# What Lies Beneath—A Survey of Affective Theory Use in Computational Models of Emotion

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**Abstract**—Studying and developing systems that can recognize, express, and “have” emotions is called *affective computing*. To create a Computational Model of Emotion (CME), one must first identify what kind of system to build, then find emotion theories that match its requirements. The relevant literature is vast. This survey aims to help design CMEs that *generate emotions*—separated into *emotion representation* and *elicitation* tasks—in computer agents and interfaces. We give an overview of 67 CMEs from different domains, and identify which emotion theories they use and why. To better understand why CMEs use some theories, we also analyze instances where these CMEs use theories to *express emotion*. Lastly we summarize how CMEs generally use each theory. The survey is meant to be a guideline for deciding which affective theories to use for new emotion-generating CME designs.

**Index Terms**—Affective computing, artificial intelligence, computational models of emotion (CME), psychology.

## 1 Introduction

Affective Computing introduces emotion as a concern in programs so that they may recognize and respond to human users more intelligently [1, pp. 3, 50]. There are three main affective computing tasks [2, pp. 4], [3, pp. 2] that enable this human-centered approach:

- *Emotion Recognition*, to capture user information like speech and gesture to infer their current affective state,
- *Emotion Generation*, to produce an affective state given the current program and environment state, and
- *Emotion Effects on Behavior*, to change a program's behavior (e.g. facial expressions, gestures, or movements) given its affective state.

Infrequently another task, *Emotion Effects on Cognitive Processes* or *Cognitive Consequences of Emotions* [4, pp. 100] is added. We choose to focus on emotion generation and some aspects of emotion effects on behavior because the relevant literature is vast.

### 1.1 Computational Models of Emotion

A Computational Model of Emotion (CME) is a software system that is influenced by emotion research, embodying at least one emotion theory as the basis for its stimuli evaluation, emotion elicitation, and emotional behavior generation mechanisms [5, pp. 2, 14].

But what are emotions? While there is no agreed-on, precise definition, researchers agree on a fuzzy working definition and typical examples of emotions, which are sufficient for meaningful comparisons between theories [6, p. 248–249]. An *emotion* is a short-term affective state representing the coordinated physiological and behavioral response of the brain and body to events that an organism perceives to be relevant [7, pp. 4], [8, pp. 249], [9, pp. 138–139], [10, pp. 349], [11, pp. 121].

Some researchers hypothesize that each emotion has a *signature*—the coordinated response pattern it typically causes in an organism [12, pp. 133], [13, pp. 108] including: behavioral and expressional characteristics; somatic and neurophysiological factors that prepare the body for action; cognitive and interpretive evaluations that give rise to the emotion; and experiential and subjective qualities unique to an individual. Elements of the signature can be innate or learned [14, pp. 6]. Emotions are also characterized by their high intensity relative to other types of affect (e.g. personality, mood), their tendency to come and go quickly, their association with a specific triggering event, object, or person, and clear cognitive contents [7, pp. 4], [9, pp. 139–140], [10, pp. 350].

These characteristics differentiate emotions from other kinds of affect such as mood (enduring, less intense, and more diffuse states than emotions, often without apparent cause and/or object) and personality (set of stable affective traits) [7, pp. 4–5], [9, pp. 140–141], [10, pp. 351]. It is common to see CMEs that model more than emotion alone, as they serve related—but different—purposes [15, pp. 88], [16, pp. 354].

Choosing emotion theories for CME creation is difficult because each theory typically focuses on a subset of emotion process stages and has their own assumptions on how different components integrate and how to differentiate emotions [2, pp. 10–11]. Given the large number of emotion theories available (we've seen at least 27), trying to understand them all is unrealistic. By first focusing on families of theories, grouped by core assumptions or focus [2, pp. 11, 20], one can identify a subset of theories that might satisfy a CME's requirements, including their level of empirical validation and how they might be used together.

This survey explores 67 CMEs that are stand-alone applications (e.g. GAMYGDALA (61)) or part of a broader system (e.g. in Kismet (53)). Its aim is to give an overview of some affective theories that appear in CME designs and the rea-

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TABLE 1
Main Theories Used

| Theory | Abbr. | References |
|---|---|---|
| **Izard** | Iz. | [18], [19], [20] |
| **Ekman** | Ek. | [21], [22] |
| **Plutchik** | Plu. | [23], [24] |
| **Valence & Arousal** | V-A | [25], [26], [27] |
| **Pleasure-Arousal-Dominance Space** | PAD | [28] |
| **Frijda** | Frj. | [8], [29] |
| **Lazarus** | Laz. | [30] |
| **Scherer** | Sch. | [13] |
| **Roseman** | Ros. | [31], [32], [33] |
| **Ortony, Clore, & Collins** | OCC | [34], [35], [36] |
| **Smith & Kirby** | S & K | [11], [37] |
| **Oatley & Johnson-Laird** | O & JL | [38], [39], [40], [41] |
| **Sloman** | Slo. | [42] |
| **Damasio** | Dam. | [43] |
| **LeDoux** | LD | [44] |

sons for that choice[1]. Seeing affective theories in context has two advantages. First, CMEs translate theories into concrete computational representations, thus dispelling the fuzziness of the theories' natural language presentations. The second and greater advantage is that a CME targeted at a specific application domain will illustrate the underlying theory's strengths and how it could be mechanized. In practice, designers often combine theories—sometimes implicitly—to achieve the desired CME functionality because single theories do not address all aspects of emotion or the available empirical data [17, pp. 10]. The role assigned to a theory in a CME could be an indicator of its strengths.

### 1.2 Paper Reading Guide

Section 2 reviews the survey's scope and methods, then Section 3 organizes CMEs into categories by the creator's original intent to help give context for their design decisions. Next, Section 4 presents how CMEs use theories for emotion representation, elicitation, and expression. In Section 5 we examine the theories that appear in CMEs at least five times (Table 1) to synthesize commonalities and strengths. We also note theory combinations. Section 6 explores other information that could be useful for designing CMEs. We use abbreviations—some of them our own—throughout the survey to increase the legibility of the text.

## 2 Survey Scope and Methods

We only include CMEs that generate emotion due to our focus. Our search protocol follows the PRISMA-S guidelines [45][2]. Fifteen systems are direct iterations of prior designs[3]. Prior systems are not surveyed unless they are sufficiently different (i.e. use different emotion theories, have differing designer intents) to warrant exploration. Prior systems that are not psychologically grounded (e.g. based on physical brain structures, empirical data) are also omitted, though mentioned when important ideas are borrowed from them.

We found 166 CMEs accompanied by a published description. We removed one because its bibliographic data was uncertain. Our selection protocol is partially based on citations, which take time to accumulate, so recent papers (2020 and later) were examined by hand for scope fit. Two of seven did. Of those from 2019 or earlier, 73 had strictly more than our threshold of 1.5 Citations per Year (C/Y). We included all CMEs with $C/Y > 2.5$ in the survey, and an additional handful chosen subjectively as they seemed to bring something interesting to the discussion. We made an exception for ELSA (26) with $0.43$ C/Y due to its unique implementation of Sch., and for Scherer's involvement in its creation (see Section 5.2). We survey 67 CMEs in total.

## 3 Classifying CMEs

We group CMEs by application domain according to the *creator's documented intent* (Table 2) because this would have guided their selection of emotion theories. These categories are not exclusive—someone could use a CME successfully in a different domain.

- *Multi-Purpose* CMEs (Systems 1–18) are not limited to one domain. These systems: explicitly list multiple, sufficiently different potential uses [12], [46, pp. 3–6], [47], [48]; name a general type of CME environment [15, pp. 10], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58, pp. 60], [59]; and allow users to integrate their own implementations of emotion theories [60], [61].
- *Natural Language Processing* CMEs (Systems 19) read, decipher, comprehend, and analyze human language, focusing on affective content [62].
- *Cognitive Architectures* (Systems 20–22) implement theories concerned with the components of the mind and interactions between them [63], [64], [65].
- *Scientific Research* CMEs (Systems 23–27) explore aspects of affect or affective system design. They are typically stricter about the system's behaviors, as they aim to test an affective theory [66], [67] or replicate observed affective phenomena [68], [69], [70].
- *Military and Emergency Training* CMEs (Systems 28–34) help train personnel for emotionally-charged scenarios in consequence-free environments [71], [72], [73], [74], or run simulations where emotion is a factor [75], [76], [77].
- CMEs for *Soft Skills Training* (Systems 35–39) help train life skills that can be difficult to hone with traditional techniques, such as emotional intelligence [78, pp. 153], problem solving under pressure [79], empathy [80], interview skills [81], healthy eating habits, and responsibility for pets [82].
- *Virtual Social Agents* with CMEs (Systems 40–48) have a virtual embodiment, interacting with users in a conversational capacity. They focus on: believability [83], [84], [85], [86]; improving interface usability [87], [88], [89], [90]; or both [78, pp. 158].
- CMEs for *Social Robots* (Systems 49–56) are different from virtual assistants because of a robot's physical

1. See [10, pp. 370–372] for some historical context too.
2. See Supplementary Material Section 1 for the full protocol.
3. See Supplementary Material Section 2 for CME "genealogy".

TABLE 2
Documented Application Domains

| Domain | Systems |
|---|---|
| **Multi-Purpose** | 1) Affective Reasoner (AffectR), 2) Cathexis, 3) Emotion Model (EmMod), 4) FLAME, 5) SCREAM, 6) MAMID, 7) TABASCO, 8) WASABI, 9) Maggie, 10) AKR Scheme, 11) General Virtual Human (GVH), 12) ParleE, 13) Interdependent Model of Personality, Motivations, Emotion, and Mood (IM-PMEB), 14) GenIA$^3$, 15) InFra, 16) FAtiMA Modular (FAtiMA-M), 17) Hybrid Model of Emotion-Eliciting Conditions (HybridC), 18) GEmA |
| **Natural Language Processing** | 19) SOM |
| **Cognitive Architecture** | 20) Soar, 21) LIDA, 22) CLARION |
| **Scientific Research** | 23) ACRES, 24) EMA, 25) Will, 26) ELSA, 27) GAMA-E, |
| **Military and Emergency Training** | 28) Émile, 29) EMOTION, 30) HumDPM-E, 31) JBdiEmo, 32) DETT, 33) EP-BDI, 34) MicroCrowd |
| **Soft Skills Training** | 35) Puppet, 36) CBI, 37) FAtiMA, 38) TARDIS, 39) PUMAGOTCHI, |
| **Virtual Social Agents** | 40) Greta, 41) ALMA, 42) Eva, 43) PPAD-Algorithm (PPAD-Algo), 44) Peedy the Parrot, 45) ERDAMS, 46) TEATIME, 47) Mobile Medical Tutor (MMT), 48) Presence |
| **Social Robots** | 49) Partially Observable Markov Decision Process for Cognitive Appraisal (POMDP-CA), 50) iPhonoid, 51) Ethical Emotion Generation System (EEGS), 52) Plutchik's Wheel of Emotions Inspired (PWE-I), 53) Kismet, 54) Roboceptionist (R-Cept), 55) GRACE, 56) TAME |
| **Art and Entertainment** | 57) Artificial Emotion Engine™ (AEE), 58) FeelMe, 59) Socioemotional State (SocioEmo), 60) The Soul, 61) GAMYGDALA, 62) Mob Simulation (MobSim), 63) Artificial Psychosocial Network (APF), 64) MEXICA, 65) Narrative Planning with Emotions (NPE), 66) Em/Oz, 67) S3A |

embodiment [91, pp. 120]. These CMEs aim to humanize robots and improve human-robot interactions by adding a social dimension to them [92], [93], [94], [95, pp. 209]—sometimes over extended time frames [91, pp. 122–124], [96]—and to provide companionship [97], [98].

