Cogn Comput (2014) 6:351–375
DOI 10.1007/s12559-013-9244-x

Development of Computational Models of Emotions for Autonomous Agents: A Review

Luis-Felipe Rodríguez · Félix Ramos

Received: 7 June 2013 / Accepted: 30 December 2013 / Published online: 12 January 2014

Abstract It has been recognized that human behavior is an observable consequence of the interactions between cognitive and affective functions. This perception has motivated the study of human emotions in disciplines such as psychology and neuroscience and led to the formulation of a number of theories and models that attempt to explain the mechanisms underlying this human process. In the field of artificial intelligence, these theoretical findings have posed a series of challenges in the development of autonomous agents (AAs) capable of exhibiting very believable and human-like behaviors. One of these challenges is the design and implementation of computational models of emotions (CMEs), which are software systems designed to provide AAs with proper mechanisms for the processing of emotional information, elicitation of synthetic emotions, and generation of emotional behaviors. In this paper, we review this type of computational model from the perspective of their development. Particularly, we investigate five design aspects that influence their development process: *theoretical foundations, operating cycle, interaction between cognition and emotion, architectural design*, and *role in cognitive agent architectures*. We provide discussions about key issues and challenges in the development of CMEs and suggest research that may lead to more robust and flexible designs for this type of computational model.

L.-F. Rodríguez (✉)
Department of Computer Science, Instituto Tecnológico de Sonora, Sonora, Mexico
e-mail: lrodrigue@gdl.cinvestav.mx

F. Ramos
Department of Computer Science, Cinvestav, Guadalajara, Mexico
e-mail: framos@gdl.cinvestav.mx

Keywords Emotions · Computational modeling · Autonomous agents · Development process

Introduction

Emotions influence human behavior in several ways. Internally, the emotional significance of perceived stimuli modulates the normal operation of cognitive processes such as perception, attention, and decision-making [1–5]. This affective regulation allows individuals to develop emotionally driven responses as well as to concentrate their internal resources on the most salient elements in the environment. Externally, the emotional state of individuals determines the configuration of their facial expressions, body postures, and voice intonation when interacting with others, revealing, via nonverbal behavior, their internal affective condition, and attitudes toward situations, objects, and people [6, 7].

The process of human emotions has been extensively researched in multiple disciplines from a variety of perspectives and at different levels of abstraction [8–10]. Researchers have focused on studying the aspects related to the emotional experience induced by the assessment of emotional stimuli [11], the antecedents and consequents of emotions such as bodily and behavioral reactions [5, 12, 13], and the brain functions, brain structures, and neural pathways involved in this process [1, 2, 14]. This multidisciplinary effort has resulted in the formulation of a great volume of theories and models that attempt to explain the several aspects of human emotions. On the one hand, theories of emotions emphasize the importance of this human function for the development of rational behaviors in humans. On the other hand, these suggest that the underlying architectures of artificial autonomous agents (AAs) should embody mechanisms for affective processing in order to allow these intelligent systems to display very believable behaviors that resemble those of humans.

In the field of AI, a variety of computational models of emotions (CMEs) have been developed to provide AAs with affective processing. These are software systems designed to synthesize the operations and architectures of some components that constitute the process of human emotions [15–17]. In general, CMEs include mechanisms for the evaluation of emotional stimuli, the elicitation of emotions, and the generation of emotional responses. In this manner, these computational models endow AAs with abilities for the recognition of emotions from human users and artificial agents, the simulation and expression of emotional feelings, and the execution of emotional responses. The importance of CMEs for AAs has been illustrated elsewhere [18–25]. For instance, Scheutz [26] suggests that emotion processing is crucial for the agent's action selection, adaptation, social regulation, sensory integration, motivation, learning, and strategic processing.

The design and development process of this type of computational model has a dual nature: a computational aspect and a theoretical one. Whereas their *computational basis* helps ensure the quality and adequacy of the algorithms implemented for the processing of emotional information [15, 27], their *theoretical foundations* help to devise, compose, and validate the internal processes, external behaviors, and underlying architectures that these computational models incorporate [16, 20, 24]. However, the volume of theoretical models suitable for providing a well-defined basis to CMEs and the diversity of computational techniques and strategies capable of assisting throughout their development process are very extensive and heterogeneous. Furthermore, although the literature reports a great number of methodologies for the development of conventional software systems, there is a lack of well-established methodologies to guide the development of CMEs [17, 25, 28].

The above are some of the issues behind the notable variability among contemporary CMEs. In fact, it seems that this lack of methodologies has led to a situation in which specific aspects of CMEs such as their target application or theoretical foundation drive their development process almost entirely, disregarding a more comprehensive approach that could promote more robust, integrative, and flexible designs. Furthermore, these issues have also hindered the creation of appropriate frameworks for assessing and comparing computational models of this type.

In this context, an inquiry into the development process of contemporary CMEs can help to better understand the following issues:

- the assumptions and motivations underlying the architectural designs and applications of this type of computational model,
- the design decisions that arise throughout their development process,
- the basic requirements driving their development, the nature of these requirements, and their interrelationships,
- the aspects that have been ignored in their development but that are recognized as crucial in the process of human emotions, and
- the common phases and activities that make up their development process.

These and other particular issues aside, we believe that the analysis of some major design aspects of CMEs may lead to a better understanding of their development process, contribute to elaborating appropriate methodologies to assist their development, and help identify crucial challenges in this regard, thus suggesting research that could lead to more robust and flexible CMEs capable of meeting the increasing affective requirements of contemporary human-centered applications of AAs.

In this paper, we present a review of CMEs from the perspective of their development. Particularly, we investigate the following five design aspects: *theoretical foundations, operating cycle, interaction between cognition and emotion, architectural design*, and *role in cognitive agent architectures*. The main intention of this review is neither to provide a comprehensive list of CMEs reported in the literature nor to formulate direct comparisons between them. This review is intended to study aspects of the development and applications of this type of computational model as well as to discuss key challenges and issues in this regard. Nevertheless, in order to illustrate the design aspects of CMEs studied in this paper, we include descriptions of particular instances of CMEs developed over the last two decades in the domain of artificial intelligence. We focus on those models frequently cited in the literature and explained in detail by their corresponding authors.

This review is organized as follows. First, we introduce the five design aspects that guide our study of CMEs. Then, we devote five sections to review these design aspects in detail. Finally, we discuss and analyze CMEs from the perspective of their design and development process.

Design Aspects of CMEs

The development of CMEs involves a variety of design decisions that must be addressed in order to achieve a model that imitates certain facets of the human emotion process and that meets a series of user and system requirements. These design decisions have to do with different aspects of CMEs such as their theoretical foundations, their underlying architecture, and the computational techniques to be used in their implementation. As mentioned above, there is a lack of well-defined methodologies that help to classify, systematize, and properly deal with these types of design aspects and decisions. We organize our study of CMEs on the basis of five design aspects that have extensively influenced the development process of this type of computational model:

- *Theoretical foundations*: Researchers usually follow particular theories and models of emotion in order to get plausible explanations about the emotional aspects being modeled. Theories of emotions help establish the architectural and functional requirements of CMEs in accordance with the process of human emotions and provide explanations of key aspects related to this human function. Although many theories and models have been reported in the literature, they explain the process of human emotions from different perspectives and at different levels of abstraction. Moreover, the research community frequently presents very different and contrasting positions about certain emotional aspects. In this context, an inquiry into the theoretical foundations of contemporary CMEs becomes important to identify the most influential theories of emotions in their development process as well as to understand how researchers interpret such theories and how they translate them into computational procedures and architectures.
- *Operating cycle*: Although some CMEs implement very specific facets of the human emotion process, most models are concerned with implementations that comprise a series of phases that supposedly constitute the emotion process. However, different theoretical models describe this process in very different ways. These varied perceptions have in turn led researchers to summarize and implement the operating cycle of CMEs in very distinctive ways. In particular, the interrelationship of the phases included in this operating cycle varies across CMEs, as do their underlying mechanisms, assumptions, objectives, and processes. In this context, a study of the operating cycle of contemporary CMEs may help to shed light on how the emotion process is abstracted and implemented in this type of computational model.
- *Interaction between cognition and emotion*: Multidisciplinary evidence suggests that human emotions are not an isolated phenomenon. The emotion process is highly interrelated with other cognitive processes such as perception, memory, decision-making, and personality. Whereas cognitive processes generate cognitive information indispensable for a consistent evaluation of emotional stimuli, the emotion process gives rise to emotional signals that influence the normal operation of cognitive systems underlying human behavior. This evidence has been recognized by researchers and widely considered in the design of CMEs. Nevertheless, the interrelationships between cognitive processes and emotional processes implemented in CMEs have been approached in very diverse ways. In this context, a study of CMEs from this perspective may help to identify cognitive processes commonly considered by researchers as well as their importance and role in CMEs, understand how these processes and their interactions with emotional mechanisms are implemented, and recognize cognitive functions that are important for the emotion process but are not considered in the design of CMEs.
- *Architectural design*: Given the interrelationship between cognitive and emotional processes, CMEs are often implemented to be included in or as part of cognitive frameworks such as cognitive agent architectures. Within these frameworks, CMEs provide adequate mechanisms for the evaluation of emotional inputs, the elicitation of synthetic emotions, and the generation of emotional responses. This aspect has influence on the architectural design of CMEs. For instance, CMEs developed within cognitive frameworks are required to meet specific constraints imposed by these cognitive models. On the other hand, CMEs developed as separate models are more focused on creating appropriate interfaces for the exchange of affective and cognitive data. In this context, a review of CMEs from this perspective may help to explain the architectural designs of contemporary CMEs as well as the practices for integrating cognition and emotion in cognitive agent architectures.
- *Role in cognitive agent architectures*: This is one of the main aspects that place restrictions on the establishment of design requirements for CMEs. The particular role that a CME will play in an agent architecture widely influences its architectural and operational design. Although CMEs are in general developed to endow AAs with mechanisms that contribute to the development of intelligent, flexible, and social behavior, most CMEs are designed to meet very specific requirements. For instance, CMEs developed to be included in conversational AAs should implement mechanisms to generate emotional signals useful for improving the conversational abilities of these intelligent systems, their verbal and nonverbal expressions, and their selection of dialog and linguistic style strategies. In this context, reviewing the application domain of emotional AAs becomes essential to understanding the various roles of CMEs as well as their impact on the design and development process of this type of computational model.

As we show in the following sections, these five aspects have extensively influenced the way contemporary CMEs are designed and implemented. Moreover, they are behind the design decisions that researchers face throughout the development of this type of computational model. At this point, however, it is important to mention that there are several other aspects involved in the design of CMEs and that studying them may also contribute to a better understanding of the development process of CMEs and of the design decisions involved. These aspects range from the philosophical and mathematical basis of some CMEs to the AI techniques used for implementing their underlying mechanisms. In the present review, we have disregarded these and other design aspects and focused on the five described above. We believe that the latter allow us to provide a consistent panorama of the development process of CMEs, to identify the main assumptions and motivations underlying their architectural and functional designs, and to provide information relevant to the formulation of well-structured methodologies for the development of this type of computational model. Moreover, these five design aspects allow us to analyze particular characteristics of CMEs that are important from the perspective of their development and application.

Theoretical Foundations

The research of human emotions in multiple disciplines has led to the formulation of a considerable number of theories and models that attempt to explain the mechanisms underlying this human function [1, 5, 9, 29–33]. These theories and models are the result of analyses of behavioral and biological data collected from experiments with humans and animals. As mentioned above, theories of emotion emphasize the importance of affective processing for the development of rational behavior in humans and suggest that intelligent AAs should include emotional processing in order to be able to show very believable, coherent, and human-like behavior [17, 34, 35].

Given that CMEs are designed to synthesize some aspects of the actual process of human emotions, their development process often adheres to certain theories and models that try to explain this human function. Although theories of emotion from various disciplines such as cognitive and affective neuroscience have contributed to the design and development of CMEs [36, 37], the most influential theories have been those proposed in the field of psychology [16, 24, 38–40]. The underlying architectures and mechanisms of CMEs usually reflect the main assumptions considered in psychological theory.

In this section, we examine the most notable theoretical approaches that have influenced the development of CMEs: *appraisal theories of emotion, dimensional theories of emotion*, and *hierarchical theories of emotion*. We review them from the perspective of their application. In addition, we present details of the internal mechanisms and processes of particular instances of CMEs in order to explain how theories of emotions are translated into computational procedures.

Appraisal Theories of Emotion

Appraisal theories explain the elicitation and differentiation of emotions on the basis of the relationship between individuals and their environment [12, 41, 42]. Appraisal theories suggest that emotions arise from the evaluation of situations, objects, and agents existing in the environment that directly or indirectly impact the individual's goals, plans, and beliefs. This assessment of the *individual–environment relationship* is carried out using a series of appraisal dimensions such as *pleasantness, goal conduciveness, suddenness, controllability*, and *self-responsibility*. Appraisal dimensions can be seen as measurement variables that help to extract and derive information about the influences between the agent and its environment [41]. Although the appraisal variables included in theories of emotion vary in number and type [13], they must be sufficient and appropriate to collect the necessary information for the elicitation and differentiation of emotions. According to the appraisal process, after the agent–environment relationship is evaluated using this type of variable, emotions can be derived. The particular type of emotion elicited depends on the specific configuration of values formed by the results in all appraisal dimensions. Furthermore, emotional reactions can be explained based on the assessment of the individual–environment relationship. For example, Frijda [8] proposes that there are different states of action readiness (dispositions or indispositions to face the appraised situation) that are elicited by different events appraised as emotionally relevant, which can take the form of approaching, protection, avoidance, attending, disinterest, apathy, and others.

