with current knowledge about biological emotion. In the following, we summarize key findings of the neuroscientific literature that highlight the gap between natural and artificial emotion. In particular, we stress the integration between emotion and perception/cognition in humans and animals at multiple levels: brain, body, and behavior.

### **3. NATURAL EMOTION: BRAIN, BODY, AND BEHAVIOR**

#### **3.1. Emotion and the brain**

Historically, the brain basis of emotion was conceptualized in an area-centric manner. For a long period, the hypothalamus was believed to be the emotion center, shifting to the amygdala in the 1980s. In the last decades, not only has the number of regions of the “emotional brain” increased steadily, but how they function via complex circuits is starting to be unraveled. These regions include the medial prefrontal cortex, the orbitofrontal cortex, the cortex of the insula, the thalamus, and many more. Critically, rather than being functionally localized in specific areas, emotion-related processes are implemented by distributed neural circuits that rely on multiple structures at the same time (Pessoa, 2017; Tovote et al. 2015; Lindquist and Barrett, 2012).

More broadly, the classical separation between emotion and cognition has been gradually eroded. Behind the blurring of their boundaries is the notion that mental processes are implemented via large-scale, distributed networks (Sporns, 2010). The networks that have been uncovered in the context of cognitive processes share many nodes (i.e. regions) with those that are important for emotion (Pessoa, 2008; Najafi et al., 2016). Thus, neural computations underlying behavior are implemented via overlapping networks. In this manner, specific brain areas affiliate, or group with, multiple large-scale networks depending on behavioral demands.

Even more generally, the separation between mental domains such as perception, cognition, action, motivation, and emotion, while possibly suitable for a textbook organization, does not reflect the organization of the brain. To understand how the brain generates complex, flexible, and adaptive behaviors it is necessary to understand how brain circuits disrespect standard boundaries. In a very real sense, the domains cannot be separated.

#### **3.2. Emotion and the body**

Intelligence is not a mere collection of computations occurring in the central nervous system but result from the coupling of the brain, the body, and the environment (Varela et al., 1992; O’Regan & Noë, 2001). From this perspective of embodied cognition, emotion is rooted in homeostatic processes that guarantee bodily integrity, and the associated construction of bodily representations capturing the

state of body at any instant. These key functions engage both subcortical and cortical areas. Thus, neuroscientifically grounded theories of emotion attribute a central role to the body in emotional-related processes. For example, in the core affect theory, bodily states are central to emotional experience (Russell, 2003). In the somatic marker theory, associations between particular situations and patterns of elicited physiological and emotional reactions are established, and help shape behavior (Damasio et al., 1996).

### **3.3. Emotion and behavior**

Emotion expressions, including those such as facial expressions, gestures, and postures, are an important feature of the relationship between emotion and the body (de Gelder et al., 2015; Cowen et al., 2019). The variety and complexity of processes involved in emotion expression and recognition underlines their importance in human social behaviors.

Emotion-behavior coupling is not limited to communicative functions but is also strongly related to motivation and action generation (Frijda 1986; Blakemore & Vuilleumier, 2017). In living organisms, motivated behaviors are represented in terms of approach and avoidance. Even ostensibly simple behaviors like escape leverage complex cognitive-emotional processes (Evans et al., 2019). More generally, survival – and autonomous function – depends on the ability to generate flexible behaviors and to adapt to dynamical environments. In sum, how an organism acts in its environment is a key problem that depends on emotion-related processes, which therefore is not confined to generating expressive behaviors for communication.