- CMEs for *Art and Entertainment* (Systems 57–67) are often used for improving agent believability, changing the focus from strict adherence to psychological validity to interesting and entertaining behaviors. However, agent behaviors must remain plausible to be effective [99, p. 216–217]. There are CMEs for: developer tools [100], [101], [102], [103], [104], [105], [106]; narrative planning [107], [108]; and agent architectures [109, pp. 31], [110].

## 4 Survey

We document the following tasks performed by CMEs:

- *Emotion Representation* (Table 3): CMEs might use a theory to specify what kinds of emotion it supports. Although several CMEs tend to use the same theory to both represent and elicit emotion, these are examined separately because differences might indicate other aspects of the theory relevant to CME design.
- *Emotion Elicitation* (Table 4): Since there are emotion theories that do not, or vaguely, describe the *process* of emotion generation, this use is separated from emotion representation to clarify the difference.
- *Emotion Expression* (Table 5): We examine affective theories selected for expression separately because they are distinct tasks. CMEs that do both generation and expression might use separate theories for each task or the same combination of theories for both.

Eight CMEs (i.e. EmMod (3), WASABI (8), FAtiMA-M (16), HybridC (17), CLARION (22), Greta (40), Presence (48), GRACE (55)) do not implement one or more theories, but instead use them as design guides. These also reveal decision rationale, so we make note of this. When a CME can be programmed with a user's choice of theories (i.e. GenIA$^3$ (14), InFra (15), FAtiMA-M (16), FeelMe (58)), we examine its default implementation.

### 4.1 Emotion Representation

Twenty-eight CMEs appear to use the same theory to represent *and* elicit emotion, with the decision driven by elicitation requirements (marked with a † in Table 3). The others make representation choices independently of elicitation or appear to start with a representation and build an elicitation process from it (see Section 4.2).

Four CMEs reference Plu. for emotion representation because of its ability to "create" new emotions as combinations of its emotion categories (i.e. InFra (15) [57, pp. 35][4], HybridC (17) alongside Iz. [58, pp. 63], SOM (19) [62, pp. 217–218], PWE-I (52)). PWE-I also uses Plu.'s emotion structure which can be implemented as a 2D space, affording emotion dynamics and interactions while also using its emotion categories [95, pp. 210–211].

Kismet (53) uses a dimensional space that includes V-A to combine disparate information sources and unify the emotion elicitation process, internal representations, and facial expression generation [91, pp. 133, 148, 151]. However, it also found that a third dimension, *stance*, was necessary to prevent accidental activation of emotions that are similar in the simpler 2D space [91, pp. 139–140]. PAD, a 3D space, appears in eleven CMEs for emotion representation as a common space to define elicitation and expression mechanisms, as well as their interactions. FeelMe (58) uses PAD because "[it] argues that any emotion can be expressed in terms of values on these three dimensions, and provides extensive evidence for this claim...makes his three dimensions suitable for a computational approach. Second, since the PAD scales are validated for both emotional-states and

4. Inferred from InFra's (15) design goals [57, pp. 27].

TABLE 3
Theories Used for Emotion Representation

| | | Iz. | Ek. | Plu. | V-A | PAD | Frj. | Laz. | Sch. | Ros. | OCC | S&K | O&JL | Slo. | Dam. | LD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | **AffectR†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 2 | **Cathexis** | R | R | – | – | – | – | – | – | – | – | – | R | – | – | – |
| 3 | **EmMod** | – | R | – | – | – | – | – | – | – | – | – | R | – | – | – |
| 4 | **FLAME†** | – | – | – | – | – | – | – | – | r | r | – | – | – | – | – |
| 5 | **SCREAM†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 6 | **MAMID†** | – | – | – | r | – | – | – | r | – | – | r | – | – | – | – |
| 7 | **TABASCO†** | – | – | – | – | – | – | – | – | – | – | r | – | – | – | – |
| 8 | **WASABI** | – | R | r | – | R | – | – | – | – | r | – | – | r | R | R |
| 9 | **Maggie** | – | – | – | – | – | – | – | – | – | r[1] | – | – | – | – | – |
| 10 | **AKR** | – | r | – | – | – | r | – | r | r | r | – | – | – | – | – |
| 11 | **GVH** | – | R | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 12 | **ParleE†** | – | – | – | – | – | – | – | – | R (4) | R | – | – | – | – | – |
| 13 | **IM-PMEB** | – | – | – | – | r (41) | – | – | – | – | r | – | – | – | – | – |
| 14 | **GenIA[3]** | – | – | – | – | r (41) | – | – | – | – | r (24, 41) | – | – | – | – | – |
| 15 | **InFra** | – | – | r | – | – | – | – | – | – | – | – | – | – | – | – |
| 16 | **FAtiMA-M†** | – | – | – | – | – | – | – | – | – | R (37) | – | – | – | – | – |
| 17 | **HybridC** | R | R | R | – | – | – | – | – | – | – | – | r | – | – | – |
| 18 | **GEmA†** | – | – | – | – | – | – | – | – | – | R | – | – | – | – | – |
| 19 | **SOM** | – | – | R | – | – | – | – | – | – | – | – | – | – | – | – |
| 20 | **Soar†** | – | – | – | – | – | – | – | r[2] | – | – | – | – | – | – | – |
| 21 | **LIDA†** | – | – | – | – | – | – | – | r[2] | – | – | – | – | – | – | – |
| 22 | **CLARION†** | – | – | – | – | – | – | – | r | – | – | – | – | – | – | – |
| 23 | **ACRES†** | – | – | – | – | – | R | – | – | – | – | – | – | – | – | – |
| 24 | **EMA†** | – | – | – | – | – | – | – | – | – | r (1) | – | – | – | – | – |
| 25 | **Will†** | – | – | – | – | – | R | – | – | – | – | – | – | – | – | – |
| 26 | **ELSA†** | – | – | – | – | – | – | – | R | – | – | – | – | – | – | – |
| 27 | **GAMA-E** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 28 | **Émile†** | – | – | – | – | – | – | – | – | – | r (1) | – | – | – | – | – |
| 29 | **EMOTION** | – | – | – | – | – | – | – | – | – | r (11)[3] | – | – | – | – | – |
| 30 | **HumDPM-E†** | – | – | – | – | – | – | – | r | – | – | – | – | – | – | – |
| 31 | **JBdiEmo†** | – | – | – | – | – | – | – | – | – | r[4] | – | – | – | – | – |
| 32 | **DETT†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 33 | **EP-BDI** | – | – | – | – | – | – | – | – | – | r[1] | – | – | – | – | – |
| 34 | **MicroCrowd†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 35 | **Puppet** | – | R | – | – | – | – | – | – | – | R | – | – | – | – | – |
| 36 | **CBI†** | – | – | – | – | – | – | R | – | – | – | – | – | – | – | – |
| 37 | **FAtiMA†** | – | – | – | – | – | – | – | – | – | r (24, 67) | – | – | – | – | – |
| 38 | **TARDIS** | – | – | – | – | r (41, 59) | – | – | – | – | r | – | – | – | – | – |
| 39 | **PUMAGOTCHI†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 40 | **Greta** | – | r | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 41 | **ALMA** | – | – | – | – | R | – | – | – | – | r | – | – | – | – | – |
| 42 | **Eva** | – | – | – | – | r (41) | – | – | – | – | r[1] | – | – | – | – | – |
| 43 | **PPAD-Algo** | – | – | – | – | R | – | – | – | – | r (41) | – | – | – | – | – |
| 44 | **Peedy** | – | – | – | R | – | – | – | – | – | – | – | – | – | – | – |
| 45 | **ERDAMS** | – | – | – | – | – | – | – | – | – | R | – | – | – | – | – |
| 46 | **TEATIME** | – | – | – | – | – | – | – | – | r | – | – | – | – | – | – |
| 47 | **MMT†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 48 | **Presence** | – | – | – | – | – | – | – | – | – | R | – | – | – | – | – |
| 49 | **POMDP-CA†** | – | – | – | – | – | – | – | – | R | – | – | – | – | – | – |
| 50 | **iPhonoid** | – | – | – | – | r | – | – | – | – | – | – | – | – | – | – |
| 51 | **EEGS†** | – | – | – | – | – | – | – | – | – | r | – | – | – | – | – |
| 52 | **PWE-I** | – | – | R | – | – | – | – | – | – | – | – | – | – | – | – |
| 53 | **Kismet** | R | R | R | R[5] | – | – | – | – | – | – | – | – | – | – | – |

*Continued on next page*

TABLE 3
(*Continued.*) Theories Used for Emotion Representation

| | | Iz. | Ek. | Plu. | V-A | PAD | Frj. | Laz. | Sch. | Ros. | OCC | S&K | O&JL | Slo. | Dam. | LD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 54 | **R-Cept** | – | **r** | – | – | – | – | – | – | – | – | – | – | – | – | – |
| 55 | **GRACE†** | – | – | – | – | – | – | – | **r** | – | **r** | – | – | – | – | – |
| 56 | **TAME** | – | **R** | – | – | – | – | – | – | – | – | – | – | – | – | – |
| 57 | **AEE** | – | **r** | – | – | – | – | – | – | – | – | – | – | – | – | – |
| 58 | **FeelMe** | – | – | – | – | **R** | – | – | – | – | – | – | – | – | – | – |
| 59 | **SocioEmo** | – | – | – | – | **r** (41) | – | – | – | – | **R**[1] (12) | – | – | – | – | – |
| 60 | **The Soul** | – | – | – | – | **R** | – | – | – | – | **r** | – | – | – | – | – |
| 61 | **GAMYGDALA** | – | – | – | – | **R** | – | – | – | – | **R** | – | – | – | – | – |
| 62 | **MobSim** | – | – | – | – | **R** | – | – | – | – | **R** | – | – | – | – | – |
| 63 | **APF** | – | – | – | – | – | – | – | – | – | **r**[4] (59) | – | – | – | – | – |
| 64 | **MEXICA** | – | – | – | – | – | – | – | – | – | **r** | – | – | – | – | – |
| 65 | **NPE** | – | – | – | – | – | – | – | – | – | **r** | – | – | – | – | – |
| 66 | **Em/Oz** | – | – | – | – | – | – | – | – | – | **R** | – | – | – | – | – |
| 67 | **S3A†** | – | – | – | – | – | – | – | – | – | **r** | – | – | – | – | – |

**R**: *Reasons for choosing the theory are clear;* **r**: *Reasons are unclear;* (**#**): *System borrowed from/is influenced by System #*
† *Used as a consequence of theories chosen for emotion elicitation (Section 4.2).*
1 *Based on [35, pp. 193], a simplified model developed by Ortony for believable "artifacts" [85, pp. 23], [48, pp. 62], [102, pp. 285].*
2 *Not yet implemented [111, pp. 271], [64, pp. 26].*
3 *Builds on [112, pp. 2], a successor of GVH (11).*
4 *Uses the OCCr model [74, pp. 195, 197], [106, pp. 702] a reinterpretation of the OCC model that aims to clarify the model's logical structure and address ambiguities [113, pp. 1].*
5 *Also uses a* `stance` *dimension to measure the approachability of a stimulus [91, pp. 133].*

traits, they provide a useful basis for a computational framework that consistently integrates states and traits...provides an extensive list of emotional labels for points in the PAD space" [101, pp. 212]. The Soul (60) uses PAD because it is "[a] simple yet powerful model for representing emotional reactions...", "... is able to represent a broad range of emotions. It can be compared to creating a whole spectrum of colors using only red, green and blue", and "...it uses only three axes, which furthermore are almost orthogonal to each other, as we are used to, for example, in 3D space" [103, pp. 338–339]. WASABI (8) uses PAD because it felt that "...three dimensions are necessary and sufficient to capture the main elements of an emotion's connotative meaning—at least in case of simpler emotions such as primary or basic ones" [15, pp. 58]. A dimensional space also affords numerical measurements and calculations so that emotions and other types of affect can influence each other and another view of the emotion state [15, pp. 89, 97].