Several particular instances of the appraisal theory have been proposed [12, 13, 41–43]. The OCC appraisal model introduced by Ortony et al. [12] is one of the most implemented in CMEs [15, 16, 25]. This model presents a taxonomy of emotions based on a systematic and structured hierarchy of their eliciting conditions. Ortony et al. [12] consider emotions as valenced reactions (positives and negatives) elicited by the aspects of objects (likes and dislikes), the actions of agents (pleasure and displeasure), and the consequences of events (approval and disapproval). In this manner, their taxonomy encompasses 22 emotions that are triggered according to their eliciting conditions and their association with the agent, object, or situation that cause them.

Another notable representative of this type of theory is Scherer's [13] sequential check model, which focuses on the processing level of the appraisals. This approach establishes the following four sequential phases in which a series of stimulus evaluation checks (SECs) assess the agent–environment relationship:

1. *Relevance* focuses on evaluating how relevant an event is for the agent and how it affects the agent's social reference group. The SECs applied in this phase are novelty (suddenness, familiarity, and predictability), intrinsic pleasantness, and goal relevance.
2. *Implication* focuses on the implications of an event and how the agent's well-being and goals are affected. The SECs applied are causality agent/motive, outcome probability, discrepancy from expectation, conduciveness, and urgency.
3. *Coping* focuses on how well the agent can cope with an event or can adjust to the consequences. The SECs applied in this phase are control, power, and adjustment.
4. *Normative significance* focuses on the significance of an event with respect to the agent's self-concept and social norms. The SECs applied are compatible with internal and external standards.

In this model, for reasons of system economy and logical dependencies, these four phases are processed in sequence and follow a fixed order. Scherer [13] argues that, for example, it is not worth processing stimuli that are not relevant to the agent, and therefore, a relevance assessment must take place at the beginning of the process.

A considerable number of CMEs have been developed on the basis of the appraisal theory (see Table 1). EMotion and Adaptation (EMA) [38] is a CME whose design is highly influenced by this type of theory. In this model, the individual–environment relationship is represented by a structure called *the causal interpretation* of the agent, which contains, among other things, explicit representations of the current state of the environment as well as the agent's beliefs, desires, and intentions. This structure is constructed and updated by perceptual and inferential cognitive processes and evaluated by appraisal processes that continuously identify and characterize every significant event in terms of a series of appraisal variables. These appraisal variables are further organized in data structures called *appraisal frames*. According to the specific configuration of the values in these appraisal variables, each frame is labeled with a specific type of emotion and its associated intensity. Finally, in order to generate the agent's affective state, all active appraisal frames are mood-adjusted, and the one resulting with the highest intensity will determine the agent's responses and emotional state [38]. Figure 1 shows an abstraction of the architecture of EMA.

Marinier et al. [52] propose a computational model that combines Scherer's multi-level appraisal theory [13] and Newell's PEACTIDM theory [53], which specifies a cycle consisting of eight cognitive functions aimed at producing cognitive behavior. During this cycle, a series of appraisal processes are distributed and operate in order to extract and derive emotional information as shown in Fig. 2. The main assumption in this integrative model is that the processes in the PEACTIDM model generate the necessary information for the elicitation of emotions. This information is evaluated using a series of appraisal variables that are organized in appraisal frames (similarly to EMA). In this model, the frame with the most extreme values along the PEACTIDM cycle is attended and processed, and eventually, it will determine the agent's active emotion and influence the action selection process. To illustrate this procedure, we can consider the role of the *encode* component in the PEACTIDM cycle. The output of this component is an evaluation of all perceived stimuli in terms of their relevance, which becomes essential for the operation of subsequent cognitive functions and the generation of emotions [54].

Table 1 includes other various instances of CMEs whose development was influenced by the appraisal theory. The operational assumptions of these models are very similar to those described for EMA and PEACTIDM. In general, they evaluate the significance of the environment to the agent with respect to its goals and other factors and then generate affective states and emotionally driven responses.

Dimensional Theories of Emotion

The main contribution of dimensional theories to CMEs is that they provide a suitable framework for representing emotions from a structural perspective [30, 50]. This psychological approach establishes that emotions can be differentiated on the basis of dimensional parameters, such as *arousal* and *valence*. Russell [55] proposes a two-dimensional framework consisting of pleasantness (pleasure/displeasure) and activation (arousal/non-arousal) to characterize a variety of affective phenomena such as emotions, mood, and feelings (see Fig. 3). In this model, in order to generate emotions, perceived events are evaluated and represented in terms of their level of pleasantness and activation and situated within a two-dimensional space in which a number of emotion labels have been previously identified. In this manner, the particular position of the events in the two-dimensional space defines the emotion to be derived. Russell [55] suggests the concept of *core affect* to explain and represent the combination of these two dimensions. The core affect is considered the essence of all affective experience; it is defined as a consciously accessible neurophysiological state that continuously represents the feelings generated by the assessment of the individual–environment relationship. Furthermore, Russell's model comprises other

Table 1 CMEs inspired by appraisal theories

Model	Theoretical foundations	Appraisal dimensions	Emotions
EMA [38]	Appraisal theory by Smith and Lazarus [44]	Relevance, perspective, desirability, likelihood, expectedness, causal attribution, controllability, and changeability	Surprise, hope, joy, fear, sadness, anger, and guilt
Flame [45]	Appraisal theory by Ortony et al. [12] and Roseman et al. [42]. Inhibition model by Bolles and Fanselow [46]	Desirability, expectation, causal attribution, and standards (or social norms)	Joy, sad, disappointment, relief, hope, fear, pride, shame, reproach, and admiration. *Complex emotions*: Anger (sad + reproach), gratitude (joy + admiration), gratification (joy + pride), and remorse (sad + shame)
Mamid [47]	Appraisal theories such as those by Lazarus [43] and Smith and Kirby [48]. Personality models such as the five factor model [49]	*Universal*: novelty, unexpectedness, intensity, threat level, desirability. *Individual and context-dependent*: individual history, experience, and expectation and goal congruence	Anxiety/fear, anger/aggression, negative affect (sadness, distress), and positive affect (joy, happiness)
Alma [39]	Appraisal model by Ortony et al. [12], five factor model of personality [49], and PAD temperament space by Mehrabian [50]	Desirability of events, praiseworthiness of actions, appealingness of objects, liking of objects, likelihood of an event occurs, and realization that an event has occurred	Admiration, anger, disliking, disappointment, distress, fear, fears confirmed, gloating, gratification, gratitude, happy for, hate, hope, joy, liking, love, pity pride, relief, remorse, reproach, resentment, satisfaction, shame
Cathexis [37]	Diverse psychological [42, 51] and neuropsychological [1] theories	The model does not report used appraisal dimensions but states that they are based on Roseman et al. [42]	*Primary emotions*: anger, fear, sadness/distress, enjoyment/happiness, disgust, and surprise. This model generates *secondary emotions* but does not provide an explicit model for the labeling of them
PEACTIDM [52]	Appraisal theory by Scherer [13] and physiological concepts of feelings by Damasio [1]	Suddenness, predictability, goal relevance, intrinsic pleasantness, outcome probability, causal agent, causal motive, discrepancy from expectation, conduciveness, control, and power	This model implements the model by Scherer [13] for the mapping of appraisal dimension values to specific model emotions
WASABI [36]	Appraisal theory by Scherer [13], PAD space by Mehrabian [50], and physiological concepts by Damasio [1]	Intrinsic pleasantness, expectation deviation, goal conduciveness, dominance, causal (mis) attribution, and coping	*Primary emotions*: angry, annoyed, bored, concentrated, depressed, fearful, happy, sad, surprised. *Secondary emotions*: hope, fears confirmed, relief

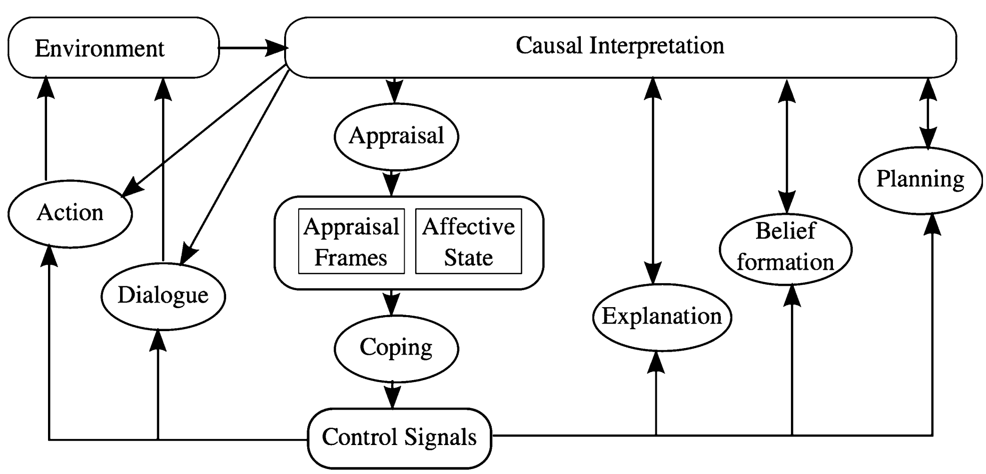

Fig. 1 Abstraction of the EMA architecture [38]

aspects related to the core affect, such as affect regulation, affective quality, and attributed affect, and considers emotions as *emotional episodes* that consist of causative events, including the antecedent event, the core affect, attributions, psychological and expressive changes, subjective conscious experiences, and emotion regulation [56, 57].

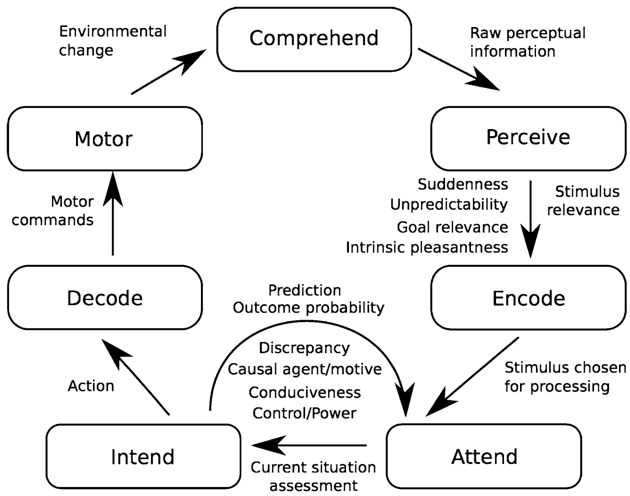

Fig. 2 The PEACTIDM architecture [52]

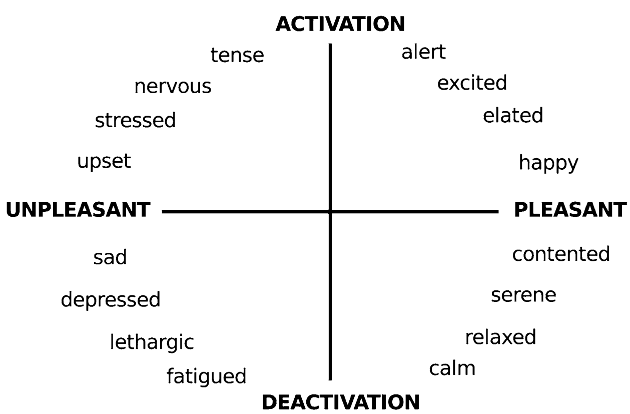

Fig. 3 Two-dimensional space for the representation of emotions [57]

Another instance of this psychological approach is the three-dimensional framework proposed by Russell and Mehrabian [58]. This model describes emotions based on their level of pleasantness, arousal, and dominance. In this model, known as the PAD model, a series of emotions are also identified within a three-dimensional space formed by the three mentioned dimensions. For example, happiness is located at (P = .81, A = .51, D = .46) and anger at (P = −.51, A = .59, and D = .25). In this manner, when perceived events are evaluated in terms of the PAD dimensions, they can be mapped into the PAD space in order to trigger a corresponding emotion. Mehrabian [50] employs the PAD model to additionally represent temperament scales, which makes it possible to define and describe personality types. In this context, points in the PAD space determine individual traits, regions define personality types, and lines that cross the intersection of the axes define particular dimensions of personality. Furthermore, by separating each axis into positive and negative, the eight resulting regions in the PAD space can be labeled as follows: +P+A+D exuberant, −P−A−D bored, +P+A−D dependent, −P−A+D disdainful, +P−A+D relaxed, −P+A−D anxious, +P−A−D docile, and −P+A+D hostile [50].

Dimensional theories have been implemented in CMEs to characterize emotional and mood states [36, 39, 59]. WASABI Affect Simulation for Agents with Believable Interactivity (WASABI) is a computational model that takes information derived from appraisal processes as inputs for the PAD space in order to represent and elicit particular emotions [36, 60]. The WASABI model considers nine basic emotions and three non-basic emotions. While the former category of emotions is represented by points in the PAD space, the latter category is represented by regions in the high and low dominance planes. Gebhard [39] implements the PAD temperament model in A Layered Model of Affect (Alma) to simulate the dynamics of mood states in conversational AAs. This computational model takes the temperament labels corresponding to the eight octants in the PAD space to determine particular mood states, which are further categorized as slightly, moderate, and fully. To calculate these mood values, the distance between the origin point in the PAD space and the point that represents the current mood is considered (see Sect. 5.2). In this way, if the agent's mood is represented by a point located at 0.25 of pleasure, −0.18 of arousal, and 0.12 of dominance, the model will determine the mood state of the AA as slightly relaxed [39].