## **4. TOWARD BETTER MODELS OF EMOTION**

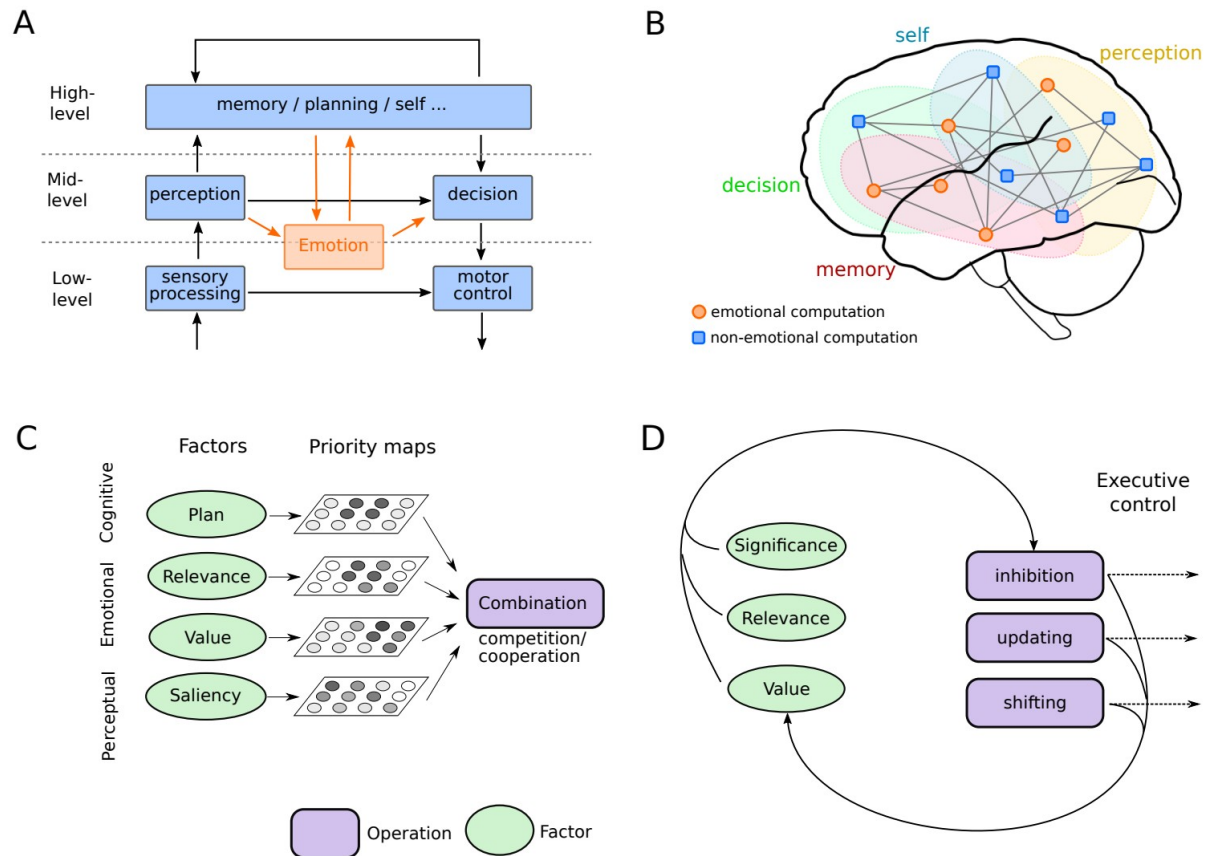
Based on the preceding discussion, we propose four principles to motivate guidelines for affective modeling in machines capable of displaying human-like intelligent behaviors. We use the term *machines* as these ideas may apply for systems ranging from simulated agents to virtual agents to robots. Yet, it is worth noting that while simulated and virtual agents can be valuable tools in many instances of emotion modeling, most of the examples and illustrations that follow involve robots. As pointed out in the previous section, interactions with the body and with the environment are key aspects of natural emotion. Therefore, because of their physical embodiment and their ability to interact with the real world, we believe that robots offer more powerful architectures for emotion modeling (see Sections 4.2 and 4.3).

### **4.1. Account for emotion-cognition integration**

The integration of emotion and cognition in the brain can be used to inform how affective processing interacts with other computational processes, and more generally the notion of architecture modularity. Consider a traditional architecture with standard components such as perception and decision-making (Figure 2A). Recognizing the utility of affective information, models have included an emotion-related component that interfaces with some of its components, for example, allowing motivational factors (“fatigue” and “cold”) to influence action selection (Avila-Garcia & Cañamero 2004). Employing affective information in a subset of processes is viable in single-purpose systems that operate in specific, controlled contexts. However, we suggest that more general-purpose architectures should be

designed such that emotion-related mechanisms interface with all of the remaining processes. This is because in unconstrained, complex environments systems with *limited computational resources* need effective ways to allocate them and to organize their behavior intelligently. This is where emotion-related processing is important, in particular the concept of value, relevance, and/or significance.

Figure 2B illustrates how all processes that are traditionally separated in distinct modules should actually be more connected and, more importantly, involve emotional processing. But how can this principle be translated into concrete implementation? Consider the example of attention, a cognitive operation central to the notion of computational resource allocation. A fruitful way to conceptualize attention is in terms of *priority maps* (Itti et al., 1998). In particular, the priority of a to-be-attended visual item depends on a series of factors, including stimulus salience and top-down control, which can be respectively labeled as perceptual and cognitive factors. Critically, priority also depends on affective and motivational significance, including reward (Anderson and Phelps, 2001; Anderson et al., 2011). For example, an item paired with aversive consequences in the past will acquire negative significance, and gain prioritized processing so that it can be adequately handled. Likewise, an item paired with reward in the past will acquire motivational value. Combined, the determination of the overall object *relevance* integrates multiple factors, typically via competition/cooperation mechanisms (Figure 2C). For example, objects with both high perceptual saliency and high value (e.g. paired with reward in the past) can outcompete objects that are goal-relevant. The ability to direct attention according to multiple factors, including affective and motivational ones, is of utmost importance for intelligent systems with finite resources dealing with real-world situations. Note that the proposed approach is different from those using neuromodulation to implement attention-related processes (e.g. Krichmar, 2013), as neuromodulation typically evolves across slower time scales than the “on-the-fly” integration of factors in Figure 2C. The two approaches are complementary.