Eleven of the CMEs using PAD pair it with OCC for emotion representation. GAMYGDALA (61) starts with OCC because it is "...a well-known and accepted theory of emotions, it is a componential model of emotion that fits the needs of a computational framework, components are generic enough to allow for a wide set of emotions, it accounts for both internal emotions and social relationships which in games are quite important, and most importantly many computational models have been built on it", combining it with PAD because it "...complements the OCC model..." [104, pp. 33, 37]. Five CMEs reference ALMA (41) for the combination of OCC and PAD [56, pp. 68], [60, pp. 5:17–5:18], [81, pp. 5], [85, pp. 24], [86, pp. 216–217, 224], [102, pp. 289], [103, pp. 340], [105, pp. 2146–2148]. ALMA maps OCC emotion categories to points in PAD space to afford interactions with other types of affect [84, pp. 31], and MobSim (62) found that using PAD as an intermediary representation between elicitation and expression prevents "erratic behaviors" due to rapid changes in emotion intensity [105, pp. 2151–2152]. APF (63) does *not* reference PAD to accompany its use of OCC, but *does* create a dimensional space using Multidimensional Scaling (MDS) [106, pp. 698–699].

Representing emotions with OCC *does* appear to be connected to how CMEs elicit emotions, perhaps by limiting which categories a CME includes due to the needs of the domain (i.e. Maggie (9) [48, pp. 62], GAMA-E (27) [70, pp. 94], EMOTION (29) [72, pp. 2], TARDIS (38) [81, pp. 2], MMT (47) [90, pp. 9844], GRACE (55) [97, pp. 137–139], NPE (65) [108, pp. 118]), but there might be other reasons too. For example, Puppet (35) and Presence (48) use OCC because it is "...readily amenable to the intentional stance, and so ideally suited to the task of creating concrete representations/models of...emotions with which to enhance the illusion of believability in computer characters." [78, pp. 151]. WASABI (8) requires an emotion representation that depends on cognition ("secondary emotions") because it "...affords a more complex interconnection of the agent's emotion dynamics and its cognitive reasoning abilities" [15, pp. 93]. It uses OCC for this, choosing a subset of emotion categories that rely on past events and future expectations [15, pp. 87, 100]. WASABI makes a clear distinction between cognitive and noncognitive-dependent emotions, choosing simpler emotion representations from other theories, even though they are defined in OCC: *Fear* as proposed by LD due to its work on animal brain studies [15, pp. 47, 87]; and Plu. to define *Anger* as a reactive response tendency [15, pp. 85].

CMEs also use OCC to represent emotion because it: distinguishes emotions about the self and about others

TABLE 4
Theories Used for Emotion Elicitation

| | | Iz. | V-A | PAD | Frj. | Laz. | Sch. | Ros. | OCC | S&K | O&JL | Slo. | Dam. | LD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | AffectR | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 2 | Cathexis | e | – | – | – | – | – | – | – | – | – | – | E | E |
| 3 | EmMod | – | – | – | – | – | – | – | e | – | – | – | e | – |
| 4 | FLAME | – | – | – | – | – | – | e | e | – | – | – | – | e |
| 5 | SCREAM | – | – | – | – | – | – | – | e (66) | – | – | – | – | – |
| 6 | MAMID | – | e | – | – | – | e | – | – | e | – | – | – | – |
| 7 | TABASCO | – | – | – | e | – | e | – | – | e | – | – | – | – |
| 8 | WASABI | – | – | – | – | – | – | – | e | – | – | e | E | E |
| 9 | Maggie | – | – | – | – | E | – | – | E[1] | – | – | – | – | – |
| 10 | AKR‡ | – | – | – | e | – | e | e | e | – | – | – | – | – |
| 11 | GVH | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 12 | ParleE | – | – | – | – | – | – | E | E (4, 66) | – | e | – | – | – |
| 13 | IM-PMEB | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 14 | GenIA[3] | – | – | – | – | – | – | – | e (24, 41, 45) | – | – | – | – | – |
| 15 | InFra | – | – | – | – | – | e | – | e (4) | – | – | – | – | – |
| 16 | FAtiMA-M | – | – | – | – | e (37) | E | – | E (37) | – | – | – | – | – |
| 17 | HybridC | – | – | – | – | – | E | E | E | – | – | – | – | – |
| 18 | GEmA | – | – | – | – | – | – | – | E | – | – | – | – | – |
| 20 | Soar | – | – | – | – | – | e[2] | – | – | – | – | – | – | – |
| 21 | LIDA | – | – | – | – | – | e[2] | – | – | – | – | – | – | – |
| 22 | CLARION | – | – | – | – | – | e | – | – | – | – | – | – | – |
| 23 | ACRES | – | – | – | E | – | – | – | – | – | – | – | – | – |
| 24 | EMA | – | – | – | – | e | – | – | e (1, 28) | – | – | – | – | – |
| 25 | Will | – | – | – | E | – | – | – | – | – | – | – | – | – |
| 26 | ELSA | – | – | – | – | – | E | – | – | – | – | – | – | – |
| 27 | GAMA-E | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 28 | Émile | – | – | – | – | E[2] | – | – | e (1, 66) | – | e | e | – | – |
| 29 | EMOTION | – | – | – | – | – | – | – | e (11)[3] | – | – | – | – | – |
| 30 | HumDPM-E | – | – | – | – | – | e | – | – | – | – | – | – | – |
| 31 | JBdiEmo | – | – | – | – | – | – | – | e[4] | – | – | – | – | – |
| 32 | DETT | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 33 | EP-BDI | – | – | – | – | – | – | – | e[1] | – | – | – | – | – |
| 34 | MicroCrowd | – | – | – | – | – | – | – | E | – | – | – | – | – |
| 35 | Puppet | – | – | – | – | – | – | – | E | – | – | – | – | – |
| 36 | CBI | – | – | – | – | E | – | – | – | – | – | – | – | – |
| 37 | FAtiMA | – | e | – | – | e (24) | – | – | e (24, 67) | – | – | – | – | – |
| 38 | TARDIS | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 39 | PUMAGOTCHI | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 40 | Greta‡ | – | – | – | – | – | – | – | e | – | e | – | – | – |
| 41 | ALMA | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 42 | Eva | – | – | – | – | – | – | – | e[1] | – | – | – | – | – |
| 43 | PPAD-Algo | – | – | E | – | – | – | – | e (41) | – | – | – | – | – |
| 45 | ERDAMS | – | – | – | – | – | E | e | E (1, 66) | – | – | – | – | – |
| 46 | TEATIME‡ | – | – | – | E | – | – | E | – | – | – | – | – | – |
| 47 | MMT | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 48 | Presence | – | – | – | e | – | – | – | E | – | – | e | e | – |
| 49 | POMDP-CA | – | – | – | – | – | – | E | – | – | – | – | – | – |
| 50 | iPhonoid | – | – | – | – | – | – | – | e | – | – | – | – | – |
| 51 | EEGS | – | – | – | – | – | e | – | e | E | – | – | – | – |
| 53 | Kismet | – | – | – | – | – | – | – | – | – | – | – | E | – |
| 55 | GRACE | – | – | – | – | – | e | – | e | – | – | – | – | – |
| 58 | FeelMe | – | – | – | – | – | e | – | – | e | – | – | – | – |

*Continued on next page*

TABLE 4
(*Continued.*) Theories Used for Emotion Elicitation

| | | Iz. | V-A | PAD | Frj. | Laz. | Sch. | Ros. | OCC | S&K | O&JL | Slo. | Dam. | LD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 59 | **SocioEmo** | – | – | – | – | – | – | – | **E** (28, 66) | – | – | – | – | – |
| 60 | **The Soul‡** | – | – | – | – | – | – | – | **e** (41) | – | – | – | – | – |
| 61 | **GAMYGDALA** | – | – | – | – | – | – | – | **E** (66) | – | – | – | – | – |
| 62 | **MobSim** | – | – | – | – | – | – | – | **E**[5] | – | – | – | – | – |
| 63 | **APF** | – | – | – | – | – | – | – | **e**[4] (59) | – | – | – | – | – |
| 64 | **MEXICA** | – | – | – | – | – | – | – | **e** | – | – | – | – | – |
| 65 | **NPE** | – | – | – | – | – | – | – | **e** | – | – | – | – | – |
| 66 | **Em/Oz** | – | – | – | – | – | – | – | **E** | – | – | – | – | – |
| 67 | **S3A** | – | – | – | **E** | – | – | – | **e** | – | – | – | – | – |

**E**: *Reasons for choosing the theory are clear;* **e**: *Reasons are unclear;* (#): *System borrowed from/is influenced by System #*
‡ *Used as a consequence of theories chosen for emotion representation (Section 4.1).*
[1] *Based on [35, pp. 193], a simplified model developed by Ortony for believable "artifacts" [85, pp. 23], [48, pp. 62], [102, pp. 285].*
[2] *Not yet implemented [111, pp. 271], [64, pp. 26], [71, pp. 331].*
[3] *Builds on [112, pp. 2], a successor of GVH (11).*
[4] *Uses the OCCr model [74, pp. 195, 197] a reinterpretation of the OCC model that aims to clarify the model's logical structure and address ambiguities [113, pp. 1].*
[5] *Process derived from [114].*

TABLE 5
Theories Used for Emotion Expression

| | | Iz. | Ek. | Plu. | V-A | PAD | Frj. | Laz. | Ros. | OCC | S&K | Slo. | Dam. | LD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | **AffectR** | – | – | – | – | – | – | – | – | **x**[1] | – | – | – | – |
| 2 | **Cathexis** | – | – | – | – | – | – | – | – | – | – | – | **x** | – |
| 3 | **EmMod** | – | **x** | – | – | – | – | – | – | – | – | – | **x** | – |
| 5 | **SCREAM** | – | **x** | – | – | – | – | – | – | **x**[2] | – | – | – | – |
| 7 | **TABASCO** | – | – | – | – | – | **X** | **x** | – | – | – | – | – | – |
| 8 | **WASABI** | – | **X** | – | – | – | – | – | – | – | – | – | – | – |
| 10 | **AKR** | – | **x** | – | – | – | **x** | – | – | – | – | – | – | – |
| 11 | **GVH** | – | **X** | – | – | – | – | – | – | – | – | – | – | – |
| 12 | **ParleE** | **X** | **X** | – | – | – | – | – | – | – | – | – | – | – |
| 14 | **GenIA**[3] | – | – | – | – | – | – | **x** (24) | – | **x**[2] | – | – | – | – |
| 15 | **InFra** | – | – | – | – | – | – | – | – | – | – | – | – | **x** |
| 20 | **Soar** | – | – | – | **X** | – | – | – | – | – | – | – | – | – |
| 22 | **CLARION** | – | – | – | – | – | – | **x** | – | – | – | – | – | – |
| 23 | **ACRES** | – | – | – | – | – | **X** | – | – | – | – | – | – | – |
| 24 | **EMA** | – | – | – | – | – | **x** | **x** | – | – | **x** | – | – | – |
| 25 | **Will** | – | – | – | – | – | **X** | – | – | – | – | – | – | – |
| 28 | **Émile** | – | – | – | – | – | – | – | – | – | – | – | **x** | – |
| 35 | **Puppet** | – | **X** | – | – | – | – | – | – | – | – | – | – | – |
| 36 | **CBI** | – | – | – | – | – | – | **X** | – | – | – | – | – | – |
| 37 | **FAtiMA** | – | – | – | – | – | – | **x** (36) | – | – | – | **x** | – | – |
| 40 | **Greta** | – | **X** | – | – | – | – | – | – | – | – | – | – | – |
| 46 | **TEATIME** | – | – | – | – | – | – | – | **X** | – | – | – | – | – |
| 48 | **Presence** | – | – | – | **X** | – | – | – | – | **X** | – | – | – | – |
| 50 | **iPhonoid** | – | **x** | – | – | – | – | – | – | – | – | – | – | – |
| 53 | **Kismet** | **X** | **x** | **X** | **X**[3] | – | – | – | – | – | – | – | – | – |
| 55 | **GRACE** | – | – | – | – | – | – | **x** | – | – | – | – | – | – |
| 60 | **The Soul** | – | **X** | – | – | **X** | – | – | – | – | – | – | – | – |
| 66 | **Em/Oz** | – | – | – | – | – | – | – | – | **X**[1] | – | – | – | – |
| 67 | **S3A** | – | – | – | – | – | – | – | – | **X** (66) | – | – | – | – |