Hierarchical Theories of Emotion

The main assumption of hierarchical theories is that there is a small set of basic, primary or fundamental emotions [1, 61], which have an evolutionary basis and are innate and instinctive. In contrast to more complex types of emotions, the eliciting conditions, expressive signals, and behavior patterns of basic emotions have been extensively investigated and therefore identified [30, 62]. Moreover, primary emotions have been studied at different levels of abstraction in various disciplines. For example, at a low level, the neurophysiological and anatomical basis of some particular instances such as fear have been explored and explained. Similarly, at a higher level, basic emotions have been considered as basic psychological building blocks that enable the construction of more complex emotions [1, 63, 64].

Although the most accepted group of basic emotions is that established by Ekman [62], the number and description of these emotions vary among theories and models (see Table 2). Nevertheless, according to Ekman, the following aspects distinguish primary emotions from one another as well as from other affective phenomena:

1. Distinctive universal signals.
2. Distinctive physiology.

Table 2 Basic emotions in different theoretical models [64]

Model	Basic emotions
Eckman [65]	Anger, disgust, joy, fear, sadness, and surprise
Izard [66]	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, and surprise
Oatley and Johnson-Laird [67]	Anger, disgust, anxiety, happiness, and sadness
Tomkins [68]	Anger, interest, contempt, disgust, distress, fear, joy, shame, and surprise

3. Automatic appraisal.
4. Distinctive universals in antecedent events.
5. Distinctive appearance developmentally.
6. Presence in other primates.
7. Quick onset.
8. Brief duration.
9. Unbidden occurrence.
10. Distinctive thoughts, memories images.
11. Distinctive subjective experience.

According to most theorists, the parallel elicitation of primary emotions leads to the generation of more complex phenomena, recognized as *secondary* or *non-basic* emotions [63]. Instances of this class are embarrassment, empathy, guilt, shame, and pride. However, although most researchers agree that secondary emotions are derived from the basic ones by diverse combinatorial methods (e.g., joy and fear produces guilt [64]), others consider that they follow basic emotions, but their composition is totally independent of them [63]. Moreover, a list of secondary emotions that is well accepted among theorists has not been established. In contrast to basic emotions, secondary emotions depend on more cognitive processing. In this manner, instead of contributing to the generation of fast reactions (essential for survival purposes), this type of affective phenomena promotes appropriate reactions in social situations, where many environmental factors are involved. In addition, it is recognized that the mechanisms associated with their elicitation process are established through experience, and that the expressions and behavior patterns that they generate are highly related to the individual's culture and educational development [62, 63].

A particular instance of this psychological approach is the model proposed by Damasio [69], which divides emotions into three general categories: *background emotions, primary emotions*, and *social emotions*. The first category is supposed to be generated by simple regulatory processes in terms of *state of being* and has little influence on the behavior of the individual. For the remaining categories, Damasio provides explanations similar to those given above for basic and non-basic emotions. However, he further proposes *a nesting principle* to explain how complex emotions are composed of more simple emotions, which suggests that background emotions are the basic building blocks of primary emotions and that primary emotions are basic building blocks of the social ones [69].

Hierarchical theories of emotions have influenced the development of several CMEs [36, 37, 45]. For example, Cathexis [37] adopts the main assumption of these theories to explain the simultaneous activation of various emotions. In this model, basic emotions are represented by individual systems (also called protospecialists [70]) that are activated when certain internal and external conditions are met. Because more than one system can be activated at the same time, secondary emotions arise as a mixture of all triggered basic emotions. WASABI [36] emphasizes the idea that secondary emotions depend on more cognitive processing, as well as the fact that primary emotions have well-defined patterns of behavior and expressions [36]. Regarding the first aspect, while the elicitation of primary emotions is directly determined by the results of appraisal processes, the elicitation of secondary emotions depends on cognitive processes that re-evaluate active and previously elicited primary emotions; with respect to the second aspect, each elicited basic emotion is associated with particular predefined facial expressions (based on Ekman's model [71]) that are implemented as automatic responses.

This concludes our analysis of major theories of emotion that have influenced the development of CMEs for AAs. In the next section, we review the operating cycle implemented in this type of computational model.

Operating Cycle

At the highest level, a CME can be abstracted as a component that transforms the stimuli perceived by an agent into emotional information. This information is then required to adjust the agent's emotional state, produce emotional reactions, and induce a variety of changes in its cognitive and affective functions [15, 16]. Moreover, the degree of such emotional influence may depend on the level of emotional significance of the stimuli perceived. However, given that CMEs are designed to meet a series of requirements and restrictions imposed by the actual functioning of human emotions (in addition to user and system requirements), their overall operation depends on a number of complicated and intertwined internal processes. Some of the requirements that researchers may consider in the design of CMEs are the following [29, 72]:

1. Each stimulus perceived by an agent has distinctive emotional characteristics that affect in some way the agent's emotional state.

2. The agent's verbal and nonverbal behavior should be consistent with its current emotional state.
3. The agent's emotions have an associated level of intensity, which decays over time.
4. Several affective and cognitive functions participate in the processing and generation of the agent's emotions.

In order to simplify and systematize the development of CMEs whose internal workings comply with these and other several restrictions, convenient abstractions of their *internal processes and operations* have been considered. Marsella et al. [16] recently presented a study that shows how the variability and complexity of the internal operations, assumptions, behaviors, and other aspects of CMEs can be systematically reduced and organized in a small set of functional modules. They proposed a *component model view of computational appraisal models* that organizes CMEs' internal operations in well-defined and sequential component models, including the appraisal and affect derivation component model, the affect intensity component model, and the affect consequent component model. These components are proposed as those that constitute the operating cycle of CMEs developed on the basis of the appraisal theory.

In order to analyze the internal workings of CMEs, in the following sections, we examine the operating cycle that these computational models implement. Inspired by the model of Marsella et al. [16], we suggest a theoretical framework that summarizes this cycle in three sequential phases: *emotional evaluation of stimuli, elicitation of synthetic emotions*, and *generation of emotionally driven responses* [73]. We first describe and provide details of each phase and then explain how some CMEs implement them.

The Phases of the Operating Cycle

In this section, we briefly describe the operating cycle of CMEs based on the framework suggested above. We discuss the main assumptions, objectives, processes, mechanisms, and other important aspects of each phase comprised in this operating cycle. Although the phases described here may not fully correspond to those considered in the operating cycle implemented by all CMEs, when these computational models implement any of these phases, they usually adhere to the descriptions given below.

The processes involved in the first phase, *emotional evaluation of stimuli*, are mainly concerned with the identification and interpretation of emotional stimuli. In this phase, the inputs are representations of the external and internal stimuli perceived by the agent, and the main output is an evaluation of these stimuli on the basis of their emotional significance. Since not all objects, agents, and situations in the environment may be emotionally significant to the agent, a recognition process should be carried out in order to determine the emotional degree of each stimulus [41]. As suggested by appraisal theories, most CMEs use appraisal variables and appraisal processes to determine the emotional significance of the agent's environment. The main purpose of the second phase, *elicitation of emotions*, is to decide the agent's emotional state on the basis of the information provided by the previous phase. In order to accomplish this, the process responsible for the elicitation of emotions also takes into account the operations and results of additional affective and cognitive phenomena, such as the agent's previous affective state, its personality, short- and long-term goals, and beliefs [72, 74]. In this context, adequate internal representations of these types of intermediate states, results, and processes are needed. Also, it is necessary to determine how they should interact in order to derive coherent emotions, their associated intensity, and ultimately, the agent's current affective state. In this phase, dimensional theories are often considered since they offer an adequate framework to derive emotions on the basis of the evaluation of the agent's environment. In the last phase, *generation of emotionally driven responses*, it is necessary to determine how elicited emotions impact the agent's internal and external condition. Particularly, emotions modulate the agent's cognitive and affective processes, leading to changes in its verbal and nonverbal behavior [1, 2, 5]. Therefore, at this stage, it is essential to decide what processes are influenced by the CMEs, the level of influence on such processes, and the type of emotional representations required by each of them. Hierarchical theories may be useful in this phase since they provide explanations of how certain emotions may induce specific patterns of behaviors and expressions.

Implementing the Operating Cycle

In this section, we explain how the operating cycle presented above has been implemented in particular instances of CMEs. Particularly, we focus on Cathexis [37], Flame [45], Alma [39], and MAMID [47]. The descriptions given are also intended to show how CMEs understand the theoretical models on which they are based and how these theories are ultimately implemented in order to contribute to meeting the functional requirements established for CMEs.

Cathexis

Cathexis [37] is a CME that considers two types of emotion elicitors: *cognitive* and *non-cognitive* (neural, sensory-motor, and motivational). These elicitors allow the agent to evaluate both internal and external stimuli. The

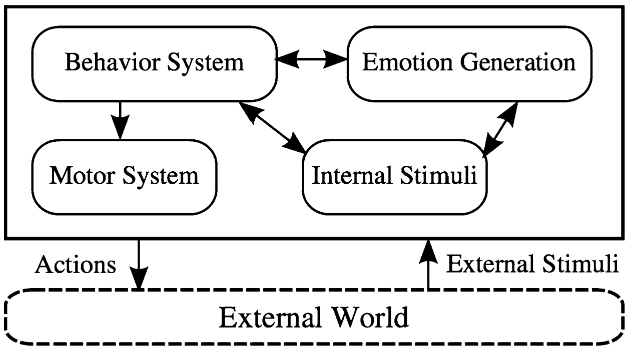

Fig. 4 The architecture of Cathexis [37]

architecture of Cathexis includes two components (the *emotion generation* and the *behavior system*) that focus on the evaluation of emotional information, generation of emotions, and development of emotional behaviors (see Fig. 4). The *emotion generation* module incorporates a network of *emotional systems* that represent groups of basic emotions. In order to elicit a particular emotion, a series of sensors that monitor external and internal events are included in each of these systems. In this manner, when the appropriate conditions in an emotional system are met, the corresponding emotions are derived and their associated intensity is calculated. In this model, multiple emotional systems can be activated simultaneously, which results in the generation of multiple basic emotions that lead to the derivation of secondary emotions [75]. The *behavior system* incorporates a network of predefined behaviors that are selected and executed according to the agent's affective state (and other internal and external factors). Each behavior in these networks is composed of two parts: the *expressive or motor component* and the *experiential component*. The mechanisms included in the first component are responsible for the generation of expressions in the agent, including facial expressions, body postures, and vocal expressions. The mechanisms in the second component are in charge of reflecting the effects of emotions on the agent's actions and cognitions, such as the agent's motivations, action tendencies, perceptual biases, and other cognitive systems [37, 75, 76].

Flame

Fuzzy Logic Adaptive Model of Emotions (flame) [45] is a CME that emphasizes memory systems and learning processes as the basis for the dynamics of emotions. In this model, a *decision-making* component is in charge of capturing the stimuli from the environment and sending them directly to an *emotional* and a *learning* component. The emotional component operates through a sequence of four processes to evaluate the external stimuli and generate

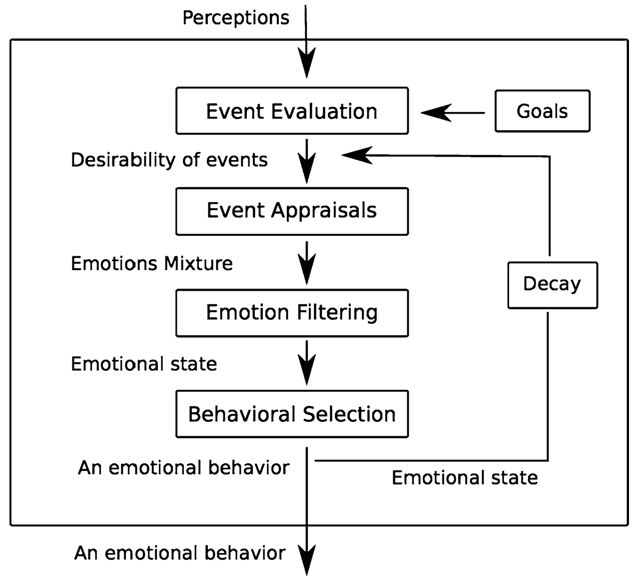

Fig. 5 The emotional component in flame [45]

emotional behavior: the *event evaluation*, the *event appraisals*, the *emotion filtering*, and the *behavior selection* (see Fig. 5). In the first phase, the agent's goals that are affected by the perceived events are identified. Then, according to the degree of such impact, the desirability of each event is determined. Using this information and other data received from the learning component in the second process, emotions are triggered and their associated intensity is calculated. In the third process, based on the current agent's motivational and mood conditions, emotions are filtered and a coherent emotional state is generated. Finally, on the basis of this information, an emotional behavior is decided [45, 77]. The resulting emotional behavior is then returned to the decision-making component, which according to the current situation, the agent's mood, the emotional state, and the received emotional behavior, selects the next action to perform [45].

Alma

A Layered Model of Affect (Alma) [39] is a CME designed to endow virtual humans with emotions, mood, and personality. In Alma, the core module in charge of processing emotions is the *emotion engine*. This component generates and updates emotions based on the 24 instances shown in Table 1. In order to elicit such emotions, each emotion has a set of particular emotion-eliciting conditions (EECs) associated with it [78]. Moreover, as Alma was designed to be primarily implemented in embodied conversational agents (ECAs), the conditions to trigger the EECs are derived from predefined *dialog act tags* and *appraisal tags*, which are attached to every expression uttered by an agent.