**Figure 2:** *Emotion integration in robot cognitive architectures. A) Traditional cognitive architecture in which emotion interacts with some of the other components. In this type of architecture, emotion is an added module that can be disconnected from others. B) Brain-like architecture in which the separation between mental processes is blurred. More importantly, all processes involve a combination of emotional and non-emotional computations. This view emphasizes that affective processing is an integral element of the system. C) The process of attention combines multiple priority maps to determine which elements in the environment the robot should attend to. Priority maps are based on multiple factors: perceptual (e.g. based on saliency), cognitive (e.g. based on current plan), but also emotional/motivational (e.g. based on value and relevance). D) The process of Executive control is based on a set of operations such as inhibiting, updating and shifting that take into account affective factors to support successful autonomous adaptive behaviors. At the same time, the very same functions help determine factors such as value, relevance, and significance.*

As another example, consider executive control (also called “cognitive control”), which includes operations involved in maintaining and updating information, monitoring conflict and/or errors, resisting distracting information, inhibiting prepotent responses, and shifting goals. A useful way to conceptualize executive control is in terms of a set of processes, including inhibition, updating, and shifting (Miyake et al., 2000). Insofar as value, relevance, and/or significance need to be taken into account for proper executive control, emotion/motivation participate in these processes. In other words,

objects or contexts that influence cognitive control processes such that rewards (respectively, punishments) ensue, become positively (respectively, negatively) relevant to guide or direct executive control. Why is the architecture in Figure 2A not sufficient? After all, information about what is emotionally/motivationally relevant will be conveyed to the particular architecture components. The central reason is that influences must be *bidirectional* (Figure 2D). For example, dealing with an emotional stimulus or situation requires multiple adjustments, including “updating” to refresh the contents of working memory, “shifting” to switch the current task subgoal, or “inhibiting” to cancel previously planned actions. In this manner, resources are coordinated in the service of proper (“intelligent”) function.

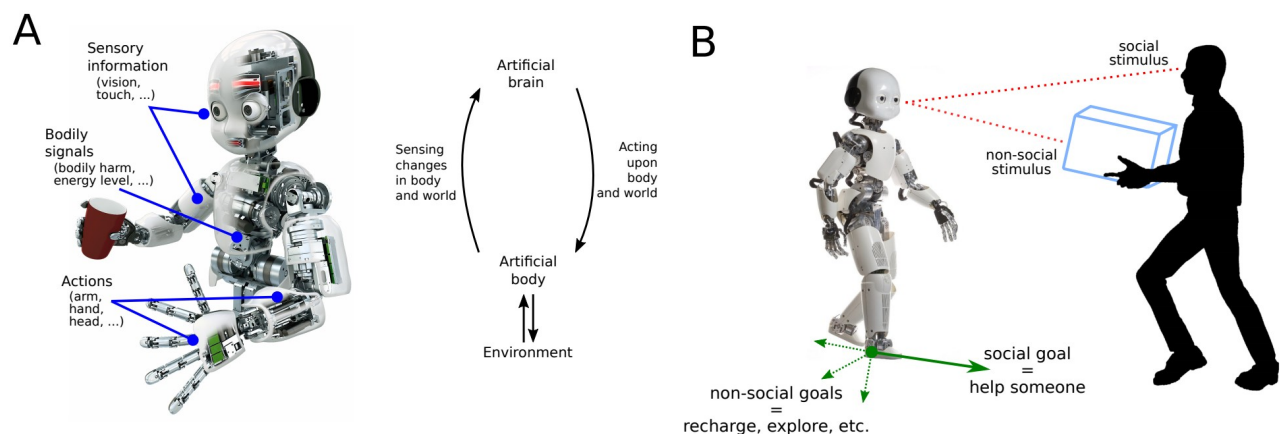
Moving from high-level descriptions such as those exposed here to an implementable model that is relevant at the psychological, neural, and behavioral levels is quite challenging. Consider a robot whose task is to prepare a dish from a complex, multi-step recipe. In addition to perception, memory, decision, and motor action, such a task may involve a combination of affective, attentional, and control processes as described above. Indeed, performing this task requires attending and manipulating specific objects according to the subgoals of the recipe steps (e.g., looking for a knife to cut some vegetable while periodically attending to the ingredients slowly simmering in the meantime). Previous work from one of the authors (Belkaid et al., 2017) provides an example of a cognitive-emotional robot architecture in which affective signals are used to determine the relevance of the objects present in the visual scene, allowing the inhibition of an irrelevant focus area when visual searching for a target object. The model is based on a dynamic, structured neural network that makes it possible to correlate (in future work) some of the implemented computational processes with the activity of certain brain circuits. Yet, many of the mechanisms listed above are missing in the model; for instance, accounting for how some objects acquire a stronger value or emotional significance (e.g., preferred ingredient attended and selected before others), how some behavioral responses are inhibited (e.g., getting too close to the hot pot), or how to shift from a subgoal to another (e.g., if an interruption is needed to give the simmering stew a quick stir).