**X**: *Reasons for choosing the theory are clear;* **x**: *Reasons are unclear;* (#): *System borrowed from/is influenced by System #*
[1] *Based on an unpublished work which AffectR describes [46, pp. 50] and Em/Oz duplicates and expands on [109, pp. 104].*
[2] *Based on [35, pp. 193, 198], a simplified model developed by Ortony for believable "artifacts" [51, pp. 234], [60, pp. 5:5].*
[3] *Also uses a `stance` dimension to measure the approachability of a stimulus [91, pp. 133, 140].*

("empathetic emotions") necessary for some conversational agents like Greta (40) [83, pp. 94, 111][5], Eva (42) [85, pp. 21, 23], and ERDAMS (45) [88, pp. 412], social simulations like GAMA-E (27) [70, pp. 94], EP-BDI (33) [76, pp. 425–426], and MicroCrowd (34) [77, pp. 91], and narrative planners like MEXICA (64) [107, pp. 90] and NPE (65) [108, pp. 118]; represents emotion as both categories and classes of triggering conditions (i.e. PUMAGOTCHI (39) [82, pp. 64], SocioEmo (59) [102, pp. 282, 285]); and its hierarchical organization of emotion categories (APF (63) [106, pp. 703], Em/Oz (66) [109, pp. 73]).

Six CMEs that aim to express emotions via facial expressions (see Section 4.3) chose an emotion representation to ensure a smooth connection between them. Ek. emotion categories appear for this, as in TAME (56) "...in part because these basic emotions have universal, well-defined facial expressions, are straightforwardly elicited, and would be expected, perhaps subconsciously, on a humanoid's face, as appearance does affect expectations" [98, pp. 211] and AEE (57) [100]. It is possible to generate expressions from affective dimensions, but these might be more difficult than distinct categories such as those provided by Ek. [96, pp. 324]. GVH (11) uses the OCC categories to define emotions, but reorganizes and expands them into the six categories defined by Ek. which "...enables us to handle relatively less number of emotional states still retaining completeness necessary for expressive conversation" [54, pp. 108–109]. Puppet (35) chose a subset of OCC emotions to match Ek. facial expressions due to evidence of the associated emotions' universality and distinctive facial expressions which children can recognize [78, pp. 155], whereas Greta (40) also cites Ek. and OCC for their representation but adds facial expressions to match the possible emotion representation states [83, pp. 91]. Representations based on categories from Ek., Iz., Plu., and/or O & JL have also been cited for reasons such as: evidence of universality and facial expressions [49, pp. 71]; "...they are easy to explain and understand" [50, pp. 65]; their association with evolutionary, cross-species, and social functions [91, pp. 129]; and their connection to emotions that are hardwired and do not require cognitive processing ("primary emotions" in WASABI (8) [15, pp. 84, 100], HybridC (17) [58, pp. 63–64]).

Three CMEs appear to choose their emotion representation before their elicitation methods because they align with the CMEs' goals. Peedy (44) represents emotion with V-A because it "...corresponds more directly to the universal responses...that people have to the events that affect them" [87, pp. 199–200]. TEATIME (46) aims to strongly connect emotion to speech acts, stating that "...emotions cannot be reduced to a label or a vector: these are only a description of the state of the individual", and therefore focuses on "...action tendency...defined as the will to establish, modify, or maintain a particular relationship between the person and a stimulus" as defined by Frj. [89, pp. 144, 145–150]. This led it to draw from both Frj. and Ros., which emphasize action tendencies in their theories, to represent emotion. In the case of AKR (10), part of its goal is to define a taxonomy of emotion and other types of affect [53, pp. 594, 596–597, 599–600, 606]. This lead it to pull from a range of emotion theories to represent emotion: Ek., presumably to connect to facial expressions; Sch., Ros., and OCC for appraisal variables, although Ros. is presumably for representing *Surprise*; and Frj. for action tendencies.

5. Inferred from Greta's example [83, pp. 84].

## 4.2 Emotion Elicitation

Three CMEs appear to choose theories for emotion elicitation based on their choice for representation (marked with a ‡ in Table 4) and six others elicit emotion independently of a theory with methods such as affine mapping and fuzzy inference mechanisms (SOM (19) [62, pp. 219, 244]), Bayesian Networks (Peedy (44) [87, pp. 204]), hard-coded values (R-Cept (54) [96, pp. 324]), and/or signal processing-based approaches (TAME (56) [98, pp. 211], PWE-I (52) [95, pp. 211–213], AEE (57) [100]). The rest ground elicitation methods directly in emotion theories. Methods can be broadly grouped into cognitive and noncognitive elicitation and a CME need not be limited to one type.

None of the CMEs implement noncognitive elicitation alone, instead realizing it as a mechanism or process that complements cognitive elicitation. One CME, Kismet (53), uses Dam. alone to create a "mixed" elicitation system [91, pp. 133–134]). Six CMEs use multiple, coexisting theories for this purpose. TABASCO (7) references Sch. and S & K to create a multi-layer appraisal system which has different appraisal mechanisms for different types of information [52, pp. 265–266, 268–269]. It also applies this to a Frj.-based monitor which ensures that actions influence appraisals. The five remaining CMEs reference at least one of Slo., Dam., and LD to define a "mixed" elicitation system. Presence (48) differentiates cognitive and noncognitive emotion processes using Slo. and Dam. so that it aligns with recent affective computing research [78, pp. 160–161]. It implements noncognitive emotions using heuristics and combines Frj.'s process with OCC in a BDI model for cognitive emotion elicitation. FLAME (4) uses LD for learning noncognitive, conditioned behavior and Ros. and OCC for cognitive appraisal [47, pp. 227–228, 237–238]. Cathexis (2) also uses LD for noncognitive behavior, this time combined with Dam. for cognitive, memory-driven emotion elicitation [49, pp. 71–72]. It references Iz. to differentiate between cognitive and noncognitive emotion elicitors.

WASABI (8) references both OCC and Dam. for the division of its cognitive layer into a reactive and reasoning layer to differentiate between cognitive and noncognitive elicitation [15, pp. 50, 54, 84, 87, 90–92, 97–98, 102]. WASABI drew assumptions about Dam.'s connection between memories and cognitive elicitation such that it could be formalized. In a separate emotion module, it uses Slo. to define a dynamics system that accepts valenced pulses as inputs and creates an "alarm" signal that is translated into PAD as a primary emotion encoded by *pleasure* and *arousal* values. WASABI uses OCC for cognitive emotion elicitation because it requires high-level reasoning, but manually codes their intensity values [15, pp. 95, 100].

The other 51 CMEs choose to focus exclusively on cognitive elicitation. Sch. appears in the three cognitive architectures [111, pp. 272–273, 277–278], [65, pp. 9, 11], chosen—at least in part—for its focus on the cognitive contents of emotion [64, pp. 26–27]. ELSA (26) chose Sch.

due to its dynamic systems view and focus on emotion as emergent phenomena of time-dependent, componential changes rather than events with specific labels [67, pp. 99–102, 143]. HumDPM-E (30) uses Sch. to generate emotion patterns such that each possible emotion type is assigned a value [73, pp. 74, 76]. This allows HumDPM-E to define different agents based on their "susceptibility" to different emotions. MAMID (6) uses Sch., in combination with S & K, for its domain independent appraisal variables, multiple levels of resolution, multi-stage appraisals, and—potentially—because they account for some effects of emotion on cognition [12, pp. 134, 136]. MAMID also draws from V-A for part of its emotion intensity specification and to serve as another perspective on the emotion state. FeelMe (58) is also based on a combination of Sch. and S & K to enable a scalable design with modular components [101, pp. 210–211, 213]. It shows that this structure can be combined with dimensions from other theories, such as PAD. Although it also draws from Sch. for emotion elicitation, EEGS (51) creates a parallel appraisal process as in S & K: "The rationale behind this is that human brain is multi-processing and several evaluations occur simultaneously. This is the reason EEGS uses multi-threading approach in order to represent the true mechanism of emotion generation that occurs in humans" [94, pp. 236]. FAtiMA-M (16), although it implements OCC as its default, generalized its design requirements so that it could represent Sch., "...one of the most complex Appraisal Theories" [61, pp. 45].

Four CMEs choose theories because they provide functionality central to their design, such as CBI's (36) use of Laz. for its integration of coping in appraisal [79, pp. 301–302, 306]. ACRES (23) and Will (25) chose their underlying theory—Frj.—because their aim is to implement that theory as a computational system [66, pp. 247], [68, pp. 138, 151–152]. POMDP-CA (49) uses Ros., not for its functionality, but because "[i]t has concrete definitions of criteria of cognitive appraisal and a structure that is amenable to computational implementation" [92, pp. 268].

Twenty-six CMEs use OCC alone to define rules and/or conditions for emotion elicitation, both independently of an architecture [51, pp. 230], [54, pp. 109, 112], [56, pp. 68], [59], [72, pp. 4–5], [81, pp. 4], [82, pp.63], [84, pp. 33], [85, pp. 23], [90, pp. 9841], [93, pp. 217, 220], [104, pp. 37–39], [106, pp. 698, 702], [107, pp. 90], [108, pp. 117, 121] or integrated into a Belief-Desire-Intention (BDI) design [60, pp. 5:2, 5:4–5:5, 5:12, 5:17–5:18], [70, pp. 92], [75, pp. 993–994], [76, pp. 424], [77, pp. 90], [78, pp. 153–154], [83, pp. 88, 94–95, 97], [88, pp. 417]. The reason for choosing OCC is not always clear, but at least four reference its computational tractability [55, pp. 135–136], [58, pp. 66], [77, pp. 89] and/or prevalence in affective computing [104, pp. 37]. Em/Oz (66) is explicit in its reasoning, stating that it chose OCC because it was "...designed to be implemented computationally...reasonably simple to understand...", and because Em/Oz's users "...will not have much formal psychology training..." [109, pp. 28, 52–54, 59–60]. The emphasis on computational tractability and intuitiveness motivated other versions of OCC (e.g. [35]) which appear in CMEs [48, pp. 62], [74, pp. 195, 197]. MobSim (62) claims that OCC allows one to "...formally define the rules that determine an agent's evaluation of its surrounding events and relationships with other agents, [providing] a suitable basis for crowd simulation applications" and uses [114] to aid in its mechanization of OCC [105, pp. 2149–2150]. SocioEmo (59) uses the OCC version in [35], partially because "[g]ame developers are usually not specialists of AI [Artificial Intelligence] or cognitive psychology. This guided us toward models which are relatively simple to use" [102, pp. 282, 285]. GEmA (18) uses OCC for "...events and actions assessment [because] it includes comprehensive local and global variables to compute intensity of emotions and methods for [assessing] events and actions." [59, pp. 2642]. AffectR (1) is less clear, but its focus on *reasoning* about an agent's emotion might be the motivation [46, pp. 27, 30]. Both AffectR and Em/Oz have influenced later CMEs, such as ParleE (12) [55, pp. 117–125], EMA (24) [69, pp. 282–283, 285], Émile (28) [71, pp. 326–329], and ERDAMS (45) [88, pp. 421–422].