In particular, the dialog tags indicate the intention of an utterance, while the appraisal tags express how a character appraises an event, action, or object referred to in the dialogs. As an example, consider the following expressions [78, 79]:

1. Speaker 1: *I did not get the job for the MTV Web page. It went to some kid that looked like Britney Spears.* Speaker 2: *Well, can you sing?* [=attack Speaker 1]
2. Speaker 3: *The weather is getting better* [=good_likely_future_event]

Here, [=attack Speaker 1] represents a dialog act tag and [=good_likely_future_event] an appraisal tag. In this manner, these tags lead, through their evaluation using EECs, to the elicitation of emotions and the calculation of their associated intensity (process in which the agent's personality profile and mood state are involved). In this model, the agent's affective state is used to influence its verbal and nonverbal behaviors, such as wording, length of phrases, facial expressions, and postures as well as to modulate cognitive processes such as decision-making and selection of dialogs and linguistic style strategies [39].

Mamid

Methodology for Analysis and Modeling of Individual Differences (MAMID) [47] associates two main concepts: a *methodology* for modeling the influences of emotions and individual differences on cognitive processing, and an *affective–cognitive architecture* that implements this methodology. The basic assumption in this model is that emotions and individual traits modulate cognitive processes through the adjustment of particular parameters. The architecture of MAMID is composed of seven sequential processes as shown in Fig. 6. The first three modules are responsible for the translation of incoming stimuli into high-level perceptions. Then, the fourth module creates expectations based on the current situations. Afterward, the *affect appraiser* component derives the agent's affective state through the operation of three processes: *automatic appraisal*, *expanded appraisal*, and *current state modulator*. In this operating cycle, a fast (or automatic) assessment of perceived stimuli is first performed based on their valence as positive or negative. Afterward, a higher-level evaluation is carried out in order to calculate specific values for the four basic emotions considered in MAMID (see Table 1). Finally, all emotions resulting in these evaluations are modulated using the results of evaluations performed in the previous execution cycle, ensuring smooth transitions between the agent's affective states [47, 80]. The affective state resulting in this cycle influences the general processing of MAMID by altering the performance of its architectural components. Specifically, derived affective states modulate the rules of the agent's goals and action selection, alter the speed and capacity in each module, and adjust priorities in the information handled by mental constructs (internal data structures used to pass information between architectural modules) [47, 81].

This concludes our review of the general operating cycle implemented in CMEs. The following section provides details of the interrelationships between cognitive and affective processes involved in the processing of emotional information in this type of computational model.

Interaction Between Cognition and Emotion

The previous section shows that diverse processes contribute to the realization of the three phases in the operating cycle of CMEs. In this section, we analyze the particular roles that some of these processes play in the generation of the agent's affective state as well as their interactions.

Basically, based on the models reviewed so far, we can argue that the inclusion of components resembling the operation of cognitive and affective functions in CMEs is a consequence of their theoretical foundations. As seen in Sect. 3, the operations and architectures of CMEs are highly inspired by theories and models developed in disciplines concerned with the study of human emotions. These theoretical models have postulated and demonstrated that human emotions alter the operation of human abilities such as attention and decision-making [1]. Also, they suggest that the generation of emotions has to do with the operation of various cognitive and affective processes [2, 5, 32]. Several particular instances of theories support these stances. For example, Damasio [1] has demonstrated that emotions are crucial in the development of appropriate decisions in social situations. Phelps [2] has explored the neural systems associated with cognitive and affective functions, showing that the neural mechanisms underlying human emotions are closely intertwined with those corresponding to processes such as learning, memory, and perception. Similarly, Rusting [74] has analyzed how temporary mood and personality traits influence the emotional information processing in different cognitive tasks.

In order to properly reflect how CMEs have adopted such evidence, the following sections explore the way certain cognitive and affective processes participate in the generation of emotions. In particular, we examine the following processes: *internal drives and motivations, mood state, personality, learning*, and *perceptual and motor processes*. Table 3 shows other cognitive and affective processes involved in the operating cycle of CMEs as well as the effects of emotions in the agent's behavior and expressions.

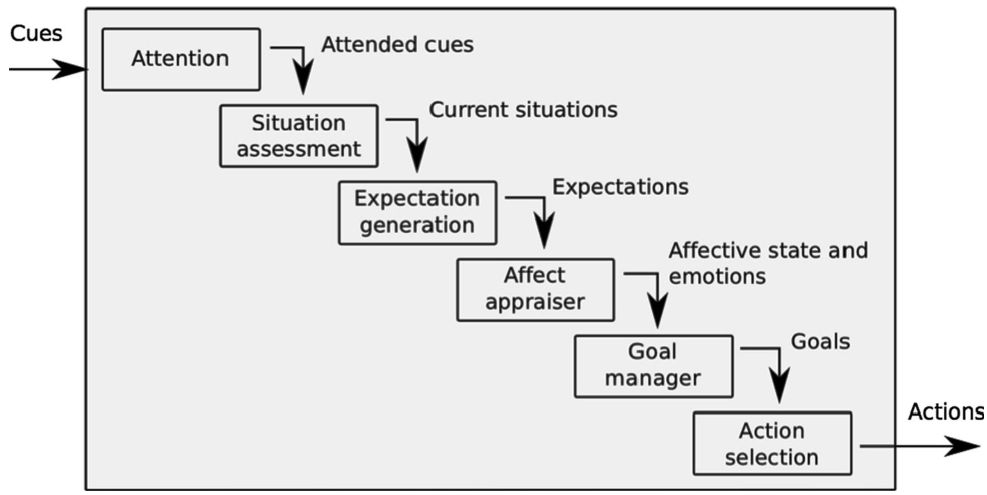

Fig. 6 The architecture of MAMID [80]

Motivations and Drives

Motivations refer to the internal phenomenon resulting from the interpretation of the agent's internal and external condition [82, 83]. They regulate the agent's behavior in order to attain a certain state of affairs. Drives are particular instances of motivations and an aspect often considered as participating in the processing of emotions in CMEs.

Kismet [82] is a social robot designed to learn from humans by interacting with them. This robot embodies a cognitive architecture that includes a motivational system designed to carry out the processing of *drives* and *emotions*. In this model, drives are considered as internal stimuli that influence emotions. The drives implemented in Kismet are *social drive, stimulation drive*, and *fatigue drive*. These represent the robot's basic needs and always have an associated intensity level, which tends to increase in the absence of stimuli and decrease when appropriate stimuli are being perceived. Furthermore, there is a bounded range called the "homeostatic regime," which establishes a desirable status for each drive (see Fig. 7). When the intensity of a particular drive is out of this range, the drive is into one of the following two states: under-stimulated (increased intensity) or overwhelmed (decreased intensity) [82, 84]. In Kismet, drives influence the dynamics of emotions by contributing to their level of valence and arousal. As shown in Fig. 7, when the intensity of a drive is within the overwhelmed regime, the valence of emotions becomes negative and their arousal high; when the drive is within the homeostatic regime, the valence is positive and arousal medium; and when the drive is within the under-stimulated regime, the valence is negative and the arousal low [82, 85]. In this manner, the intensity of emotions in Kismet depends on the status of its drives.

In Flame [45], as described above, the emotional component of its architecture executes four sequential processes (event evaluation, event appraisals, emotion filtering, and behavior selection processes) that operate in order to generate emotional behavior. In the second process, the appraisal component generates various emotions that are then processed by the emotion-filtering component. In this module, emotions are filtered by, among other things, motivational states, which inhibit or enhance the emotions. In this manner, Flame is able to obstruct the effects of emotions in the agent's behavior when it is imperative to satisfy its needs. However, this model works under the assumption that in certain situations, the execution of emotionally driven behaviors is more important than the execution of behaviors driven by the agent's needs. Thus, before inhibiting emotions, a situation assessment is carried out to decide which of these two modulating factors will direct the agent's next action.

Mood State

In most CMEs, the mood state is considered an internal affective phenomenon that lasts longer than emotions and has a lower arousal. It regulates the agent's behavior by influencing processes such as perception, memory, and emotions [38, 52].

Emotion and adaptation [38] is a CME that considers the agent's mood state as one factor that influences the elicitation of emotions and generation of behaviors. In this model, mood results from the aggregation of appraised events represented by appraisal frames (see Sect. 3.1 for an explanation of appraisal frames in this model). This allows the derivation of a mood state that is disassociated from eliciting events and tends to vary slowly over time. A mood state is represented by a set of emotion labels that have an associated level of intensity, which results from the sum of all intensities corresponding to the same emotion in the appraisal frames existing in the agent's causal

Table 3 Cognitive and affective processes involved in the processing of emotions in CMEs

Model	Cognitive processes	Affective processes	Effects of elicited emotions
EMA [38]	Provides support for cognitive, perceptual, and motor operators. However, the model does not implement such processes directly	Emotions and mood	Agent's expressions, attentional processes, beliefs, desires, and intentions
Kismet [82]	Perception and attention processes, learning mechanisms, behavior and expressive systems, and motor functions	Emotions and internal drives	Attentional focus, learning mechanisms, and expression and behavior selection
Flame [45]	Decision-making process, memory and experiential systems, and learning and adaptability processes	Emotions, motivational states, and mood	Action selection
Mamid [47]	Perceptual and attentional processes, memory systems, expectation and goal managers, and decision-making processes	Emotions and personality	Goal and action selection and attentional functions
Alma [39]	Dialog generation processes, decision-making and motivation functions, and behavior and expression generation systems	Emotions, mood, and personality	*Verbal and nonverbal expressions* such as wording, length of phrases, and facial expressions. *Cognitive processes* such as decision-making
Cathexis [37]	Perceptual processes, memory systems, behavior systems, and motor processes	Emotions, drives, mood, and personality	*Agent's expressiveness* such as facial expressions and body postures. *Cognitive processes* such as perception, memory, learning, and action selection
PEACTIDM [52]	Perceiving, encoding, attending, comprehending, tasking, intending, decoding, and motor functions	Emotions, mood, and feelings	Cognitive behavior in general
WASABI [36]	Perception and reasoning processes, memory systems, and processes for the generation of expressions and voluntary and nonvoluntary behaviors	Emotions and mood	Facial expressions, involuntary behaviors such as breathing, and voluntary behaviors such as verbal expressions

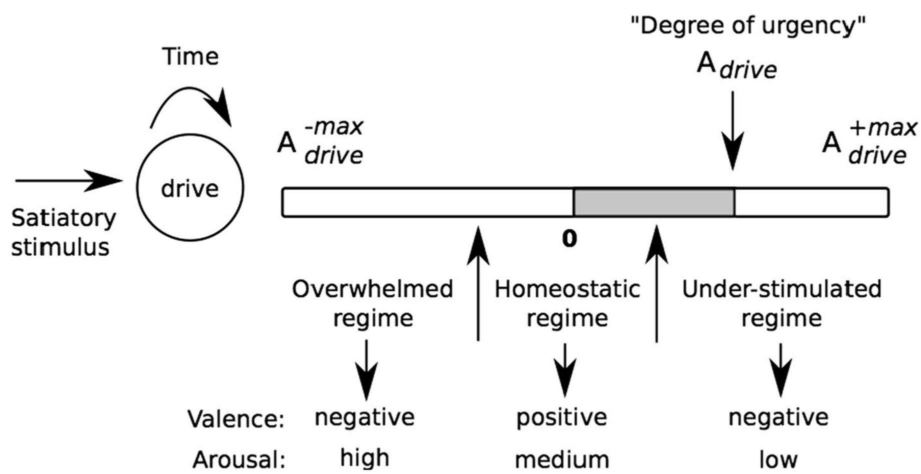

Fig. 7 The model of internal drives in Kismet [82]

interpretation (see Sect. 3.1). In this way, when deciding the agent's next behavior, all competing appraisal frames are first mood-adjusted, and then, the frame with the highest emotional intensity will determine the agent's response.

In the PEACTIDM model [52], the mood state also results from the aggregation of past emotions and is represented by an appraisal frame (see Sect. 3.1 for an explanation of appraisal frames in this model). The mood state is modified by each emotion generated in the agent. The dimensions in the appraisal frame representing the mood state are approached in a certain ratio to those dimensions in the appraisal frame corresponding to the current emotion. Furthermore, the agent's mood is decayed in each execution cycle according to a determined rate. In this model, the mood state helps to calculate a third affective aspect: feelings, which ultimately influence the agent's behavior.

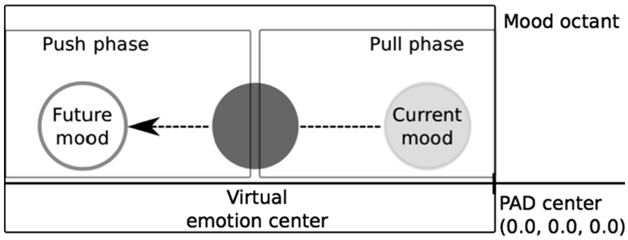

Fig. 8 The model of mood dynamics in Alma [39]

In Alma [39], a more elaborate model for the dynamics of mood states is proposed. In this case, mood states are represented by points in the Mehrabian's PAD temperament space [50] (as explained in Sect. 3.2). The dynamics of the agent's mood depend on the intensity of elicited emotions. A *pull-and-push mood change function* implemented in Alma is in charge of performing this procedure. This function first calculates a virtual point in the PAD space that corresponds to the average of all active emotions. Afterward, this function moves the mood point in the PAD space according to the calculated virtual center of emotions (see Fig. 8). If the current mood position is between the PAD origin point and the emotion center point, then the mood is approached to the emotion center (the pull phase). If the current mood is beyond the emotion center, the mood is pushed away into the octant in which the mood is located (push phase). In order to determine the level of attraction or repulsion of the mood (with respect to the emotion virtual point), the function uses the average intensity of all active emotions. Finally, a decay function is used to slowly move the mood state back to a default value. In Alma, the mood state influences, among other things, the selection of wording, phrasing, and dialog strategies in conversational agents.

Personality

This term is approached by CMEs as the set of individual traits or consistent patterns of behavior that provide support to individual differences [86, 87].