## 4.2. Subscribe to principles of embodiment

To stress the importance of embodiment for artificial intelligence, roboticists often use arguments related to morphology and physical interaction with the environment (Brooks, 1991; Pfeifer et al., 2007). Consider a system that must learn the concept of a “chair”. Purely vision-based approaches (e.g. using deep neural networks) would need a massive amount of data and would only be able to recognize chairs by shape. In contrast, a humanoid robot able to sit on a flat surface could learn that sitting minimizes energy loss and thus start to learn the functional aspects of chairs. In other words, disembodied machines cannot make sense of the world the same way as humans do. In the context of emotion, we believe that the same reasoning applies. For instance, human-like facial expression recognition should be embedded in a system that can produce expressive behavior and associate it with its own internal states in order to process what is being expressed, by the system itself or others (see also Sagar et al., 2016, on the importance of modeling low-level brain-body mechanisms to produce

realistic face animations). Otherwise, it will be little more than a detection device of stereotypical patterns labeled as ‘happy’ or ‘afraid’, and thereby unlikely to reach human-level performance.

When addressing emotion embodiment in artificial systems, there has been a focus on how emotion is expressed through the body (e.g. emotion recognition in computer vision, face actuators in social robotics, synthesis of social cues in computer animation). But, for models of emotion and cognition to be more truly embodied, the behavior they implement must be driven by signals related to potential bodily harm, safety, satiation, energy depletion, and so on (Figure 3A; see also Froese & Ziemke, 2009, and Man & Damasio, 2019). In particular, the successful execution of higher-order goals partly depends on the association between a set of actions with their affective and motivational consequences (positive or negative). Therefore, building a robot capable of autonomously and intelligently exploring an unknown environment requires mechanisms to monitor energy level, avoid physical harm, develop a preference for safe locations, attend to objects which are relevant to goals/plans, and switch between goals and behaviors depending on current own and external states (Figure 3B), all of which rely on embodied emotional-cognitive processes.



**Figure 3:** Embodiment and emotion for intelligent robots. **A)** As embodied intelligent machines, robots are able to acquire information about, and to act upon, the world through a variety of sensors and actuators. The notion of embodiment also includes the processing and regulation of bodily signals related to bodily harm, safety, and energy depletion. **B)** Effective integration of emotion allows robots to generate and coordinate intelligent behaviors in complex situations involving social and non-social interactions. The illustration of iCub robot in A) is reproduced with permission from Antoni Gracia.

### 4.3. Support both social and non-social behaviors and interactions

Real-world situations consist of a combination of social and non-social interactions with the environment. In order to properly operate in such situations, machines need architectures that can support both types of interactions. In the context of attentional processes, social (e.g. other agents) and non-social (e.g. objects) stimuli can have different types of relevance to the system and should capture



attention accordingly. In addition, goals can be social (e.g. helping someone) or non-social (e.g. reaching a location, grasping an object; see Figure 3B). Accordingly, architectures should be able to direct processing and allocate resources in a manner that takes into account both social and non-social priorities. From an engineering perspective, autonomous cars could be safer if they had the capacity to interpret social cues (e.g. pedestrian patterns and interactions); industrial robots could be more efficient if they were able to manage both independent and collaborative tasks; and companion robots could be more engaging and fun if they could develop a “personality” from both social and non-social experiences.