Fifteen CMEs also use OCC for emotion elicitation but combine it with other theories for their unique strengths, such as:

- Emotion intensity functions based on a PAD vector space (PPAD-Algo (43) [86, pp. 217, 223–224]), single dimensions like *arousal* (FAtiMA (37) [80, pp. 131]), and explicit plan representations in Slo. and/or O & JL (ParleE (12) [55, pp. 117–125], Émile (28) [71, pp. 328])
- Ros. for defining eliciting conditions for *Surprise* (ParleE (12) [55, pp. 118–119, 135–136], HybridC (17) [58, pp. 66]) or *Anger* (ERDAMS (45 [88, pp. 417]))
- Appraisal variables from Sch. (InFra (15) [57, pp. 30, 32], HybridC (17) [58, pp. 66], ERDAMS (45) [88, pp. 416], EEGS (51) [115, pp. 214–216], GRACE (55) [97, pp. 137–138])
- Elicitation process from Frj. because it "...complements the OCC model" (S3A (67) [110, pp. 48])
- Laz. process (FAtiMA-M (16) [61, pp. 44, 46–48], EMA (24) [69, pp. 272]), coping (Émile (28) [71, pp. 331], FAtiMA (37) [80, pp. 130–134]), or emotion themes (Maggie (9) [48, pp. 60]) which are integrated into emotion elicitation
- Dam. to define a deliberative architecture layer that relies on cognition (EmMod (3) [50, pp. 63])
- O & JL to frame cognition as a knowledge transformation process to drive cognitive appraisals (Greta (40) [83, pp. 94])

### 4.3 Emotion Expression

Twenty-nine emotion-generating CMEs also specify how the emotion state is expressed. Two CMEs draw from emotion theories to define an interface between internal emotion states and external behavior systems (e.g. InFra (15) uses LD to define an emotion-to-expression interface [57, pp. 27]) and Presence (48) uses OCC emotion types and V-A values to annotate actions such as speech and body gesture generation [78, pp. 161–162]). One CME relates their potential emotions to the functions they serve (Kismet (53) references Iz. and Plu. for this [91, pp. 129]), but eleven reference action tendencies—"...readiness for different actions having the same intent" and that "...account for behavior flexibility" [8, pp. 70–71].

CMEs use four emotion theories to define action tendencies (e.g. Laz. in FAtiMA (37) [80, pp. 131, 134], Ros. in

TEATIME (46) [89, pp. 149–150]), the most commonly referenced ones being Frj. and OCC. AKR is unclear in its choice to use Frj. for this [53, pp. 596–597], whereas TABASCO (7)—which uses an underlying system that is "very close to the functionality" of Frj.—compares the action tendencies to "flexible programs" that allow behavior variations and can be influenced by feedback processes [52, pp. 267]. ACRES (23) is an implementation of Frj. [66, pp. 247]. With Will as ACRES's successor [68, pp. 138, 146], Frj.'s use in these two CMEs is unsurprising.

Two CMEs use a "simplified" version of OCC [51, pp. 234], [60, pp. 5:5–5:6] that includes a hierarchy of response tendencies grouped by type [35]. The hierarchy might be a simplification of unpublished work intended for the full theory, which AffectR (1) and Em/Oz (66)—which S3A (67) builds on [110, pp. 52–53]—incorporate [46, pp. 50–53], [109, pp. 86, 100, 104]. The hierarchy elements are not uniquely associated with OCC emotion categories, so the hierarchy can be implemented to allow the categorization of display mechanisms—encouraging modular development—and assign the same behavior to different tendencies, affording more control over emotional displays.

CMEs targeting specific domains typically specify what types of behaviors their CMEs produce. At least nine systems intended for face-to-face interactions with people use facial expressions to convey emotion. Ek. is often referenced for this. For example, GVH (11) is concerned with the facial representation of virtual humans and uses Ek.'s facial expression specification because they are "...recognized as universal by many facial expression and emotion researchers" [54, pp. 108–109]. Puppet (35) chose Ek. due to evidence of the associated emotions' universality and distinctive facial expressions that children can recognize [78, pp. 155]. ParleE (12) cites the universality of Ek. and Iz.'s given facial expressions, building a generation system on FACS [22] [55, pp. 142–143, 146]. Although unclear, several other CMEs also seem to cite Ek. for its work on facial expressions [15, pp. 84, 100], [50, pp. 66], [53, pp. 596–597][6], [116, pp. 740], potentially in connection to FACS [22] which documents facial muscles with respect to expressions [83, pp. 91]. Kismet (53) and The Soul (60) use Ek. to define points in dimensional models so that facial expressions can be procedurally generated [91, pp. 140, 143], [103, pp. 338, 340–343]. SCREAM (5) references Ek.'s rules for when emotions are outwardly displayed given social and interaction contexts ("display rules") to regulate when their CME can show their emotions [51, pp. 231–232].

Specific effects of emotions on behavior can also refer to the effects that emotions have on other processes within or directly connected to the CME. Cathexis (2), EmMod (3), and Émile (28) reference Dam. to specify how emotion influences decision-making and planning [49, pp. 72], [50, pp. 63], [71, pp. 330]. EMA (24) draws from Frj. and S & K to define attentional focus necessary for coping [69, pp. 286, 297].

CMEs tend to use Laz. when coping itself is central to the CME's purpose (CBI (36) [79, pp. 302, 306]) whose design has been adopted by others (FAtiMA (37) [80, pp. 131, 134]), and because it can be implemented with a planner when viewed as a "planful process" (TABASCO (7) [52, pp. 267]). EMA (24) and GRACE (55) are unclear in their reasons for choosing Laz. for coping [69, pp. 272, 278], [97, pp. 136, 138]. CLARION (22) uses Laz. for coping so that emotions can influence decision-making, goal management, and regulatory processes [65, pp. 10, 12]. GenIA[3] (14) is more modest in its use of Laz.-based coping, allowing it to return to a previous emotion state and/or modify the agent's beliefs [60, pp. 5:5–5:6]. Emotions can also influence: learning, such as in Soar's (20) use of V-A to define reward signals for reinforcement learning because the dimensions can be unified with appraisal theories [111, pp. 279–280]; and emotion-driven plan selection such as the use of Slo. in FAtiMA (37) [80, pp. 134].

6. This decision is inferred.

TABLE 6
Number of Uses of Emotion Theories

| | Emotion Representation | Emotion Elicitation | Emotion Expression | Total |
|---|---|---|---|---|
| **OCC** | 42 | 46 | 6 | 94 |
| **Ek.** | 12 | – | 11 | 23 |
| **Sch.** | 8 | 15 | – | 23 |
| **PAD** | 13 | 1 | 1 | 15 |
| **Frj.** | 3 | 7 | 5 | 15 |
| **Laz.** | 1 | 6 | 7 | 14 |
| **Ros.** | 5 | 7 | 1 | 13 |
| **Dam.** | 1 | 5 | 3 | 9 |
| **V-A** | 3 | 2 | 3 | 8 |
| **Plu.** | 6 | – | 1 | 7 |
| **S & K** | 2 | 4 | 1 | 7 |
| **Iz.** | 3 | 1 | 2 | 6 |
| **O & JL** | 2 | 3 | – | 5 |
| **Slo.** | 1 | 3 | 1 | 5 |
| **LD** | 1 | 3 | 1 | 5 |

## 5 Observations from the Survey

Surveying CMEs and the affective theories they use brought out some commonalities. We discuss some *use trends* for each theory and *psychologist influences*.

### 5.1 Use Trends

The CMEs use a variety of theories for different purposes (Table 6). The reasons for choosing particular theories are not always clear. However, there are clear trends in *how* CMEs use affective theories. Even in CMEs without a documented choice rationale, these uses align with different aspects of the theories. This is indicative of their strengths, which tend to be similar within each perspective.

We use the broad categories of [4]—*discrete*, *dimensional*, *appraisal*, and *neurophysiologic*—to organize emotion theories. Other ways are available, such as [117, pp. 280].

#### 5.1.1 *Discrete Theories*

These appear when emotion "types" must be clearly distinguished. This reflects a strength of discrete theories, which build a small set of emotion categories that are theorized to have evolved via natural selection [118, p. 305]. The discrete perspective is associated with the most empirical evidence of observed emotion effects to emotions [17, pp. 10]. However, discrete theories do not give many details on emotion generation processes, so they are often combined with another theory or used in hand coded designs (e.g. R-Cept (54) [96, pp. 324]). This is due to a core assumption that emotions are innate, hard-wired features with dedicated neural circuitry which circumvents cognitive processing [6, pp. 250]. There are differences in the definition of "primary" emotions but these are not mutually exclusive [119, p. 2–3]. However, they do change which emotions are considered "basic". Ek. and Iz. are part of the "biologically basic" view, which tend to focus on facial expressions as indicators of primality, whereas Plu. is part of the "elemental" view that seeks emotions that cannot be defined with other emotions (i.e. "mixtures" of other emotions). Still, identifying and labeling emotion categories helps delimit them, making it easier to talk about them both formally and informally [10, pp. 353], [117, pp. 286].

5.1.1.1 Izard (Iz.): Although it does not tend to appear by itself, CMEs use Iz. to define facial expressions along side Ek. (e.g. ParleE (12)) and "mixed" emotions and the functional role of emotions with Plu. (e.g. HybridC (17) and Kismet (53)). This is likely because Iz. shares some of the same assumptions with them [120, pp. 64–65, 83, 85–92, 97]. However, there could be untapped potential in Iz., such as its differentiation between cognitive and noncognitive emotion elicitors (e.g. Cathexis (2)).

5.1.1.2 Ekman (Ek.): This theory is common in CMEs that express emotions via facial expressions (Section 4.3), and often use Ek.'s emotion categories to ensure a one-to-one mapping from internal state to facial configuration. This aligns with Ek.'s focus [21, pp. 1] and the resulting FACS [22], which breaks the face down into individual muscles and shows how they can combine into expressions. This makes Ek. a strong candidate, potentially "...the de facto standard for analysis and description of facial expressions, and serves as the foundation of...the synthesis of emotion expressions in virtual agents and robots." [17, pp. 4].

Ek. could be combined with: Iz. (e.g. ParleE (12)), which shares similar views [21, pp. 3] and also has a system for identifying facial expressions [121]; and O & JL (e.g. Cathexis (2)) as there is deliberate overlap in their "primary" emotion categories [39, pp. 209, 217].

5.1.1.3 Plutchik (Plu.): Plu. appears most often when CMEs want to represent "mixed" emotions as combinations of emotion categories, which allows a CME to add "more" emotion types. This is unsurprising, as Plu. "...has one of the better developed theories of emotion mixes" [44, pp. 113] and experiments have shown that laypeople tend to agree on the components of emotion "mixtures" [24, pp. 204–205]. Plu. identifies its "primary" emotions from evidence of a finite set of adaptive behaviors that aim to maintain internal homeostasis by acting on the environment [24, pp. 203, 215]. This effectively connects behaviors to action tendencies [8, pp. 72] and motivations [2, pp. 13], which can help specify an emotion's function (e.g. WASABI (8), Kismet (53)).