Personality is implemented as a long-term affective modulator in Alma [39]. The model of personality in this CME is inspired by the five factor model (FFM) [49], which characterizes personality profiles on the basis of five dimensions: *openness, conscientiousness, extraversion, agreeableness*, and *neuroticism* (or emotional stability). In Alma, personality profiles are defined for AAs by assigning specific values to the dimensions in the FFM and by defining a series of appraisal rules that determine how the agent appraises its environment. The agent's personality profile is then used to calculate the initial values of its mood state as well as to control the associated intensity and decay rate of elicited emotions [79]. Given that the mood state of AAs in Alma is represented by a point in the PAD space, its initial values are determined based on the agent's personality as follows:

- Pleasure := 0.21 · extraversion + 0.59 · agreeableness + 0.19 · neuroticism
- Arousal := 0.15 · openness + 0.30 · agreeableness − 0.57 · neuroticism
- Dominance := 0.25 · openness + 0.17 · conscientiousness + 0.60 · extraversion − 0.32 · agreeableness

In Alma, personality traits impact the agent's emotional state by establishing a baseline intensity for all elicited emotions. In this manner, an *agreeable* agent will experience more happiness than an agent with a neurotic personality will.

In MAMID [47], personality traits influence the agent's cognition and behavior. As mentioned in Sect. 4.2.4, this model includes a methodology for modeling the effects of individual differences such as emotions and personality in cognitive–affective architectures. In this context, specific personality profiles are characterized in terms of parameters that control the processing (e.g., speed), structure (e.g., long-term memories), and content (e.g., beliefs) of architectural components. The personality traits considered in this model are extraversion, introversion, aggressiveness, and conscientiousness. During the agent simulation, particular values of these dimensions are translated into adequate signals that alter the functioning of architectural parameters. In particular, in the *affect appraiser* module, which is responsible for deriving the agent's affective state, personality contributes to the elicitation of particular emotions. For example, high neuroticism and low extroversion make the agent susceptible to negative valenced emotions as well as negative and anxiety affect.

Learning

The learning process refers to the ability of individuals to make the needed changes in their knowledge and skills in order to adapt to dynamic environments and create expectations of what is going to happen in a determined situation [88, 89].

Kismet [85] refers to a physical robot that learns from humans by interacting with them. In this model, the robot's emotional state plays a critical role in measuring and regulating the quality of learning. The main assumption is that individuals' emotions and internal drives impact the establishment of environments that are conducive for social interactions. Furthermore, the exchange of emotional facial expressions between the robot and human is what allows this learning environment to exist. In particular, the robot includes learning algorithms for the acquisition of communication skills and for understanding their impact on social interactions. Kismet perceives affective cues through visual and auditory channels and responds with affective signals based on facial expressions, gaze direction, body posture, and vocal babbles. While the human communicates reward and punishment signals to tell the robot to regulate the intensity of the affective interactions, the robot uses emotional facial expressions to inform whether it feels overwhelmed or under-stimulated, and in this way to promote and maintain a suitable learning environment. Moreover, this affective communication allows the robot to manipulate the human. so that its drives are satisfied.

In order to simulate the adaptiveness of emotionally driven reactions and emotional experiences in autonomous agents, Flame [45] implements a series of learning mechanisms. In particular, this model was designed on the basis of a number of aspects that are central to the dynamics of emotions. For example, if an event is happening repeatedly, emotional responses tend to decrease in intensity; if several events typically happen in sequence, an agent tends to develop expectation for what is going to happen next; and if certain signals in the environment occur when agents are experiencing certain emotions, the agents become conditioned to those patterns. The underlying architecture of Flame includes a learning component that covers such aspects. This component implements four learning mechanisms that allow the agent to associate an emotion with the object that triggered it, evaluate events according to the its goals, learn patterns of events, and learn actions that please or displease the agent or the user [45]. In this manner, an adequate learning environment allows this model to implement believable autonomous agents by adapting their emotional responses and experience as the environment unfolds.

Perceptual and Motor Cognitive Processes

As we mentioned before, a CME can be abstracted as a component that receives raw data and delivers affective information. From this perspective, perceptual processes are recognized as those responsible for sending the raw data and motor processes as those that receive the affective information and implement affective responses in AAs [38, 82, 90]. Several CMEs recognize these roles of perceptual and motor cognitive functions and incorporate them within their underlying architecture.

Emotion and adaptation [38] specifies a series of perceptual operators that construct and maintain the *causal interpretation of the agent* (see Sect. 3). Cathexis [37] includes in its underlying architecture both a perceptual and a motor system (see Fig. 4). The perceptual system captures the stimuli from the environment and sends them to other components such as the emotional system, the behavior system, and the motor system. The motor system executes actions that correspond to the behaviors selected by the behavior system. Similarly, the architecture of MAMID [80] (see Fig. 6) is composed of a series of modules that embody cognitive perceptual and motor functions, such as the *sensory preprocessing* module, which is in charge of translating incoming stimulus into perceptual cues; the *attention* module, which selects a subset of these cues for further processing; and the *action selection* module, which selects appropriate actions for goal achievement. Kismet [82] also implements a *perception system* to create internal representations of the stimuli captured from the world, an *attention system* to determine which of all captured elements are important, and a *motor system* to execute facial expressions and motor actions.

This concludes our analysis of the cognitive and affective processes involved in the processing of emotional information in CMEs and their interrelationship. In the following section, we discuss some aspects related to the architectural design of this type of computational model.

Architectural Design

In disciplines such as psychology and neuroscience, cognitive and affective functions underlying human behavior have usually been investigated and modeled separately [89]. This approach has led to the formulation of theories and models that focus on explaining very specific processes such as planning and decision-making [4, 91]. In the field of artificial intelligence and affective computing, this methodology has inspired the development of computational models that synthesize individual cognitive and affective functions [92, 93]. Regarding the synthesis of human emotions, several CMEs have been developed as *stand-alone models* based on this methodology. Nevertheless, given that CMEs are intended to model the actual process of human emotions, some of them have been developed based on a more integrative approach. These *integrative models* are inspired by theories that support the idea that emotions stem from the joint operation of several brain functions. We define stand-alone models as components that are built independently of other type of processes such as perception, memory, and motor functions. These models are included as extensions in already developed cognitive frameworks or architectures in order to provide them with proper mechanisms for the processing of affective data [39, 94]. With respect to integrative models, these take into account other processes as part of their operating cycle, or are entirely designed and implemented within a particular cognitive framework [47, 82]. Table 4 provides a classification of representative CMEs based on their structural design as integrative or stand-alone models.

The notion of integrative models is not new, but the notion of integrative models that include emotions is

Table 4 Structural approaches in the design of particular CMEs ("S" stands for stand-alone model and "I" for integrative model)

Model	Design	Description
EMA [38]	S	Included in the SOAR cognitive architecture [95]
Kismet [82]	I	Includes a comprehensive software and hardware architecture to allow the generation of expressions and behaviors
Flame [45]	S	Implements a component dedicated to providing affective information to decision-making models
Mamid [47]	I	Implements a module for affective processing as part of an integrative cognitive–affective architecture
Alma [39]	S	Implements a component that delivers affective information to improve the lifelike qualities of conversational virtual humans
Cathexis [37]	I	Implements an architecture that comprises an affective, a sensory, a behavioral, and a motor system
PEACTIDM [52]	I	Integrates affective processing within a cognitive framework
WASABI [36]	I	Integrates affective processing within the cognitive architecture of a virtual human

relatively recent [24, 53, 90, 96]. As an example, we can consider cognitive architectures such as Soar [95] and ACT-R [97], which are cognitive frameworks that were originally designed without including mechanisms for emotional processing. These models are mainly concerned with implementing mechanisms that enable the modeling of cognitive functions such as planning, attention, and perception. However, since the role of emotions in other human functions began to be recognized and widely studied, cognitive architectures were improved to include emotional processing [98, 99]. In addition, as shown in previous sections, many CMEs integrate a variety of cognitive components into their architecture. The next section discusses some of the implications in the development of both types of CMEs.

Implications of the Structural Design

The benefits and disadvantages of both structural approaches vary. For instance, the use of stand-alone models to extend the functionality of cognitive frameworks allows the use of previously tested components. In addition, this enables the fast and easy integration of additional processing. Existing architectures use these independent components by sending them raw data and receiving back emotionally processed information, which is then used to influence the normal operation of many other functions [39, 94]. Nevertheless, this approach also presents many disadvantages. For example, since cognitive frameworks are composed of heterogeneous modules that require different types of affective data in order to work appropriately, independent components may be unable to meet all those data requirements.

On the other hand, as the development of integrative CMEs follows a more natural design, they are not built as architectural extensions, but as processes that emerge from the joint operation of multiple mechanisms [80, 90]. As a result, their construction becomes more complicated, and as many other aspects inherent to the architecture in which they are included should be understood, their implementation is more prone to errors. In addition, they are the most likely to inherit the problems from the theories on which they are based. However, many benefits may also be gained by using this approach. For example, because the design of these models is inspired by the way cognitive and affective functions arise from the operation in the human brain, they may be easily adapted to include other processes such as personality, mood, and perception without changing many of the already implemented mechanisms [73]. In addition, these developments may serve as experimental frameworks in areas studying brain processing in healthy subjects or subjects with cognitive or emotional problems.

Particularly, the incorporation of emotional processing into cognitive frameworks using individual components may be disadvantageous. This suggests that emotional processing is handled by a single process, but since CMEs are based on theories that investigate the mechanisms underlying human emotions, this approach becomes contradictory [18]. Multi-disciplinary studies have demonstrated that emotions refer to a process that emerges from the joint operation of many brain structures [89]; they are not the result of a single component that receives raw inputs and delivers emotional outputs. Additionally, to talk about the interactions between emotions and cognition contributes to perceiving emotions as separate from cognition. Although this independence has been useful for achieving organized designs [39, 90], it is far from reality. Furthermore, although it seems that some brain structures process more cognitive information than affective, and vice versa, a widely accepted theory is that cognitive and affective processes emerge from the operation of the same brain structures and operations [2, 52, 89].

In order to show how CMEs have benefited from implementing, the two structural approaches discussed above, in the following section, we focus on examining some particular examples.

Stand-Alone and Integrative CMEs

Alma [39] is a stand-alone CME whose *affect computation module* is incorporated into the architectures of conversational virtual humans. This component interacts with a *dialog generation module* that provides inputs in terms of verbal expressions (as explained in Sect. 4.2.3). These verbal expressions include a series of dialog act tags and appraisal tags that characterize the dialogs between virtual humans. These tags enable the generation of emotions as well as the calculation of their associated intensity. In turn, the affective data derived from the affect module influence the operations of the dialog generation module. Specifically, this information affects processes such as the selection of dialog and linguistic style strategies, intonation, and turn-taking behavior. In Flame [45], the *emotional module* is implemented as a stand-alone component that processes emotional data based on internal and external information (see Fig. 5). As explained in Sect. 4.2.2, this component receives environmental stimuli from a *decision-making module* and internal information from a *learning module*. Based on this information, the emotional component generates the agent's affective and mood states and selects an appropriate emotional behavior. Along with other internal and external information, the emotional behavior influences the process responsible for choosing the behavior that the agent will ultimately implement.

A representative instance of integrative models is the MicroPsi agent architecture, which emphasizes the interactions between emotions, motivations, and cognitions [100]. This affective–cognitive model is based on the psychological theory by Dietrich Dörner [101], which proposes a framework for the implementation of agent behavior. In this model, the main assumption is that the agent's emotions are defined by the modulation of cognitive processes on the basis of certainty and competence. Emotions are not implemented by explicit mechanisms in the agent architecture; they are rather seen as dispositions to action, perception, and planning. Thus, the agent's affective state is characterized by the modulation of several processes which always reflect a specific configuration of the agent's cognitive system and motivational states [102].

As explained in Sect. 4.2.4, MAMID [47] includes a methodology to implement the influences of emotions in cognition, as well as an architecture that implements it. This architecture includes an *affect appraiser* module that determines the agent's emotional state as well as other modules that implement cognitive mechanisms to carry out functions such as perception, attention, and decision-making. With such methodology and cognitive–affective architecture, MAMID recognizes the importance of integrative models since it explicitly implements the influences between emotions and cognition and generates the agent's behavior on the basis of such interactions. Furthermore, this model includes a series of adequate structures to carry out the interaction between affective and cognitive components. Marinier et al. [52] combine the PEACTIDM theory for cognitive behavior and the appraisal theory for the generation of emotions. As seen in Sect. 3.1, this model uses the data processed by cognitive functions to derive the affective state of the agents and the data generated by appraisal processes to influence these cognitive functions. In this manner, they advocate the idea that cognition and emotions arise from the operation of the same brain mechanisms.

This concludes our review of the architectural designs of CMEs. In the following section, we explore the functional roles of CMEs in AAs and provide details of case studies in which they have been evaluated.

Role in Cognitive Agent Architectures

There is a large volume of literature that explores the potential applications of computational systems that embody mechanisms for emotional information processing [16–20, 22, 26, 103]. In these types of computational systems, emotions play different roles depending on the purpose of the application. For instance, experimental applications may focus on implementing procedures for the collection of human emotional signals (e.g., electrical brain activity, gestures, and postures) in order to interpret the affective state of individuals. Similarly, applications may be developed to produce artificial emotional stimuli that are useful for conducting experiments and research on emotional disorders, emotional influences on decision-making, and emotional influences on many other human functions [19, 22].