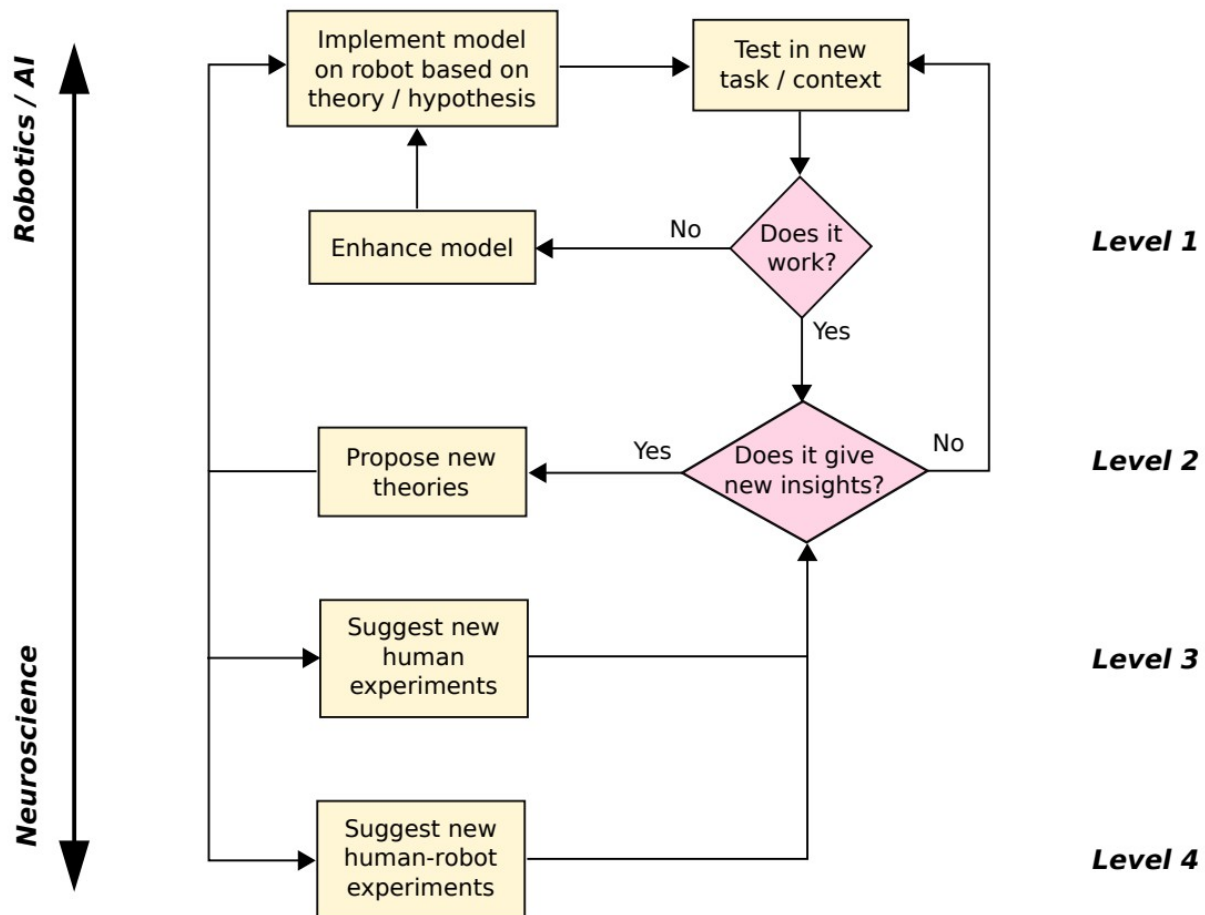
Developing human-like models of emotion for robots has the potential to enable intelligent behaviors that are relevant for both social and non-social contexts. In Section 3.1, we highlighted the importance of integrating emotional factors with attentional processes, which is relevant in non-social situations so that machines can autonomously allocate computational resources to the most important stimuli. But the other side of visual attention is gaze, which is a powerful social cue. Translating a robot’s attention into gaze-orienting behaviors provides an intuitive way for signaling to-be-attended objects, preferred objects, or to-be-avoided objects (Belkaid et al., 2017; illustrated in Fig 1) described an approach for top-down modulation of a robot’s attention based on emotional signals, such as frustration and boredom, derived from the agent’s own evaluation of ongoing performance. Similarly, Broekens & Chetouani (2019) described a model in which emotional expressions rely on reinforcement learning variables (e.g. prediction errors) to define affective states such as joy and distress. Thus, overall, models of emotion can jointly contribute to social and non-social interactions. Returning to the example of collaborative robots, while some aspects of emotion may not be relevant for these applications, this approach would allow the generation of socially relevant behaviors which are grounded in the very same processes that enable them to function autonomously in non-social situations; as opposed to being triggered by ad-hoc modules in a pre-scripted fashion.

#### **4.4. Inform research on natural emotion and cognition**

Computational and robotic models have the potential to play increasingly important roles in the study of the neural basis of emotion (Arbib & Fellous, 2004; Cañamero, 2019). To do so, machines should be conceived as models which can advance our understanding of human intelligence through the process of recreating it (for example, see Lewis et al., 2019). Can we build machines able to process different types of stimuli and events, to safely explore an unknown environment, to self-regulate and adapt behavior in the face of diverse contexts, to develop long-term knowledge, preferences, goals, and relationships? In doing so, designing intelligent machines can benefit not only *from* but also *to* the study of natural intelligence.

Computational models can inform research on human emotion and cognition at four levels: 1) testing existing theories, 2) proposing new theories, 3) proposing new experiments, and 4) creating opportunities for new experiments (Figure 4). For instance, does the current understanding of how we process social and non-social stimuli (e.g. threatening face vs. snake) suffice to implement similar mechanisms in a robot? Assessment of the current state of knowledge will reveal ambiguities and important gaps in the literature (level 1). For example, how is processing prioritized in the presence of

diverse types of distractors (social, non-social, positive, negative)? The process of testing theories should be hypothesis-driven and based on scientific knowledge, rather than solution-oriented (i.e. engineering a functional system) to contribute to the development of new theories (level 2). The process can then suggest new experimental designs to test the validity of the proposed hypotheses (level 3). Finally, modeling intelligent behavior in machines has the potential to lead to innovative experimental research (level 4). For instance, there is a growing body of research investigating aspects of social cognition using robot-based paradigms (Henschel et al., 2020; Belkaid et al., 2021). Indeed, robots offer a unique opportunity to create real-time, yet controlled, interactions.