Using self-reports on the meanings of emotion words, Plu. arranges its emotion categories on a circumplex [24, pp. 204]. This affords the use of arbitrarily chosen axes because they are only reference points [122, pp. 13], which can serve as affective dimensions. The result is a 3D color space analogy—with intensity as the third dimension—that is familiar to computer scientists [15, pp. 21]. There is also evidence that the circumplex can act as a common space for different types of affect [122, pp. 30–31], which can help visualize affective dynamics using Plu.'s color analogy (e.g. PWE-I (52)).

### 5.1.2 *Dimensional Theories*

These appear when CMEs need a simple and effective emotion model, as another perspective of emotion categories, and/or as a common space for modeling different affective phenomena and their interactions. The dimensional perspective's strength lies in its description of affect in a simple way—usually two or three dimensions [4, pp. 97]—where any affective phenomena, including emotions [17, pp. 9], can be mapped. However, the dimensions can lose information about an emotion state if it has a higher information resolution than their dimensions can represent [10, pp. 353], [123, pp. 172]. This might not be appropriate for all CMEs. Dimensional theories focus on what kind of mental states emotions are, how to construct them, and how they fit into a general taxonomy of mental states [6, p. 250]. Consequently, they say little about how to generate emotions and what their effects are [17, p. 10], making them unsuitable for defining a complete computational model [6, p. 250].

5.1.2.1 Valence-Arousal (V-A): The *valence* and *arousal* dimensions are the two most widely agreed on affective dimensions [1, pp. 168] and are common in dimensional theories [117, pp. 280]. They form a simple model that captures most affective phenomena, including aspects of emotion, in a numerical form that is computationally efficient and can be used in emotion intensity functions (e.g. MAMID (6)), as inputs to other CME processes (e.g. Soar (20)), and to coordinate emotion expression modalities (e.g. Presence (48)) and/or generation (e.g. Kismet (53)).

The ability to represent different kinds of affective information can make V-A useful for combining disparate information sources and external behavior systems with a single representation, helping them work in concert so that the CME "...not only does the right thing, but also at the right time and in the right manner" [91, pp. 151]. However, two dimensions might not be enough to distinguish between every emotion a CME might need [91, pp. 139–140]. This implies that V-A is only ideal for CMEs with a set of emotions that are conceptually easy to distinguish both as internal representations and external expressions.

5.1.2.2 Pleasure-Arousal-Dominance Space (PAD): PAD is similar to V-A. Its *pleasure* dimension fills the same role as *valence*, and *arousal* is shared by both theories. The third dimension, *dominance*, distinguishes emotions such as *Anger* and *Fear* that are otherwise indistinguishable (i.e. have similar *valence* and *arousal* values) by quantifying how much control one believes they have (i.e. one tends to feel that they have low control when experiencing *Fear*, and high control in *Anger*) [28, pp. 263–264]. The empirical nature and ability to map emotions to three continuous dimensions might make PAD easy to understand using parallels to RGB color space [103, pp. 339] and "...suitable for a computational approach" [101, pp. 212].

As with V-A, CMEs often choose PAD to specify a simple model for representing emotion and its interactions with other types of affect (e.g. CMEs 41, 50, 58) that can also be used in numerical-based functions such as emotion intensity (e.g. PPAD-Algo (43)), affective dynamics (e.g. WASABI (8)), facial expression generation (e.g. The Soul (60)) and behavior mediation (e.g. MobSim (62)), or as an alternate view of emotion categories (e.g. WASABI (8), GAMYGDALA (61)). PAD's pervasiveness in CMEs suggests its usefulness for creating a unified space for multiple types of affect and interfacing between theories. Caution is required as soundness depends on how rigorously concepts are matched.

### 5.1.3 Appraisal Theories

CMEs often use these theories [4, pp. 97], [124, pp. 55]. This might be due to the theories' ability to comprehensively represent the complexity of emotion processes, receiving consistent empirical support for their hypothesized mechanisms [117, pp. 281–282]. However, they are based on cognition and CMEs seeking to use these theories must be able to account for it [10, pp. 354].

Appraisal theories emphasize distinct components of emotion, including appraisal dimensions or variables [4, pp. 97]. Analyzing stimuli for meaning and consequences with respect to an individual produce values for these variables [6, pp. 250], [125, pp. 819], regardless of process sophistication [69, pp. 273] and independent of biological processes [126, pp. 559]. Appraisals are continuous and change with the situation, the individual's behaviors, and their attempts to appraise the situation differently [127, pp. 28]. This can account for the personal, transactional, and temporal character of emotion with respect to a changing environment, applied coping strategies, and continuous appraisals. This makes appraisal theories of particular interest for decision-making, action selection, facial animations, and personality [69, pp. 274]. However, there is little empirical data associating individual appraisal variables to expressive behaviors or behavioral choices [17, pp. 10].

5.1.3.1 Frijda (Frj.): CMEs tend to use Frj. to explicitly connect emotions to action tendencies (e.g. TEATIME (46)) and define an action-driven appraisal process (e.g. CMEs 7, 23, 25). This aligns with Frj.'s proposal that emotions—outputs of a continuous information processing system—are changes in action readiness [8, pp. 453, 466]. "Action readiness" refers to motivational states which are associated with goals rather than actions or behaviors [29, pp. 143]. Frj.'s description of action tendencies appears to transfer to designs that do not implement its appraisal process (e.g. AKR (10), Presence (48)), since many of the identified action tendencies are associated with an emotion label [8, pp. 87–90].

The conceptualization of emotion elicitation as an information processing system is a useful analogy and can provide the necessary mechanization framework for structure-oriented theories like Ros. (e.g. TEATIME (46)) and OCC (e.g. S3A (67)). It is also possible to abstract and apply different elements independent of the broader theory, such as implicit appraisal checks (e.g. TABASCO (7)), information filtering (e.g. S3A (67)), and mechanisms whose behavior changes with the system state (e.g. EMA (24), TAME (56)).

5.1.3.2 Lazarus (Laz.): CMEs tend to use Laz. to specify coping behavior, a deliberative process whereby the individual can suppress action tendencies and choose other strategies to influence the current situation [128, pp. 628]. The appearance of Laz. in this context is unsurprising, as coping plays a critical role in the theory [30, pp. 39–40]. Coping can be incorporated directly into the appraisal process as an influencing factor (e.g. CMEs 14, 24, 36) and to plan agent behaviors (e.g. CMEs 7, 22, 28, 55). FAtiMA (37) successfully paired Laz. with a separately defined component for quick, reactionary behaviors. The coping models in EMA (24), Émile (28), and CBI (36) have been particularly influential for other CMEs [129, pp. 353], [130].

Laz. also describes a reappraisal process to explain the continuous and responsive nature of the emotion system [30, pp. 134]. This is directly tied to coping which can affect changes in an individual's interpretation of the environment. This concept has also appeared alone in CMEs that reprocess information after deliberative processes like coping (e.g. FAtiMA-M (16), FAtiMA (37)), which could result in different emotions compared to purely reactive systems.

Another feature of Laz. is its connection between relational themes and emotions [30, pp. 122] which treats appraisal as a comprehensive unit rather than a set of individual dimensions. This emulates discrete categories, allowing CMEs to treat each emotion separately (e.g. Maggie (9)).

5.1.3.3 Scherer (Sch.): Sch. tends to appear where CMEs need multi-level and/or multi-stage appraisals (e.g. CMEs 6, 7, 58), allowing them to use different appraisal mechanisms and/or sources of variable complexity together. These features are inherent in Sch. [13, pp. 99, 103]. Notably, the list of CMEs that use Sch. include the cognitive architectures (e.g. CMEs 20–22). This is likely because Sch. "...is the most elaborate appraisal theory, [and] doesn't necessarily make it the most suitable starting point for an affective computing researcher" [124, pp. 58]. FAtiMA-M (16) explicitly mentioned this complexity in their requirements to ensure that it could support Sch. if desired. ELSA (26) calls itself a neural network (NN), which makes it difficult to understand [67, pp. 143–144], but aligns with NN-based illustrations of connections and activation patterns in Sch. [13, pp. 105].

CMEs can simplify Sch. by only using its appraisal variables (e.g. AKR (10))—sometimes combining them with variables from other theories like OCC (e.g. CMEs 15, 17, 45, 51)—or take inspiration from its process model to connect emotion generation to other subsystems (e.g. GRACE (55)). HumDPM-E (30) cleverly leverages Sch.'s "modal" emotions [13, pp. 113], allowing it to produce and store different emotions simultaneously. This suggests that some CMEs can comfortably use pieces of Sch. independent of the complete theory.

5.1.3.4 Roseman (Ros.): CMEs commonly use Ros. to define *Surprise* as an emotion because they use other theories—usually Sch. and/or OCC—that do not explicitly define it (e.g. 10, 12, 17). These unions appear to be sound. OCC agrees with Ros. that *unexpectedness* elicits *Surprise* [34, pp. 32], and Sch.'s *suddenness* variable in the novelty check appears to do a comparable evaluation [13, pp. 95]. *Anger* is an emotion that Ros. shares with OCC, but it limits its scope to events caused by other agents, which a CME might find more helpful (e.g. ERDAMS (45)). Ros. can also help define action tendencies and map emotions to them (e.g. TEATIME (46), combined with Frj.).

Choosing Ros. is partially driven by its computational tractability. POMDP-CA (49) cites this, also noting that—of the two theories identified in [1] for cognitive appraisal—Ros. systematically built a model between appraisal variables and emotions from empirical studies [31, pp. 267–268] which makes it more plausible [92, pp. 265]. The larger issue is that Ros. does not specify an emotion generation process. CMEs have compensated for this by using Markov Models (e.g. POMP-CA (49) [92, pp. 267]), fuzzy logic (e.g. FLAME (4) [47, pp. 227–228]), and combining Ros. with process-based theories like Sch. (e.g. HybridC (17)) and Frj. (e.g. TEATIME (46)).

5.1.3.5 Ortony, Clore, and Collins (OCC): This is the most used [70, pp. 91], [97, pp. 136], [131, pp. 292] and widely accepted theory in affective computing [72, pp. 1] despite cautioning that "...we view each emotion specification, or characterization, as a *proposal* rather than as an empirically established fact." [34, pp. 87–88] and not being as popular in psychology [69, pp. 278].

The widespread use of OCC is partially due to its hierarchical emotion structure and event-driven eliciting conditions [34, pp. 18–19] (e.g. CMEs 5, 17, 18, 33, 34, 39, 47, 61–64) which feels familiar to computer scientists [15, pp. 44], [124, pp. 57] and is more amenable to computation than other theories [1, pp. 195], [10, pp. 362], [17, pp. 8], [34, pp. 2, 181–182]. There has been significant strides towards refining [114], formalizing [113], [132], and re-framing OCC for applications like agent believability [35]. A further benefit of OCC's comparison to a computational approach is that it can be easier to understand without a background in psychology [102, pp. 282], [109, pp. 28]. This might make it more "clear and convincing" [116, pp. 741] than other appraisal theories.