Marsella et al. [16] classify the applications of CMEs based on their use in three major areas: psychological research on emotions, AI and robotics, and human computer interactions. In the first case, CMEs become useful in the formulation, formalization, improvement, assessment, and completion of theories addressing human emotions, as well as for carrying out experimentation that enables the evaluation of emotionally driven responses in artificial systems rather than using human subjects. In the second area, emotions are mainly combined with cognitive systems in order to implement autonomous agents that have more intelligent, flexible, and social behavior. In the last one, the agent's emotional displays such as facial expressions and postures become helpful for conveying its beliefs, intentions, desires, and mental states, facilitating and improving social interactions between humans users and computer systems. Scheutz [26] highlights the importance of emotional processing in AI applications by identifying a number of functional roles of emotions in AAs, including action selection, adaptation (in terms of short- or long-term changes in behavior), social regulation, sensory integration, alarm mechanisms for interrupting the normal functioning of processes, motivation, goal management, learning through emotional evaluations, attentional focus of emotionally salient objects, memory control such as memory access and retrieval, strategic processing, and self-modeling.

With regard to the evaluation of this type of computational models, Marsella et al. [16] additionally suggest that such assessments depend on the particular role that emotions play in the different applications. For example, in psychological research, CMEs are designed to accurately imitate the dynamics of human emotions; in AI and robotics, CMEs are intended to efficiently process emotional data in order to modulate some agent's cognitive functions such as perception and planning; and finally, for human–computer interactions, the goal is to achieve more effective, efficient, and pleasant interactions by displaying and interpreting emotional cues.

In the remainder of this section, we explore the role of CMEs in software and physical emotional AAs and examine how these models have been evaluated in various application domains (see Table 5 for an overview).

Software Emotional Agents

As mentioned before, CMEs are implemented to be included in cognitive agent architectures and thus provide AAs with mechanisms to process emotional information. The results of processing this information are then used to influence the operation of other processes. Alma [39] was implemented in embodied conversational agents in order to provide them with emotionally processed information useful for improving their conversational abilities. Particularly, the emotional information generated by Alma was used to modulate the verbal and nonverbal expressions of these agents and inform their selection of dialog and linguistic style strategies. Reithinger et al. [104] describe how Alma is incorporated into the virtual human system, a knowledge-based framework aimed at creating 3D interactive applications for multi-user/agent settings. Alma allows these virtual humans to maintain affective conversations by implementing emotional reactions and expressions (see Fig. 9). Furthermore, in order to evaluate the plausibility of Alma et al. [105] carried out an experiment in which the emotional and mood states induced in virtual agents were evaluated. In this case, people were asked to evaluate the model based on textual representations of the affective states elicited. According to the authors, such evaluations validate Alma as a model that produces coherent affective states in virtual humans with respect to their human counterpart.

Emotion and adaptation [38] has been incorporated into the architectures of virtual humans developed to simulate a variety of scenarios. In the *the mission rehearsal exercise* project, a virtual-based training program intended to teach soldiers how they should act in stressful situations, EMA was used to influence the decision-making of virtual humans and thus allow them to achieve more realistic and human-like behaviors (see Fig. 10). Similarly, the dynamics of the internal and external behavior of EMA have also been evaluated with respect to human data. The dynamic changes of its multiple variables (as responses to evolving events) have proven to be consistent with subjective data collected from human subjects, who reported their feelings when imagining how they would respond in particular slowly evolving situations [106].

Flame was used in the implementation of an interactive emotional pet called PETEEI (*PET with evolving emotional*

Table 5 Roles of CMEs in AAs and applications

Model	Main roles
EMA [38]	Decision-making in virtual humans developed for training purposes
Kismet [82]	Emotional expressions in robots as an aspect that improves a learning environment
Flame [45]	Decision-making in virtual pets that show believable behavior
Mamid [47]	Virtual humans for training and psychotherapy environments
Alma [39]	Embodied conversational agents
Cathexis [37]	Decision-making in virtual and physical agents
PEACTIDM [52]	Goal-directed autonomous agents
WASABI [36]	Emotional expressions and responses in virtual players

Fig. 9 Conversational agents implementing the model of emotions of Alma [39]

Fig. 10 Virtual agents implementing the model of emotions of EMA in the mission rehearsal exercise [108]

intelligence) [45]. By simulating different emotional states, PETEEI allows the evaluation of the emotion generation mechanisms provided by Flame. The simulation of this software pet provides predefined user and pet actions, which are aimed at producing different emotions. Since Flame incorporates learning components and is implemented using fuzzy logic techniques, PETEEI was evaluated in the following four scenarios: (1) simulation with random emotions and random behaviors; (2) simulation with no fuzzy logic or learning; (3) simulation with fuzzy logic but no learning; and (4) simulation with fuzzy logic and learning. Different elements in the simulations were evaluated, including the pet's intelligence, learning, and behavior. The experiments demonstrate that the learning component improves the pets' believability and that the fuzzy logic is a useful technique for modeling emotions, which also affects the pets' believability [45]. In addition, Flame has been integrated in models that generate facial expressions, providing emotional information used to dynamically modify the facial expressions of an interactive agent [107].

Physical Emotional Agents

Some CMEs have also been incorporated into the architectures of physical agents. However, the applications for this type of implementations are more restricted. One of the main reasons is that abilities such as perception and motor action are highly dependent on hardware sensors and actuators, which are commonly used to capture stimuli from real (and therefore too complex) environments and to allow the agent to act on it. In this section, we address two particular instances of this type of applications.

Cathexis [37, 76] was incorporated in a physical agent called Yuppy that takes the role of an emotional pet. This robot was situated in various controlled environments in order to evaluate the model of emotions provided by Cathexis. In different experiments, Yuppy was expected to display certain emotional behaviors such as approaching people, avoiding obstacles, and expressing emotions according to the particular situations in which the robot was involved. These experiments demonstrated that Cathexis is an appropriate model for the development of emotional agents whose expressions and behaviors, developed in controlled situations, are believable. Another instance of physical emotional agents is Kismet [82], which implements emotional displays such as facial expressions in order to communicate its affective internal state (see Fig. 11). This robot is placed in learning environments (see Sect. 5.4) in order to measure the extent to which emotional expressions and behaviors improve the learning experience in infant-caregiver models (the robot taking the role of an infant and the human of caregiver). Kismet has been evaluated in environments involving face-to-face interactions between the robot and humans, as well as in experiments where toys are used to stimulate the agent's affective state [82, 109]. In these experiments, people were asked to evaluate the plausibility of the emotional displays developed by Kismet. According to the authors, people (mostly children) were able to interpret the robot's facial expressions and postures appropriately.

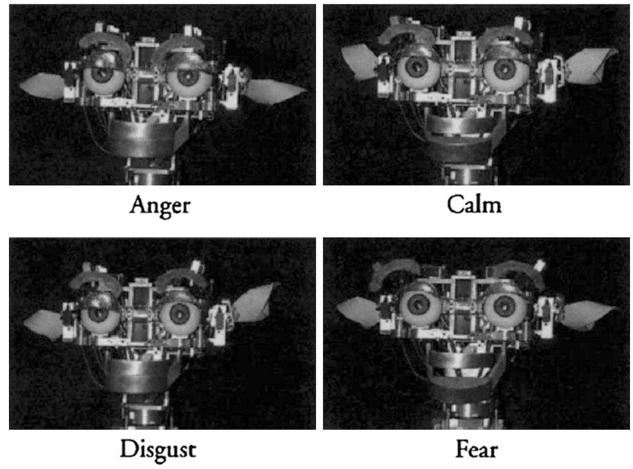

Fig. 11 Facial expressions of the emotional robot Kismet [85]

This concludes our review of CMEs for AAs based on five design aspects that have influenced their development process. In the following section, we analyze CMEs from this perspective and attempt to provide a coherent panorama of key issues that remain to be addressed regarding their development process. In addition, we identify and discuss some challenges and suggest research that may lead to more robust, integrative, and flexible designs for this type of computational models.

Analysis and Discussions

The previous sections suggest that the design and implementation of CMEs requires a multi-disciplinary effort and that the course of their development process depends on very complex design decisions. In the remainder of this section, we provide an analysis of the development process of this type of computational model based on the five design aspects investigated above and discuss key challenges and research directions that may be crucial to achieving more robust, flexible, and integrative CMEs for AAs.

As shown in Table 1, the development of CMEs is greatly influenced by psychological theories and models of emotion. Psychological approaches study human emotions from a functional perspective and focus on explaining the inputs, outputs, and behaviors of the components that constitute the emotion process. One of the main contributions of psychological theories to CMEs is that they provide suitable guidelines for the organization of the architectural design of this type of computational model. This type of theory provides useful information about components that are essential for the modeling of the various facets of the human emotion process, the functional sequence they may follow, and their multiple interactions [15, 30]. Nevertheless, psychological theories present various limitations [40]. As an illustration, appraisal theories, the approach most often implemented, do not provide detailed descriptions of the appraisal processes underlying the assessment of emotional stimuli nor do they explain the internal mechanisms involved in the elicitation of emotions [110, 111].

Aside from psychologically inspired CMEs, the literature also reports some CMEs that implement mechanisms whose designs reflect key assumptions of theories from other fields such as cognitive and affective neuroscience [36, 37]. Theories and models from these fields explain emotions in terms of brain functions, brain structures, and neural pathways [1, 2, 33]. In this manner, they provide a deeper understanding of the internal workings of the components that constitute the process of human emotion, and therefore, these are able to appropriately inform the development of computational algorithms and data structures to be included in CMEs.

Regardless of the theoretical foundations of CMEs, most theories have limitations that affect the design, implementation, and ensuing analysis of these computational models. For example, due to the complexity in the research of human emotions, theoretical models concentrate on the study of specific facets of the emotion process and explain them at different levels of abstraction and from diverse perspectives [30]. Furthermore, the number and types of the components that constitute the emotion process and the concepts and definitions used to describe them differ widely among theoretical approaches [40, 112, 113]. Nevertheless, although these issues cause a marked variability regarding the architectures and mechanisms implemented in CMEs, theoretical models may complement each other in order to allow the construction of functional CMEs.

Regarding the operating cycle implemented in CMEs, this is a design aspect that helps to devise, organize, and determine the processes and mechanisms to be implemented in the CME. Identifying the phases of this cycle is also important to determine the functional scope of the model and its architecture. In particular, we studied the operating cycle of CMEs by separating it into three sequential phases: *evaluation of emotional stimuli, elicitation of synthetic emotions*, and *generation of emotionally driven responses*. In the first phase, CMEs evaluate the emotional significance of perceived stimuli using a series of criteria. For example, MAMID [47] performs an assessment of stimuli in terms of their valence using a number of appraisal variables such as expectation and novelty. In the second phase, this type of information is used to elicit particular emotions and determine their associated intensity. For instance, WASABI [36] uses a three-dimensional space to decide which emotions will be elicited. In the last phase, elicited emotions influence other agents' functions such as decision-making [47], conversational skills [39], and facial expressions [36]. These three phases of the operating cycle of CMEs cover basic requirements of emotional AAs, including the evaluation of affective stimuli collected from the environment, the recognition of emotions from human users and artificial agents, the interpretation of this emotional information in terms of emotional labels, the simulation and expression of emotional feelings, and the execution of emotional responses. Nevertheless, there is no general and widely accepted operating cycle for CMEs. And as discussed above, the phases included in the operating cycle, the sequence they follow, and the mechanisms implemented in each phase differ across CMEs.

As seen in previous sections, the development of CMEs has to do not only with the modeling of emotion-related mechanisms, but also with the design of models that maintain a continuous and reciprocal interaction with cognitive functions implemented in cognitive agent architectures. Most CMEs recognize this requirement and are designed to influence certain cognitive abilities of AAs such as their decision-making and planning (Table 3 provides an overview of cognitive and affective processes involved in the development of CMEs). In fact, the interaction between cognitive and affective processing is a fundamental concern in the design of CMEs. First, biological and psychological theories of emotion suggest that cognitive and affective mechanisms are highly interrelated in humans. Second, one of the main purposes of including CMEs in the architecture of AAs is to implement mechanisms capable of generating emotional signals to appropriately influence the processes underlying the behavior of AAs and thus allow the generation of very believable and emotional responses. In general, in order to address this design aspect, it is necessary to understand the type of interaction between cognitive and affective processes that is required. This can be done by specifying the behaviors to be generated by the CME (in order to meet its design requirements) and thus identifying the cognitive information required and the cognitive processes that should interact with the CME. In this manner, appropriate interfaces are designed to facilitate the exchange of data between emotion processes implemented in CMEs and cognitive processes implemented in cognitive agent architectures. Moreover, this facilitates the design or adaptation of mechanisms for the processing of cognitive information in CMEs. Nevertheless, although several efforts are devoted to creating CMEs that interact with cognitive processes, these interactions are specifically designed to meet the requirements established for the CME (as suggested above). In this sense, it is necessary to create CMEs that include adequate mechanisms to interpret all cognitive information that a cognitive agent architecture is able to offer, not only a subset. Similarly, it is necessary for CMEs to implement mechanisms that deliver normalized emotional signals that are useful for affecting the normal operations of all cognitive processes in cognitive agent architectures.