**Figure 4:** Schematic of how emotion modeling in robots can inform neuroscientific research. Levels at which modeling can help advance neuroscientific knowledge: 1) testing existing theories, 2) proposing new theories, 3) proposing new experiments, and 4) creating opportunities for new experiments. Embracing an interdisciplinary approach will be beneficial to both the robotics and the neuroscience communities.

## 5. DISCUSSION

Recent advances in neuroscience emphasize the importance of emotion in human intelligence and stress the interdependent relationship between brain, body, and environment. Modeling and integrating emotion in “cognitive architectures” thus has the potential to help build autonomous social robots able to behave intelligently in diverse and challenging real-world situations. Indeed, several research groups have advocated for interdisciplinary approaches to emotion modeling in machines (e.g. Sloman & Croucher, 1981; Arbib & Fellous, 2004; Cañamero & Gaussier, 2005; Cañamero, 2019). Previous research in social robotics, neurorobotics, and affective computing have made considerable progress in this regard. Yet, modeling human-like emotion in robots remains a challenge.

In this paper, we provided an overview of the state of the art in affective modeling. Rather than a comprehensive literature review, we sought to summarize the research landscape from different areas by selecting representative examples. This allowed us to characterize the affective modeling literature with respect to five criteria: embodiment, behavior, architecture design, theoretical approach, and research goal. By linking this literature to current knowledge about human emotion, we identified a set of potential issues that can be summarized as follows. On the one hand, emotion-based robotic architectures are often domain-specific, where emotion-related mechanisms are restricted to specific processes or modules. As a result, these models fail to capture fundamental aspects of affective processes and, importantly, to account for their multiple roles across diverse functions. On the other hand, neuroscience-informed models of emotion that describe affective processes more accurately are generally tested via simulations using rather simplified inputs; they have not been implemented on embodied machines that interact with the physical and social worlds. We hope our proposal contributes to the development of research guidelines for designing autonomous social machines in a manner that is centered on the integration between emotion and cognition.

A question this paper might raise is ‘how much human-like emotion do we want machines to have?’. Our goal is to encourage a focus on “affective processing” that is separate from the subjective experience of emotion *per se*. We propose that key features of affective processes are constitutive and inseparable from human-like intelligence, and that modeling those features is essential if we want to build autonomous social robots able to tackle real-world problems. Moreover, we argue that the process of seeking to model animal- and human-like emotion in machines following an interdisciplinary approach has the potential to unravel fundamental computational principles that may be difficult to capture through current neuroscientific methods. Further understanding those principles would help answer the question of whether their implementation in machines is ultimately desirable for human society.

## References

Arbib, M. A., & Fellous, J. M. (2004). Emotions: from brain to robot. *Trends in cognitive sciences*, 8(12), 554-561.

Anderson, A. K., & Phelps, E. A. (2001). Lesions of the human amygdala impair enhanced perception of emotionally salient events. *Nature*, 411(6835), 305-309.

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences*, 108(25), 10367-10371.

Avila-Garcia, O., & Cañamero, L. (2004). Using hormonal feedback to modulate action selection in a competitive scenario. *From animals to animats*, 8, 243-252.

Balkenius, C., Morén, J., & Winberg, S. (2009). Interactions between motivation, emotion and attention: From biology to robotics. In *Proceedings of the Ninth International Conference on Epigenetic Robotics: Modeling Cognitive Development in Robotic Systems*.

Belkaid, M., Cuperlier, N., & Gaussier, P. (2017). Emotional metacontrol of attention: Top-down modulation of sensorimotor processes in a robotic visual search task. *PloS one*, 12(9).

Belkaid, M., Cuperlier, N., & Gaussier, P. (2018). Autonomous Cognitive Robots Need Emotional Modulations: Introducing the eMODUL Model. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(1), 206-215.

Belkaid, M., Kompatsiari, K., de Tommaso, D., Zabliith, I., & Wykowska, A. (2021). *Mutual gaze with a robot affects human neural activity and delays decision-making processes. Science Robotics*, 6(58), eabc5044

Blakemore, R. L., & Vuilleumier, P. (2017). An emotional call to action: Integrating affective neuroscience in models of motor control. *Emotion Review*, 9(4), 299-309.

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International journal of human-computer studies*, 59(1-2), 119-155.

Broekens, J., & Chetouani, M. (2019). Towards transparent robot learning through tdrl-based emotional expressions. *IEEE Transactions on Affective Computing*.

Brooks, R. A. (1991). Intelligence without representation. *Artificial intelligence*, 47(1-3), 139-159.