OCC's structure also shows which variables contribute to an emotion's intensity, proposing that it is evaluated with a weighted function [34, pp. 69, 82]. Unfortunately, it does not propose what those weights should be, nor the function's nature. CMEs have compensated by designing a separate tool for empirically deriving intensity parameters (e.g. ALMA (41) [133, pp. 209], The Soul (60)), translating OCC emotion categories to a dimensional space (e.g. PPAD-Algo (43)), defining their own functions or values from OCC variables with no clear empirical basis (e.g. CMEs 4, 8, 9, 18, 32, 42, 45, 47, 50, 51, 61, 64, 66, 67), or not concerning themselves with intensity at all (e.g. CMEs 1, 27, 39).

Strictly speaking, the weighted function used by these CMEs is not an intensity function. OCC proposes that a weighted combination of the variables leading to an emotion category along the hierarchy is an *emotion potential*—a higher potential means a higher chance of experiencing that kind of emotion [34, pp. 81–82]. The *difference* between an emotion threshold and this value is its intensity, which MMT (47) incorporates [90, pp. 9844]. CMEs have also used this difference modulate to simulate other types of affect [15, pp. 92–93], [50, pp. 65–66], [55, pp. 119], [59, pp. 2645], [61, pp. 48], [80, pp. 131], [83, pp. 103, 109–110], [110, pp. 51].

Ironically, OCC's authors believe that computers *cannot* have emotion but it is still useful to reason about them: "...we do not consider it possible for computers to experience anything until and unless they are conscious. Our suspicion is that machines are simply not the kinds of things that can be conscious...There are many AI endeavors in which the ability to understand and reason about emotions or aspects of emotions could be important" [34, pp. 182]. AffectR (1) adheres to this when reasoning about another agent's actions [46, pp. 27]. One could also view narrative planners (e.g. MEXICA (64), NPE (65)) as an exercise in reasoning about character emotions. However, OCC can be applied to emotion generation as well [1, pp. 195], also shown by AffectR, because the process of reasoning about emotions could be understood as reasoning about the emotional significance of an event to the agent [51, pp. 230]. The focus on reasoning makes OCC amenable to an intentional stance, which enhances agent believability [78, pp. 151–152], because users can "see" the agent's thought processes.

The "fortunes of others" emotions (e.g. *Happy-For*) might be unique to OCC which rely on evaluations of how *someone else* feels. These are critical for empathetic agents (e.g. Greta (40), ERDAMS (45)) and agents that model relationships (e.g. CMEs 27, 33, 34, 42, 59, 61, 63–65). However, OCC does not include *Surprise*—which is important for some CMEs—because they believe that it is not inherently positive or negative [34, pp. 32]. Instead, they categorize it as a cognitive state tied to a global *unexpectedness* variable. CMEs that need *Surprise* draw from Ros. (e.g. ParleE (12), HybridC (17)) because it shares this hypothesis and explicitly defines *Surprise* as an emotion [31, pp. 269].

A shortcoming of OCC is a lack of emotion elicitation processes. This is a deliberate omission because OCC views it as a general cognitive psychology problem, but stresses the role of cognition in such processes [34, pp. 2]. CMEs have realized OCC in plan-based systems (e.g. CMEs 12, 24, 28, 37, 64, 65), which are a step towards explainable behaviors. They provide context for elicited emotions [71, pp. 328], aligning with the OCC's focus on reasoning about emotions [34, pp. 182]. Another approach, supported by [36], is to integrate OCC in a biologically-inspired approach (e.g. Maggie (9), IM-PMEB (13)) or architecture (e.g. EmMod (3), WASABI (8)) due to OCC's reliance on cognition. CME commonly use a BDI-inspired system or architecture to account for cognitive activities (e.g. CMEs 14, 27, 31–35, 45), but this can make the CME difficult to modify if it is integrated too deeply into the host architecture [83, pp. 111–112]. Other approaches include combining OCC with process-oriented theories like Frj. (e.g. S3A (67)) or Sch. (e.g. HybridC (17), GRACE (55)), other resources such as [1] (e.g. AKR (10)), and fuzzy logic (e.g. CMEs 4, 15, 38, 39). Many CMEs set their emotion model between input and output modules to mediate their interactions (e.g. CMEs 11, 29, 37, 41, 42, 50, 59, 63). If the goal is not to create "correct" behaviors, this strategy is sufficient if it meets the CME's other design goals [109, pp. 44–45].

5.1.3.6 Smith & Kirby (S & K): This theory only seems to appear when CMEs want to integrate multiple, parallel input sources into one unit for appraisal, which is its distinguishing feature [11, pp. 129–130].

S & K always appears with Sch. to combine appraisal information from sources on multiple levels of resolution (e.g. CMEs 6, 7, 51, 58). This might be because Sch. is better validated [11, pp. 129] and computationally tractable. Scherer also draws parallels between sequential check registers and S & K's integrated appraisal [13, pp. 105, 120]. Another possibility for this pairing is a misconception that Sch. is strictly a sequential appraisal process [94, pp. 236] when it is not [13, pp. 100, 103].

An exception is EMA (24), which combines S & K with Frj. to define an attention mechanism [69, pp. 286]. This is likely because [29, pp. 149] compares its "blackboard control structure" to S & K's appraisal register. This suggests that CMEs can combine S & K with other theories that have some comparable work to the appraisal register concept.

5.1.3.7 Oatley & Johnson-Laird [7] (O & JL): CMEs use O & JL to define what emotions they support and connect emotion intensity to changes in computational plans. O & JL typically have a supporting role for defining emotions in CMEs with Ek. as the main theory present for defining CME emotions (e.g. CMEs 2, 3, 17). This connection is sound, as O & JL considered Ek. as evidence when identifying their set of basic emotions [40, pp. 57–61].

O & JL propose that there is no emotion process, arguing that emotions are states entered at plan junctures, that might include conflicts between different goals, agents, and resource demands [40, pp. 22, 24–25, 31–36]. CMEs have taken this information to define emotion intensity in relation to an agent's goals and plans (e.g. ParleE (12), Émile (28)). This also frames cognition as a knowledge transformation process, which is amenable to computation (e.g. Greta (40)).

Perhaps the most useful element of O & JL is its focus on the social and communicative role of emotions [38, pp. 41–42]. This has implications for multi-agent applications with affective content because each agent is an independent module in a larger system [40, pp. 178, 181–182]. Conversational agents might also benefit from this view, which casts conversations as a form of mutual planning. As the field of social affective agents progresses, O & JL could come to play a larger role in the field.

### *5.1.4 Neurophysiologic Theories*

Biological neural circuitry and brain structures inspire the *neurophysiologic* theories of affect, which offer a grounded view of how emotion systems might be organized and connected to the body [4, pp. 98–99]. They tend to appear when a CME wants to distinguish between reactive, noncognitive and deliberative, cognitive emotion processes. All three theories claim mechanisms for fast, "stupid" reactions and slower, deliberative plans that people collectively call "emotions" [42, pp. 230], [43, pp. 133], [44, pp. 161–165].

5.1.4.1 Sloman [8] (Slo.): Slo. conceptualizes emotion as a product of a central information-processing system, distinguishing between types of emotion based on their architectural requirements [42, pp. 204, 211]. CMEs use this distinction to specify elicitation mechanisms with varying performance requirements (e.g. WASABI (8), Presence (48)). The distinction also makes it possible to specify individual aspects of a CME such as goal importance for emotion intensity functions (e.g. Émile (28)) and emotion-driven plan selection (e.g. FAtiMA (37)).

WASABI (8) explicitly models aspects of Slo. for emotion elicitation using signal impulses that "disturb" its homeostatic state [15, pp. 90]. Slo. views these "disturbances" as a kind of emotion [42, pp. 230] which could be useful for CMEs that do not have deliberative processes. When deliberative processes are needed, Slo. might be particularly amenable to BDI-based CMEs because it explicitly references "beliefs", "desires", and "intentions" as architectural features [42, pp. 208].

5.1.4.2 Damasio (Dam.): Dam. proposes two emotion types: innate, evolution-based primary emotions and learned, cognition-driven secondary emotions that trigger the primary system [43, pp. 131–139]. CMEs use this to motivate multiple, coexisting emotion elicitation processes (e.g. 2, 8, 48).

Two of Dam.'s features have proven useful for CMEs. One is emotion's influence on decision-making [43, pp. 126, 128] which can drive the design of CME behavior (e.g. Cathexis (2), Émile (28)) and/or the design of connections between emotion elicitation and cognitive processes (e.g. EmMod (3)). Directly related to decision-making, the second feature is the Somatic Marker Hypothesis (SMH) which describes how secondary emotions are learned and connected to the primary emotion system [43, pp. 137, 145, 174]. CMEs have used the SMH as-described to elicit emotions from memories via learned associations between stimuli and emotions (e.g. Cathexis (2)) and as a clever way to mark different types of inputs with common information to coordinate further functions (e.g. Kismet (53)).

Damasio posits that CMEs *cannot* use this theory because of the biological connection between the mind and body [43, pp. 249–250], suggesting that Dam. cannot be implemented in agents without a physical body. However, there is a version of SMH that bypasses the body [43, pp. 155–158] which WASABI (8) uses successfully in a virtual agent [15, pp. 50, 56].

5.1.4.3 LeDoux (LD): LD views emotions as biological functions with different neural systems that evolution maintained across species [44, pp. 106–107, 171]. It proposes that each emotion has a mechanism programmed to detect and react to innate stimuli relevant to the system's function [44, pp. 134, 143, 161–163, 165, 175–176]. This suggests that some emotions like *Fear* do not necessarily require higher reasoning to elicit (e.g. WASABI (8)) and they could be a direct map to behaviors (e.g. InFra (15)). This proposal also sets the stage for LD's work on emotional conditioning mechanisms—specifically *Fear* [44, pp. 127–128]—suggests methods for emotional learning in CMEs (e.g. FLAME (4)).

Damasio and LeDoux applaud each other's—mutually relevant—work [43, pp. 133], [44, pp. 250, 298]. One focuses on the "low road" (i.e. noncognitive) and the other on the "high road" (i.e. cognitive) which could explain their co-use or connection in some CMEs (e.g. Cathexis (2), WASABI (8)).

7. Although it does not name appraisal dimensions, O & JL talk about evaluating events relevant to plans and goals such that changes in achievement probability induce emotions [40, pp. 50]. Therefore, it is grouped with the appraisal theories.

8. Since Sloman views the brain as an information processing system [42, pp. 206–207], it is grouped with the neurophysiologic theories.

### 5.2 Psychologists Directly Involved in CME Design

Translating a psychological theory into a CME is difficult because it involves formalizing informal concepts and documenting hidden assumptions [134, pp. 22–23]. CMEs designed with the participation of the theory's creator stand out as being "truest" to the theory.

Frijda supervised the development of both ACRES (23) and the Will architecture (25). ACRES is designed as a partial test of its functionality, treating the theory as a design specification [66, pp. 237, 247]. Will—the spiritual successor of ACRES—proposes a reasonable extension of Frj.: emotion, moods, sentiments, and personality are related by focus and duration [68, pp. 135–136, 138]. This is convenient for CMEs as it shows that these affective types can share the same underlying structure. Scherer directly influenced the design of ELSA (26) which is particularly relevant as its purpose is to show that Sch.—which takes an information systems view on emotion processes [13, pp. 103]—can be implemented and used as a research tool [67, pp. 142–143]. Ortony provided direct supervision for AffectR (1) [46, pp. iv] which presumably makes it the most faithful account of OCC emotion generation processes and action tendency hierarchy.

In other cases, theory creators acted as consultants to CME designers [15, pp. vii], [52, pp. 281], [69, pp. 303], [71, pp. 332], [135, pp. 89] and/or drew from other CMEs that were developed under that creator's guidance [71, pp. 325]. Caution must be used in evaluating their faithfulness to the theories, as it is usually not documented what parts relied on consultation and which did not.