The underlying architecture of CMEs is another design aspect to be considered in the development of this type of computational model. In this paper, we studied this aspect based on two structural approaches: *stand-alone models* and *integrative models*. We defined the first type of model as components developed to receive specific inputs and send back the results of their emotional evaluation. The second type was defined as models whose behavior stems from the collective operation of processes belonging to CMEs and processes included in cognitive agent architectures. Here, we complement the discussions provided above about the benefits and disadvantages of each design approach in order to emphasize the importance of this design aspect in the development of CMEs. For stand-alone models, the main concern is the development of adequate *interfaces* that facilitate the exchange of data between CMEs and cognitive architectures. This type of model should include mechanisms to generate useful affective information needed by cognitive agent architectures to reflect an emotional bias in the behavior of AAs. Furthermore, these models should provide very open and robust interfaces capable of handling the information sent from cognitive agent architectures, even when this information is variable or incomplete. This characteristic can help to achieve more reusable CMEs as their interfaces are flexible enough to handle cognitive information from different cognitive agent architectures. For integrative models, the main concern is how to take advantage of available cognitive information from cognitive agent architectures to generate consistent affective information. Given that integrative models are developed within cognitive frameworks and therefore closely interact with various cognitive processes and have access to their intermediate and final results, they need to incorporate mechanisms to handle all those cognitive data and appropriately combine them with affective information. Similarly, the intermediate and final results of all emotion processes taking place in the CME should be represented in a convenient manner, so that they can be used by cognitive processes of agent architectures to generate more consistent and believable responses in AAs. Regardless of the type of architecture implemented in CMEs, this design aspect represents an opportunity to address and meet key requirements and challenges of contemporary applications of emotional AAs, such as more scalable architectures to easily incorporate new aspects of human emotions.

As we discussed above, the architectural and functional design of a CME depends largely on the role that this model will play within the cognitive architecture of an AA. As suggested by Scheutz [26], emotional information generated by CMEs may be used in AAs to influence their action selection, perception, adaptation, social regulation, motivations, goal management, learning, attention, memory control, among other things. In general, CMEs are developed to properly interact and exchange information with some of these processes (usually a subset of the cognitive processes implemented in the architectures of AAs). In this sense, design aspects of CMEs such as their theoretical foundations, architectures, and operating cycle are analyzed and approached taking into account the functional and architectural requirements of the cognitive processes that will use the affective signals coming from the CME. However, current applications of AAs demand more robust and flexible designs for CMEs. For instance, for applications in which AAs are expected to exhibit social behaviors, mechanisms underlying their decision-making, perception, attention, planning, motor action, facial expressions, and verbal expressions have to consider in their internal workings the emotional cues processed by CMEs in order to allow AAs to show this type of behavior. A major challenge for contemporary CMEs is therefore to incorporate adequate architectures and mechanisms for a dynamic exchange of information between affective and cognitive processes in the architectures of AAs. Furthermore, research efforts should be focused on creating strategies to develop CMEs whose design does not depend on the particular role they will play in AAs.

Although most CMEs have been implemented to meet very specific requirements and to be used in very particular scenarios, the study of CMEs based on the five design aspects considered in this paper highlights a series of characteristics of this type of computational model that may be crucial when selecting a model for its adaptation and implementation in different scenarios or applications. In this sense, besides providing understanding of the development process of CMEs, the five design aspects considered in this review can be used to form a framework

Table 6 Design aspects approached from a practical perspective

Design aspect	Description
Theoretical foundations	Knowing the theoretical foundations of a CME might help to understand which kind of emotions a CME generates and how these are represented. For example, if the design of a CME is inspired by hierarchical theories, then this model may be capable of eliciting basic (primary) and non-basic (secondary) emotions. Moreover, if the model is inspired by dimensional theories, elicited emotions might be represented in terms of a few dimensions such as valence and arousal
Operating cycle	The elements associated with this design aspect may be of great interest from a practical standpoint. We can understand details such as the type of stimuli a CME is capable of evaluating (e.g., objects in the environment and agent's actions) and how they should be represented, what emotion labels are used to represent the emotions and emotional states generated (e.g., happiness, anger, and sadness), whether the model implements decay and intensity functions, what kind of information (additional to elicited emotions) the model provides as output (e.g., emotional significance of the stimuli perceived by an AA), whether the model generates any kind of emotional behaviors, and what are the main components involved in the processing of emotional information
Interaction between cognition and emotion	Approached from a practical perspective, this design aspect provides useful information for defining an interface for information exchange between the CME and the components comprising the cognitive architecture of an AA. Particularly, evaluating CMEs from this perspective provides understanding of what kind of information is necessary for the evaluation, elicitation, and differentiation of emotions (e.g., agent's personality, goals, and memories). Similarly, this allows the developer to determine what kind of cognitive components can be modulated with the information a CME is able to provide as output, and thus ultimately understand the effects this may have on the AA's emotional behavior
Architectural design	The implications of the architectural design of a CME are of special interest when evaluating this type of model from a practical perspective. Whether the CME is implemented as a stand-alone model or as an integrative model, a careful study of this aspect should be conducted in order to understand the particularities of the architecture of the CME and thus modify it according to the needs of a given application or scenario. This design aspect also contributes to defining an interface for information exchange between the CME and the components making up the cognitive agent architecture that will implement the CME
Role in cognitive agent architectures	Evaluating CMEs from this perspective allows the developer to know what abilities of an AA (e.g., its conversational abilities) will reflect an emotional bias. This design aspect also provides information of the methods and scenarios that have been used to evaluate CMEs and the results of such evaluations. Importantly, all this information contributes to generalizing and classifying the scenarios and applications in which a particular CME can be employed (e.g., conversational agents and virtual humans). Knowing the role that CMEs play in a cognitive agent architecture also helps to infer what kind of emotional behaviors an AA will be capable of exhibiting

for studying and evaluating CMEs from a practical perspective. In this case, however, whereas some of the details investigated for each design aspect become highly important, others become irrelevant. For example, from a practical perspective, it may not be essential to study and understand the theoretical foundations of a CME to decide whether the model is suitable to be used in a given scenario or application. On the contrary, it might be crucial to know whether a CME is capable of eliciting basic and non-basic emotions. Thus, it becomes necessary to determine which details of each design aspect are important and which are not. In Table 6, we suggest and describe some details that are worth reviewing when studying and evaluating CMEs from a practical perspective (proposing a complete and detailed framework for assessing CMEs from a practical perspective is beyond the scope of this paper). The information presented in this table serves as a reference when identifying and investigating the characteristics of CMEs that can be relevant to a given scenario or application. Furthermore, Table 5 describes scenarios in which representative CMEs have been implemented. These scenarios can therefore serve as a basis for generalizing and determining other type of scenarios in which a particular CME can be employed.

As with the development of conventional software systems, the testing of CMEs is a crucial phase. Case studies to evaluate CMEs are usually designed to assess specific characteristics implemented in these computational systems. For example, their adequacy for influencing the decision-making or learning processes of AAs, the consistency of the emotional and mood states elicited, and the emotional expressions and responses induced. Most case studies are carried out in the domain of human-computer interaction. As an illustration, in these case studies researchers create virtual scenes populated with AAs and present them to human users. Then, regardless of the specific situation recreated in these virtual simulations, human users are asked to evaluate the affective behavior of AAs and provide feedback by filling out questionnaires, which help the researcher to determine the plausibility of the model of emotions implemented in the CME and identify the internal mechanisms to be modified or redesigned. However, in contrast to the availability of methodologies for the assessment of conventional software systems, the testing process for CMEs is highly subjective since the evaluation of the model is strongly influenced by the idiosyncrasies of human users and researchers. In this context, the design of well-defined, well-structured, and generally accepted frameworks for the evaluation of this type of computational model can help to efficiently assess specific characteristics of CMEs and to provide more readable results that can be interpreted by the research community [17, 23, 114].

Conclusions

The development process of CMEs demands a multi-disciplinary research. Important design objectives such as those identified in this study should be investigated by following multi-disciplinary approaches. As observed in this paper, there is still a need for suitable methodologies, techniques, tools, and strategies to address a series of challenges related to such developments. Most of these challenges stem from the dual nature of CMEs (i.e., their theoretical and computational nature). In this sense, since the development process of CMEs is supported by theories of human emotions and computational principles, it is important to find a balance between the application of both approaches. This consideration may lead to CMEs whose architectural and operational assumptions are, at the same time, theoretically and computationally plausible. Moreover, it is necessary to devise novel methodologies and make use of proper computational techniques to achieve organized designs and scalable architectures that allow CMEs to be updated and thus remain valid according to novel theories of human emotions. Advanced software tools must also be developed to take full advantage of the evidence and knowledge originating in the disciplines related to the development of CMEs. Another challenge has to do with the potential of CMEs to provide feedback to the theories and models on which they are based. As computational models are required to implement well-defined and systematic procedures in order to achieve working computational systems, CMEs are able to assist in the completion, improvement, validation, and evaluation of theoretical models [16, 17]. However, as seen in this review, most CMEs are designed and implemented based on a series of requirements postulated mainly by their application domain, leaving aside the opportunity to provide such feedback.

References

1. Damasio AR. Descartes' error: emotion, reason, and the human brain. 1st ed. New York: Putnam Grosset Books; 1994.
2. Phepls EA. Emotion and cognition: insights from studies of the human amygdala. Annu Rev Psychol. 2006;57:27–53.
3. Clore GL, Palmer J. Affective guidance of intelligent agents: how emotion controls cognition. Cogn Syst Res. 2009;10(1): 21–30.
4. Loewenstein G, Lerner JS. The role of affect in decision making. In: Handbook of affective sciences. New York, NY: Oxford University Press; 2003. p. 619–42.
5. Gros C. Cognition and emotion: perspectives of a closing gap. Cogn Comput. 2010;2(2):78–85.
6. Scherer KR. Vocal communication of emotion: a review of research paradigms. Speech Commun. 2003;40(1–2):227–256.
7. Planalp S. Communicating emotion in everyday life: cues, channels, and processes. In: Andersen PA, Guerrero LK, editors. Handbook of communication and emotion. San Diego: Academic Press; 1996. p. 29–48.
8. Frijda NH. The emotions. Cambridge: Cambridge University Press; 1986.
9. Panksepp J. Affective neuroscience: the foundations of human and animal emotions. New York: Oxford University Press; 1998.
10. Trappl R, Petta P, Payr S, editors. Emotions in humans and artifacts. Cambridge: MIT Press; 2003.
11. Barrett LF, Mesquita B, Ochsner KN, Gross JJ. The experience of emotion. Annu Rev Psychol. 2007;58(1):373–403.
12. Ortony A, Clore GL, Collins A. The cognitive structure of emotions. Cambridge: Cambridge University Press; 1990.
13. Scherer KR. Appraisal considered as a process of multi-level sequential checking. In: Scherer KR, Schorr A, Johnstone T, editors. Appraisal processes in emotion: theory, methods, research. New York: Oxford University Press; 2001. p. 92–120.
14. LeDoux JE. Cognitive–emotional interactions in the brain. Cogn Emot. 1989;3(4):267–289.
15. Hudlicka E. Guidelines for designing computational models of emotions. Int J Synth Emot (IJSE). 2011;2(1):26–79.
16. Marsella S, Gratch J, Petta P. Computational models of emotion. In: Scherer KR, Bänziger T, Roesch EB, editors. Blueprint for affective computing: a source book. 1st ed. Oxford: Oxford University Press; 2010.
17. Broekens J, Bosse T, Marsella SC. Challenges in computational modeling of affective processes. IEEE Trans Affect Comput 2013;4(3):242–245.
18. Ziemke T, Lowe R. On the role of emotion in embodied cognitive architectures: from organisms to robots. Cogn Comput. 2009;1(1):104–117.
19. Tao J, Tan T. Affective computing: a review. In: Tao J, Tan T, Picard R, editors. Proceedings of the international conference on affective computing and intelligent interaction (ACII 2005). Berlin: Springer; 2005. p. 981–95.
20. Fellous JM, Arbib MA, editors. Who needs emotions?: the brain meets the robot. Oxford: Oxford University Press; 2005.
21. Martínez-Miranda J, Aldea A. Emotions in human and artificial intelligence. Comput Hum Behav. 2005;21(2):323 – 341.
22. Picard RW. Affective computing. Cambridge, MA: MIT Press; 1997.
23. Rumbell T, Barnden J, Denham S, Wennekers T. Emotions in autonomous agents: comparative analysis of mechanisms and functions. Auton Agents Multi-Agent Syst. 2012;25(1):1–45.
24. Samsonovich AV. Emotional biologically inspired cognitive architecture. Biol Inspir Cogn Archit. 2013;6(0):109–125.
25. Lin J, Spraragen M, Zyda M. Computational models of emotion and cognition. Adv Cogn Syst. 2012;2:59–76.
26. Scheutz M. Useful roles of emotions in artificial agents: a case study from artificial life. In: AAAI'04: Proceedings of the 19th national conference on Artifical intelligence. AAAI Press; 2004. p. 42–7.