Cañamero, L., & Gaussier, P. (2005). Emotion understanding: robots as tools and models. *Emotional Development*, 235-258.

Cañamero, L. (2019). Embodied Robot Models for Interdisciplinary Emotion Research. *IEEE Transactions on Affective Computing*.

Coppin, G. and Sander, D. (2012). Contemporary theories and concepts in the psychology of emotions. In Pelachaud, C., editor, *Emotion-Oriented Systems*, pages 1–31. Wiley Online Library.

Correia, F., Alves-Oliveira, P., Maia, N., Ribeiro, T., Petisca, S., Melo, F. S., & Paiva, A. (2016, August). Just follow the suit! trust in human-robot interactions during card game playing. In *2016 25th IEEE international symposium on robot and human interactive communication (RO-MAN)* (pp. 507-512). IEEE.

Courgeon, M., Clavel, C., Tan, N., & Martin, J. C. (2011). Front view vs. side view of facial and postural expressions of emotions in a virtual character. In *Transactions on edutainment VI* (pp. 132-143). Springer, Berlin, Heidelberg.

Courgeon, M. (2011). *Marc: modèles informatiques des émotions et de leurs expressions faciales pour l'interaction Homme-machine affective temps réel* (Doctoral dissertation, Université Paris Sud-Paris XI).

Cowen, A., Sauter, D., Tracy, J. L., & Keltner, D. (2019). Mapping the passions: Toward a high-dimensional taxonomy of emotional experience and expression. *Psychological Science in the Public Interest*, 20(1), 69-90.

Cully, A., Clune, J., Tarapore, D., & Mouret, J. B. (2015). Robots that can adapt like animals. *Nature*, 521(7553), 503-507.

Damasio, A. R., Everitt, B. J., and Bishop, D. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex [and discussion]. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 351(1346):1413–1420. 75

de Gelder, B., De Borst, A. W., & Watson, R. (2015). The perception of emotion in body expressions. *Wiley Interdisciplinary Reviews: Cognitive Science*, 6(2), 149-158.

Doncieux, S., Filliat, D., Díaz-Rodríguez, N., Hospedales, T., Duro, R., Coninx, A., ... & Sigaud, O. (2018). Open-ended learning: a conceptual framework based on representational redescription. *Frontiers in neurorobotics*, 12, 59.

Evans, D. A., Stempel, A. V., Vale, R., & Branco, T. (2019). Cognitive control of escape behaviour. *Trends in cognitive sciences*.

Frijda, N. H. (1986). *The emotions: Studies in emotion and social interaction*.

Froese, T., & Ziemke, T. (2009). Enactive artificial intelligence: Investigating the systemic organization of life and mind. *Artificial Intelligence*, 173(3-4), 466-500.

Gratch, J., & Marsella, S. (2004). A domain-independent framework for modeling emotion. *Cognitive Systems Research*, 5(4), 269-306.

Grossberg, S. (2018). Desirability, availability, credit assignment, category learning, and attention: Cognitive-emotional and working memory dynamics of orbitofrontal, ventrolateral, and dorsolateral prefrontal cortices. *Brain and Neuroscience Advances*, 2, 2398212818772179.

Henschel, A., Hortensius, R., & Cross, E. S. (2020). Social cognition in the age of human–robot interaction. *Trends in Neurosciences*, 43(6), 373-384.

Hudlicka, E. (2011). Guidelines for designing computational models of emotions. *International Journal of Synthetic Emotions (IJSE)*, 2(1), 26-79.

- Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on pattern analysis and machine intelligence*, 20(11), 1254-1259.
- Karaouzene, A., Gaussier, P., & Vidal, D. (2013, August). A robot to study the development of artwork appreciation through social interactions. In *2013 IEEE Third Joint International Conference on Development and Learning and Epigenetic Robotics (ICDL)* (pp. 1-7). IEEE.
- Karaouzene, A. (2017). *Construction sociale d'une esthétique artificielle: Berenson, un robot amateur d'art* (Doctoral dissertation, Université de Cergy Pontoise).
- Khan, I., & Cañamero, L. (2018). Modelling adaptation through social allostasis: Modulating the effects of social touch with oxytocin in embodied agents. *Multimodal Technologies and Interaction*, 2(4), 67.
- Kowalczyk, Z., & Czubenko, M. (2016). Computational approaches to modeling artificial emotion—an overview of the proposed solutions. *Frontiers in Robotics and AI*, 3, 21.
- Krichmar, J. L. (2013). A neurobotic platform to test the influence of neuromodulatory signaling on anxious and curious behavior. *Frontiers in neurobotics*, 7, 1.
- Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford University Press on Demand.
- Lewis, M., Canamero, L., & Fineberg, N. (2019). A robot model of oc-spectrum disorders: Design framework, implementation and first experiments. *Computational Psychiatry*.
- Lindquist, K. A., & Barrett, L. F. (2012). A functional architecture of the human brain: emerging insights from the science of emotion. *Trends in cognitive sciences*, 16(11), 533-540.
- Lowe, R., Almér, A., & Balkenius, C. (2019). Bridging connectionism and relational cognition through bi-directional affective-associative processing. *Open Information Science*, 3(1), 235-260.
- Man, K., & Damasio, A. (2019). Homeostasis and soft robotics in the design of feeling machines. *Nature Machine Intelligence*, 1(10), 446-452.
- Marsella, S., Gratch, J., and Petta, P. (2010). Computational models of emotion. In Scherer, K. R., Bänziger, T., and Roesch, E., editors, *A Blueprint for Affective Computing - A sourcebook and manual*, pages 21–46.
- Masuyama, N. (2016). *Quantum-inspired associative memories for incorporating emotion in a humanoid* (Doctoral dissertation, University of Malaya).
- Masuyama, N., Loo, C. K., & Seera, M. (2018). Personality affected robotic emotional model with associative memory for human-robot interaction. *Neurocomputing*, 272, 213-225.
- Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Petersen, S. (2015). Human-level control through deep reinforcement learning. *Nature*, 518(7540), 529-533.
- Moerland, T. M., Broekens, J., & Jonker, C. M. (2018). Emotion in reinforcement learning agents and robots: a survey. *Machine Learning*, 107(2), 443-480.