## 6 Discussion

In our examination of these CMEs, we also found design decisions and trade-offs relevant to *implementing theories*, *how CMEs could combine theories from different perspectives*, *CME realism versus efficiency*, and *other sources of design influence*.

### 6.1 Implementing Theories

Implementing an affective theory is challenging. Some theories—Frj., Sch., OCC, O & JL, and Slo.—were explicitly designed to be computationally tractable [66, pp. 247], [117, pp. 279], [34, pp. 181], [38, pp. 30], [136, pp. 231] while others—like Dam. and LD—argue that their theories *cannot* be computationally realized [43, pp. 249–250], [44, pp. 41, 176]. Regardless, they have been implemented. Nonetheless, how accurately a CME adheres to a theory and/or observed emotion phenomenon tends to be directly proportional to how complex the CME is.

Neurophysiologic theories might be more plausible than appraisal theories [49, pp. 72–73] and align with current findings better [78, pp. 160]. However, they require modeling parts of the brain and body, which this is neither feasible nor desirable for many CMEs. Furthermore, the resulting system will not necessarily be accurate due to gaps in our understanding of anatomical structures and functions (although complete accuracy might not be useful to anyone [124, pp. 60]).

Appraisal theories might be best suited for CMEs as they touch on all components and phases of emotion processing [2, pp. 13]. They are also relatively easy to implement as they are often rule-based [1, pp. 225] and built on information processing analogies [124, pp. 59]. While some have integrated neurophysiologic aspects, this increases their complexity. For example, empirical test of Sch. have been relatively successful in predicting different patterns in emotion processes [13, pp. 93, 103, 117–118] but it is very complex and involves implementations of components like the Autonomic Nervous System (ANS) and memory while allowing for multiple levels of information processing. This might be why Sch. is favored by cognitive architectures and research CMEs like CLARION (22) and MAMID (6), whose assumptions closely follow Sch.'s [12, pp. 136], [65, pp. 6]. These systems purposefully sacrifice computational efficiency for accuracy since their aim is to study emotion phenomena. This complexity also makes them are to explain and debug [67, pp. 143–144].

### 6.2 How CMEs Could Combine Perspectives

Some theories are easily combined as they share a perspective based on coherent assumptions. For example, Izard, Ekman, and Plutchik agree on the function of at least four primary emotions—*Joy/Happiness*, *Sadness*, *Anger*, and *Fear*—and their ability to interact to produce what people recognize as other, more complex, emotions [20, pp. 254, 258–259], [21, pp. 69], [24, pp. 200, 204–205]. Similar overlaps exist in the appraisal theories' evaluation dimensions and how they label distinct combinations. The dimensional theories, V-A and PAD, are also obviously compatible—one could directly layer V-A over the P-A plane. By staying within one perspective, a CME design can use the individual strengths of each theory with little worry of conflicting assumptions or views.

Combining theories from *different* perspectives poses a more complex challenge, but often necessary to address all aspects of affect needed in the design. For example, OCC is frequently combined with Ek.—which focuses on automatic, hard-wired appraisals rather than evaluations [137, pp. 51]—to produce facial expressions from cognitively-evaluated events [54, pp. 109], [58, pp. 66], [78, pp. 155], [116, pp. 740–741]. This connection is presumably due to the OCC's association of characteristically similar "linguistic tokens" with each emotion [34, pp. 1–2, 87–88]. By finding similar words, one can fit the discrete theories' emotions into the OCC structure. However, this relies on subjective interpretations, and even the given lists lack empirical validation [34, pp. 172–176]. More pressingly, emotions of the same name might represent different concepts. *Fear* and *Anger* in OCC, as with many appraisal theories, are complex emotions requiring flexible, cognitive evaluations [15, pp. 85, 87] but the same emotions in discrete theories are simpler, triggered by inflexible hard-wired systems. While they might be expressed with the same physiological changes, behaviors, and expressions, their eliciting mechanisms are not of the same kind [2, pp. 15–16]. Whether or not this distinction is important for a CME, it should still be addressed as it affects how accurately the theories are modeled. Similar considerations must be made when attempting to align the dimensional theories with the dimensions of appraisal theories and locating discrete emotions in dimensional space.

These conceptual mismatches does not mean that there are "correct" and "incorrect" theories or that they are in-compatible, especially considering how they overlap and converge on the role of emotion [2, pp. 10–11, 14–15], [10, pp. 352, 354–355], [117, pp. 281]. Rather, they are different views—perspectives—of a complete system, each focusing on different aspects of emotions [8, pp. 259]. Emotion systems seem to rely on both fast, primary and deliberative, secondary emotions [1, pp. 70]. This idea of two emotion types is present in some affective theories, such as [19, pp. 74], [137, pp. 51], [29, pp. 155], [13, pp. 102], and [138, p. 93], and is also supported by empirical investigations of the brain [43, pp. 136–139], [44, pp. 177–178]. Some CMEs have explicitly modeled these two "pathways", including [15, pp. 98], [49, pp. 73], [50, pp. 63], and [78, pp. 160]. Correspondingly, one way that each perspective could be assigned roles in CME designs to address different aspects of emotion generation is:

- *Neurophysiologic theories* provide guidelines for how to unite disparate emotion processing pathways into a coherent system,
- *Discrete theories* drive the creation of a limited set of fast, hard-wired [10, pp. 366] reactions to specific stimuli ("primary emotions", "low road"),
- *Appraisal theories* drive the deliberative, slower systems for emotion elicitation that require planning and/or reasoning ("secondary emotions", "high road") that can account for language and sociocultural factors, allowing for a broader range of identifiable emotions, and
- *Dimensional theories* provide a common space for merging the outcomes of each emotion pathway in the spirit of appraisal registers [13, pp. 105], [138, p. 93] while allowing other types of affect to interact with emotion.

### 6.3 CME Realism versus Computational Efficiency

For CMEs that focus on agent believability, enforcing realism and rational intelligence can be detrimental to their goals [109, pp. 11]. These systems typically interact with users in (soft) real-time, so efficiency is more important than accuracy. Being able to test and debug models is also important. For example, dimensional theories are arguably the simplest to implement efficiently. However, they also have the lowest affective resolution. Nevertheless they are considered "universal" and individual emotion "points" can be labeled as needed [2, pp. 12, 15]. However, since they do not define emotion generation, the designer must determine how much of it they want to implement.

Efficient implementation of *believable* but not necessarily sound emotion generation can be done in myriad ways: with metadata [51, pp. 236], [84, pp. 33]; concepts like Bayesian Networks [54, pp. 108], [87, pp. 204], Markov Models [53, pp. 603], [55, pp. 115], and fuzzy logic [47, pp. 229], [57, pp. 29–30], [81, pp. 3, 7], [82, pp. 68]; and AI techniques like behavior trees and goal-oriented action planning [106, pp. 698]. Other theories—typically appraisal—are also conscripted, but might not be modeled in full [104, pp. 36], [109, pp. 52]. CMEs have also improved their efficiency by considering their target domain's limitations, which might require fewer emotion categories [48, pp. 58], [54, pp. 109], [72, pp. 2], and appraisal variables [89, pp. 150], [108, pp. 118], while others are able to scale as needed [51, pp. 239], [57, pp. 27], [61, pp. 44], [98, pp. 217], [101], [104, pp. 35]. As these have all found some success in achieving their goals, this further emphasizes that accuracy is not always necessary. This opens up the design space to create a CME that behaves "well enough" for its intended tasks.

### 6.4 Other Sources of Design Influence

A number of systems strengthen or extend their chosen theoretical foundations by supporting it with other comparable or complementary theories [53, pp. 594, 599–600, 606], [57, pp. 27], [58, pp. 63–64], [62, pp. 218, 247], [83, pp. 91], [91, pp. 129], [100]. Some cite additional work to support perceived short-comings in a foundational theory [47, pp. 223, 233–234, 239] or formally define concepts[9] [92, pp. 269]. Yet other CMEs use additional sources to connect emotions with other system components, such as social variables [70, pp. 93], [85, pp. 22], [102, pp. 288], [106, pp. 698] and emotion contagion [73, pp. 77], [77, pp. 91], [105, pp. 2151].

Emotion theories do not address all aspects of emotion generation, such as emotion intensity and cognitive organization. Other sources of information are needed. Three stand out: the work of Picard [1], Minsky's theory [140], and empirical data.

A pioneer of affective computing, Picard offers a computer science-friendly view of emotion, proposing models and ideas for CMEs that often guide the selection of their underlying emotion theories. AKR (10) references them to justify its use of Markov Models for emotion dynamics [53, pp. 603]. IM-PMEB (13), FAtiMA (37), and SocioEmo (59) reference Picard to define an emotion intensity decay function [56, pp. 68], [80, pp. 130–131], [102, pp. 289]. Presence (48) cites Picard for their separation of primary and secondary emotion processing channels, motivating its use of Slo. and Dam. [78, pp. 160]. Greta (40) cites Picard's "tub of water" metaphor, comparable to Plu., for addressing coexistent emotions in its design considerations [83, pp. 99]. TAME (56) uses Picard for defining emotion dynamics as a system response [98, pp. 211].

Minsky offers a model of human intelligence amenable to AI. Since many emotion theories—especially appraisal theories—rely on cognition, Minsky's *Society of Mind* presents a way to model it. O & JL explicitly draw parallels to it [38, pp. 32, 39]. EmMod (3) cites Minsky as the main inspiration for its architecture, producing complex behaviors via the interactions of many, simple units [50, pp. 63]. Cathexis (2) compares its models of secondary emotions to Minsky *k*-lines, connecting primary emotions to encountered stimuli [49, pp. 73].

Empirical data, as the best source for replicating observable phenomena, has been used for: defining degrees of emotion positivity and negativity [141, pp. 4] and emotion effects [12, pp. 136]; deriving emotion intensity functions [88, pp. 419]; quantifying the relationship between emotion intensity, desires, and expectations [47, pp. 232], [55, pp. 125]; and gesture models [79, pp. 302]. Some systems have moved to purely data-driven approaches (e.g. [142], [143]).

9. POMDP-CA (49), which uses [139] to define *unexpectedness*, similar to *suddenness* in Sch. [13, pp. 95]. This is necessary to appraise *Surprise* in both Ros. [31, pp. 267] and OCC [34, pp. 126].

# 7 Conclusion

We have examined how CMEs from different application domains use emotion theories for emotion generation (i.e. for emotion representation and elicitation) and expression. We found that each type of emotion theory filled a similar role regardless of the domain: *discrete* theories define which emotions a CME can represent and express, and how it does so; *dimensional* theories can provide a simple and powerful representation that describes emotion numerically and with respect to other types of affect; *appraisal* theories chiefly drive the elicitation process; and *neurophysiologic* theories unite the reactionary and deliberative emotion views, tying them to measurable body states.

These roles can be complementary. Appraisal theories seem the best starting point for emotion generation CMEs, as they explicitly describe emotion processes and are relatively easy to implement. Discrete theories can improve a CME's comprehensibility, and dimensional theories are useful for their quantitative representation of emotions (and other types of affect) in a common space. The neurophysiologic theories can contribute to emotion process definitions, but tends to increase a CME's overall complexity—they should be used with care. Generally, the less realistic that generated emotions need to be, the more efficient a CME can be.

There are even more theories (e.g. see [117, pp. 280–281]), models, and data to draw from for CME designs. For example, if one is considering V-A then they might consider [144] too due to their similarities. Lastly, future CMEs might get inspiration from unlikely places (e.g. [145]). This survey aims to be a resource for creating new CME designs, providing a practical view of *some* emotion theories and existing CMEs to borrow from and build on.

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