27. Plaut DC. Methodologies for the computer modeling of human cognitive processes. In: Boller F, Grafman J, Rizzotti G, editors. Handbook of Neuropsychology. 2nd ed. Amsterdam: Elsevier; 2000.
28. Rodríguez LF, Ramos F, García G. Computational modeling of brain processes for agent architectures: issues and implications. In: Hu B, Liu J, Chen L, Zhong N, editors. Proceedings of the international conference on brain informatics (BI-2011). Lanzhou: Springer; 2011.
29. Ortony A. On making believable emotional agents believable. In: Trappl R, Petta P, Payr S, editors. Emotions in humans and artifacts. Cambridge, MA.: MIT Press; 2003. p. 189–212.
30. Scherer KR. Emotion and emotional competence: conceptual and theoretical issues for modelling agents. In: Scherer KR, Bänziger T, Roesch EB, editors. Blueprint for affective computing: a source book. Oxford: Oxford University Press; 2010.
31. Davidson RJ, Sherer KR, Goldsmith HH, editors. Handbook of affective sciences. Oxford: Oxford University Press; 2009.
32. LeDoux JE. The emotional brain: the mysterious underpinnings of emotional life. New York City: Simon and Schuster; 1993.
33. Lane RD, Nadel L, editors. Cognitive neuroscience of emotion. Oxford: Oxford University Press; 2002.
34. Arbib MA, Fellous JM. Emotions: from brain to robot. Trends Cogn Sci. 2004;8(12):554 – 561.
35. Fellous JM. From human emotions to robot emotions. In: 2004 AAAI Spring Symposium. Architectures for modeling emotion: cross-disciplinary foundations. American Association for Artificial Intelligence; 2004. p. 37–47.
36. Becker-Asano C, Wachsmuth I. Affective computing with primary and secondary emotions in a virtual human. Auton Agents Multi-Agent Syst. 2010;20(1):32–49.
37. Velásquez JD. Modeling emotions and other motivations in synthetic agents. In: Proceedings of the 14th national conference on artificial intelligence and ninth conference on innovative applications of artificial intelligence. Providence, Rhode Island: AAAI Press; 1997. p. 10–15.
38. Marsella SC, Gratch J. EMA: a process model of appraisal dynamics. Cogn Syst Res. 2009;10(1):70–90
39. Gebhard P. ALMA: a layered model of affect. In: Proceedings of the 4th international joint conference on autonomous agents and multiagent systems; 2005. p. 29–36.
40. Cambria E, Livingstone A, Hussain A. The hourglass of emotions. In: Esposito A, Esposito AM, Vinciarelli A, Hoffmann R, Müller VC, editors. Cognitive behavioural systems. vol. 7403 of lecture notes in computer science. Berlin: Springer; 2012. p. 144–157.
41. Frijda NH, Kuipers P, ter Schure E. Relations among emotion, appraisal, and emotional action readiness. J Pers Soc Psychol. 1989;57(2):212 – 228.
42. Roseman IJ, Spindel MS, Jose PE. Appraisals of emotion-eliciting events: testing a theory of discrete emotions. J Pers Soc Psychol. 1990;59(5):899 – 915.
43. Lazarus RS. Emotion and adaptation. Oxford: Oxford University Press; 1991.
44. Smith CA, Lazarus RS. Emotion and adaptation. In: John OP, Robins RW, Pervin LA, editors. Handbook of personality: theory and research. New York City: Guilford Press; 1990. p. 609–637.
45. El-Nasr MS, Yen J, Ioerger TR. FLAME–fuzzy logic adaptive model of emotions. Auton Agents Multi-Agent Syst. 2000;3(3): 219–257.
46. Bolles RC, Fanselow MS. A perceptual-defensive-recuperative model of fear and pain. Behav Brain Sci. 1980;3(2):291–301.
47. Hudlicka E. This time with feeling: integrated model of trait and state effects on cognition and behavior. Appl Artif Intell 2002; 16(7-8):611 – 641.
48. Smith CA, Kirby LD. Toward delivering on the promise of appraisal theory. In: Scherer KR, Schorr A, Johnstone T, editors. Appraisal processes in emotion. New York: Oxford University Press; 2001.
49. McCrae RR, John OP. An introduction to the five-factor model and its applications. J Pers. 1992;60(2):175–215.
50. Mehrabian A. Pleasure-arousal-dominance: a general framework for describing and measuring individual differences in temperament. Curr Psychol. 1996;14(4):261–292.
51. Ekman P. An argument for basic emotion. Cogn Emot. 1992;6(3):169–200.
52. Marinier RP, Laird JE, Lewis RL. A computational unification of cognitive behavior and emotion. Cogn Syst Res. 2009;10(1): 48 – 69.
53. Newell A. Unified theories of cognition. Cambridge: Harvard University Press; 1990.
54. Marinier RP, Laird JE. Computational modeling of mood and feeling from emotion. In: Proceedings of 29th meeting of the cognitive science society; 2007. p. 461–466.
55. Russell JA. Core affect and the psychological construction of emotion. Psychol Rev. 2003;110(1):145 – 172.
56. Russell JA. Emotion, core affect, and psychological construction. Cogn Emot. 2009;23(7):1259–1283.
57. Russell JA, Barrett LF. Core affect, prototypical emotional episodes, and other things called emotion: dissecting the elephant. J Pers Soc Psychol. 1999;76(5):805–819.
58. Russell JA, Mehrabian A. Evidence for a three-factor theory of emotions. J Res Pers. 1977;11(3):273 – 294.
59. Kuremoto T, Obayashi M, Kobayashi K, Feng LB. An improved internal model of autonomous robots by a psychological approach. Cogn Comput. 2011;3(4):501–509.
60. Becker-Asano C, Wachsmuth I. WASABI as a case study of how misattribution of emotion can be modelled computationally. In: Scherer KR, Bänziger T, Roesch EB, editors. Blueprint for affective computing: a source book. 1st ed. Oxford: Oxford University Press; 2010.
61. Ekman P. Are There basic emotions? Psychol Rev. 1992;99(3): 550–553.
62. Ekman P. Basic emotions. In: Dalgleish T, Power MJ, editors. Handbook of cognition and emotion. New Jersey: Wiley; 1999. p. 45–60.
63. Lewis M, Sullivan MW, Stanger C, Weiss M. Self development and self-conscious emotions. Child Dev. 1989;60(1):146–156.
64. Ortony A, Turner TJ. What's basic about basic emotions? Psychol Rev. 1990;97(3):315–331.
65. Ekman P, Friesen WV, Ellsworth P. What emotion categories or dimensions can observers judge from facial behavior? In: Ekman P, editor. Emotion in the human face. Cambridge: Cambridge University Press; 1982. p. 39–55.
66. Izard CE. The face of emotion. New York, NY: Appleton-Century-Crofts; 1971.
67. Oatley K, Johnson-laird PN. Towards a cognitive theory of emotions. Cogn Emot. 1987;1(1):29–50.
68. Tomkins SS. Affect theory. In: Scherer KR, Ekman P, editors. Approaches to emotion. Hillsdale, NJ: Erlbaum; 1984. p. 163–195.
69. Damasio AR. Looking for spinoza: joy, sorrow and the feeling brain. 1st ed. Boston: Houghton Mifflin Harcourt; 2003.
70. Minsky M. The society of mind. New York City: Simon and Schuster; 1986.
71. Ekman P. Facial expression and emotion. Am Psychol. 1993;48(4):384–392
72. Pfeifer R. Artificial intelligence models of emotion. In: Hamilton V, Bower GH, Frijda NH, editors. Cognitive perspectives on emotion and motivation. vol. 44 of behavioural and social sciences. Berlin: Kluwer Academic Publishers; 1987. p. 287–320.

73. Rodríguez LF, Ramos F, García G. An integrative computational model of emotions. In: D'Mello S, Graesser A, editors. Proceedings of the 4th international conference on affective computing and intelligent interaction (ACII 2011). vol. 2. Memphis, US: Springer; 2011. p. 72–79.
74. Rusting CL. Personality, mood, and cognitive processing of emotional information: three conceptual frameworks. Psychol Bull. 1998;124(2):165–196.
75. Velásquez JD. When robots weep: emotional memories and decision-making. In: Proceedings of the 15th national/10th conference on Artificial intelligence/innovative applications of artificial intelligence. Madison, US: American Association for Artificial Intelligence; 1998. p. 70–5.
76. Velásquez JD. Modeling emotion-based decision-making. In: Proceedings of the 1998 AAAI fall symposium emotional and intelligent; 1998. p. 164–9.
77. El-Nasr MS, Ioerger TR, Yen J. PETEEI: a PET with evolving emotional intelligence. In: Proceedings of the third annual conference on autonomous agents (AGENTS '99). New York, NY: ACM; 1999. p. 9–15.
78. Gebhard P, Kipp M, Klesen M, Rist T. Adding the emotional dimension to scripting character dialogues. In: Proceedings of the 4th international workshop on intelligent virtual agents; 2003. p. 48–56.
79. Gebhard P, Klesen M, Rist T. Coloring multi-character conversations through the expression of emotions. In: Proceedings of the tutorial and research workshop on affective dialogue systems; 2004. p. 128–41.
80. Hudlicka E. Beyond cognition: modeling emotion in cognitive architectures. In: Proceedings of the international conference on cognitive modeling (ICCM'04). CMU, Pittsburgh, PA; 2004.
81. Hudlicka E. Two sides of appraisal: implementing appraisal and its consequences within a cognitive architecture. In: Proceedings of the AAAI spring symposium: architectures for modeling emotion. AAAI Press; 2004. p. 24–31.
82. Breazeal C. Emotion and sociable humanoid robots. Int J Hum Comput Stud. 2003;59(1–2):119–155.
83. Stone CP. Motivation: drives and incentives. In: Moss FA, editor. Comparative psychology. psychology series. New York, NY: Prentice-Hall; 1934. p. 73–112.
84. Breazeal C, Scassellati B. How to build robots that make friends and influence people. In: Proceedings of the international conference on intelligent robots and systems (IROS '99). vol. 2; 1999. p. 858–63.
85. Breazeal C, Scassellati B. Infant-like social interactions between a robot and a human caregiver. Adapt Behav. 2000;8(1):49–74.
86. Hampson SE. State of the art: personality. Psychol. 1999;12(6): 284–288.
87. John OP, Robins RW, Pervin LA. Handbook of personality: theory and research. New York City: Guilford Press; 2008.
88. Byrne JH, editor. Concise learning and memory. 1st ed. Waltham: Academic Press; 2008.
89. Kandel ER, Schwartz JH, Jessell TM. Principles of neural science. 4th ed. New York: McGraw-Hill; 2000.
90. Gray WD, editor. Integrated models of cognitive systems. 1st ed. Oxford: Oxford University Press; 2007.
91. Tanji J, Hoshi E. Behavioral planning in the prefrontal cortex, vol. 11. Amsterdam: Elsevier Science Ltd; 2001. p. 164–70.
92. Busemeyer JR, Johnson JG. Computational models of decision making. In: Koehler DJ, Harvey N, editors. Blackwell handbook of judgment and decision making. Hoboken: Blackwell Publishing Ltd; 2008. p. 133–54.
93. Morén J, Balkenius C. A computational model of emotional learning in the amygdala. In: From animals to animats 6: proceedings of the 6th international conference on the simulation of adaptive behaviour. Cambridge, MA: MIT Press; 2000.
94. Sollenberger D, Singh M. Koko: an architecture for affect-aware games. Auton Agents Multi-Agent Syst. 2010;p. 1–32.
95. Laird JE, Newell A, Rosenbloom PS. SOAR: an architecture for general intelligence. Artif Intell. 1987;33(1):1–64.
96. Busemeyer JR, Dimperio E, Jessup RK. Integrating emotional processes into decision-making models. Integr Model Cogn Syst. 2007;p. 213–29.
97. Anderson JR, Lebiere C. The atomic components of thought. Mahwah, NJ: Lawrence Erlbaum Associates; 1998.
98. Fum D, Stocco A. Memory, emotion, and rationality: an ACT-R interpretation for gambling task results. In: Proceedings of the 6th international conference on cognitive modeling. Pittsburgh; 2004. p. 106–11.
99. Laird JE. Extending the soar cognitive architecture. In: Proceeding of the conference on artificial general intelligence (2008). Amsterdam: IOS Press; 2008. p. 224–35.
100. Bach J. Principles of synthetic intelligence PSI: an architecture of motivated cognition. Oxford: Oxford University Press; 2009.
101. Bach J. The micropsi agent architecture. In: Proceedings of the international conference on cognitive modeling (ICCM-5); 2003. p. 15–20.
102. Bach J, Vuine R. Designing agents with micropsi node nets. In: Günter A, Kruse R, Neumann B, editors. Advances in artificial intelligence. vol. 2821 of lecture notes in computer science. Berlin: Springer; 2003. p. 164–78.
103. Scheutz M, Schermerhorn P. Affective goal and task selection for social robots. In: Vallverdú J, Casacuberta D, editors. The handbook of research on synthetic emotions and sociable robotics: new applications in affective computing and artificial intelligence. IGI Global; 2009. p. 74–87.
104. Reithinger N, Gebhard P, Löckelt M, Ndiaye A, Pfleger N, Klesen M. Virtual human: dialogic and affective interaction with virtual characters. In: ICMI '06: Proceedings of the 8th international conference on multimodal interfaces. New York; 2006. p. 51–8.
105. Gebhard P, Kipp KH. Are computer-generated emotions and moods plausible to humans? In: Proceedings of the 6th international conference on intelligent virtual agents; 2006. p. 343–56.
106. Gratch J, Marsella S. Evaluating a computational model of emotion. Auton Agents Multi-Agent Syst. 2005;11(1):23–43.
107. El-Nasr MS, Ioerger TR, Yen J, House DH, Parke FI. Emotionally expressive agents. In: Proceedings of the computer animation (CA '99). Washington, DC: IEEE Computer Society; 1999. p. 48.
108. Swartout W, Gratch J, Hill RW, Hovy E, Marsella S, Rickel J, et al. Toward virtual humans. AI Mag. 2006;27(2):96–108.
109. Breazeal C. Toward sociable robots. Robot Auton Syst. 2003;42(3-4):167–75.
110. Scherer KR. Psychological models of emotion. In: Borod J, editor. The neuropsychology of emotion. Oxford: Oxford University Press; 2000. p. 137–166.
111. Wehrle T, Scherer KR. Toward computational modelling of appraisal theories. In: Scherer KR, Schorr A, Johnstone T, editors. Appraisal processes in emotion: theory, methods, research. New York: Oxford University Press; 2001. p. 350–365.
112. Moors A. Theories of emotion causation: a review. Cogn Emot. 2009;23(4):625–662.
113. Davis DN. Cognitive architectures for affect and motivation. Cogn Comput. 2010;2(3):199–216.
114. Gratch J, Marsella S, Wang N, Stankovic B. Assessing the validity of appraisal-based models of emotion. In: Proceedings of the international conference on affective computing and intelligent interaction and workshops (ACII). IEEE; 2009. p. 1–8.