- Moulin-Frier, C., Fischer, T., Petit, M., Pointeau, G., Puigbo, J. Y., Pattacini, U., ... & Chang, H. J. (2017). DAC-h3: a proactive robot cognitive architecture to acquire and express knowledge about the world and the self. *IEEE Transactions on Cognitive and Developmental Systems*, 10(4), 1005-1022.
- Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex “frontal lobe” tasks: A latent variable analysis. *Cognitive Psychology*, 41(1), 49-100.
- Najafi, M., McMenamin, B. W., Simon, J. Z., & Pessoa, L. (2016). Overlapping communities reveal rich structure in large-scale brain networks during rest and task conditions. *Neuroimage*, 135, 92-106.
- Neftci, E. O., & Averbeck, B. B. (2019). Reinforcement learning in artificial and biological systems. *Nature Machine Intelligence*, 1(3), 133-143.
- Ochs, M., & Blache, P. (2016). Virtual reality for training doctors to break bad news. In *European Conference on Technology Enhanced Learning* (pp. 466-471). Springer, Cham.
- Ojha, S., Vitale, J., & Williams, M. A. (2021). Computational emotion models: a thematic review. *International Journal of Social Robotics*, 13, 1253-1279.
- O'Regan, J. K. and Noë, A. (2001). What it is like to see: A sensorimotor theory of perceptual experience. *Synthese*, 129(1):79–103.
- Pelachaud, C. (2009). Modelling multimodal expression of emotion in a virtual agent. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1535), 3539-3548.
- Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews Neuroscience*, 9(2):148–158.
- Pessoa, L. (2013). *The cognitive-emotional brain: From interactions to integration*. MIT press.
- Pessoa, L. (2017). A network model of the emotional brain. *Trends in Cognitive Sciences*, 21(5), 357-371.
- Pfeifer, R., Lungarella, M., & Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. *Science*, 318(5853), 1088-1093.
- Phelps, E. A., & LeDoux, J. E. (2005). Contributions of the amygdala to emotion processing: from animal models to human behavior. *Neuron*, 48(2), 175-187.
- Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological review*, 110(1), 145.
- Sagar, M., Seymour, M., & Henderson, A. (2016). Creating connection with autonomous facial animation. *Communications of the ACM*, 59(12), 82-91.
- Sánchez-López, Y., & Cerezo, E. (2019). Designing emotional BDI agents: good practices and open questions. *The Knowledge Engineering Review*, 34, e26.

Sloman, A., & Croucher, M. (1981). Why robots will have emotions. In *Proceedings of the 7th international joint conference on Artificial intelligence*

Smith, G. M., & Carette, J. (2022). What lies beneath—A survey of affective theory use in computational models of emotion. *IEEE Transactions on Affective Computing*, 13(4), 1793-1812.

Sporns, O. (2010). *Networks of the Brain*. MIT press.

Tovote, P., Fadok, J. P., & Lüthi, A. (2015). Neuronal circuits for fear and anxiety. *Nature Reviews Neuroscience*, 16(6), 317-331.

Varela, F. J., Evan, T., and Eleanor, R. (1992). *The embodied mind: cognitive science and human experience*. MIT Press.

Wiese, E., Metta, G., & Wykowska, A. (2017). Robots as intentional agents: using neuroscientific methods to make robots appear more social. *Frontiers in psychology*, 8, 1663.

Yacoubi, A., & Sabouret, N. (2018). TEATIME: A Formal Model of Action Tendencies in Conversational Agents. In *ICAART* (2) (pp. 143-153).