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A Review of Affective Computing Research Based on Function-Component-Representation Framework

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Abstract—Affective computing, a field that bridges the gap between human affect and computational technology, has witnessed remarkable technical advancement. However, theoretical underpinnings of affective computing are rarely discussed and reviewed. This paper provides a thorough conceptual analysis of the literature to understand theoretical questions essential to affective computing and current answers. Inspired by emotion theories, we proposed the function-component-representation (FCR) framework to organize different conceptions of affect along three dimensions that each address an important question: function of affect (why compute affect), component of affect (how to compute affect), and representation of affect (what affect to compute). We coded each paper by its underlying conception of affect and found preferences towards affect detection, behavioral component, and categorical representation. We also observed coupling of certain conceptions. For example, papers using the behavioral component tend to adopt discrete representation, whereas papers using the physiological component tend to adopt dimensional representation. The FCR framework is not only the first attempt to organize different theoretical perspectives in a systematic and quantitative way, but also a blueprint to help conceptualize an AC project and pinpoint new possibilities. Future work may explore how the identified frequencies of FCR framework combinations may be applied in practice.

Index Terms—Affective Computing, Review, Survey, Conceptual Analysis, Emotion Theory, Framework.

1 Introduction

Affect refers to general phenomena that subsume emotions (short-lived, intense affective states with clear causes or referents), moods (mild affective states that last for days as a background activity), interpersonal stances (affective stance taken toward another person in interactions), attitudes (enduring affectively colored beliefs, preferences, and predispositions toward objects or persons), and emotional dispositions (emotionally-laden, stable traits like neuroticism and extraversion) [1]. Because affect fundamentally impacts our health and well-being [2], a field that studied and built technologies with affective capabilities emerged and was later named as "affective computing" by Rosalind Picard [3]. In this survey, we follow Picard's definition of AC as "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" and use "affect" and "emotion" interchangeably.

The AC community has been focusing on resolving technical challenges. A number of surveys summarized these research efforts. For example, Martinez et al. reviewed different technologies for emotion recognition using facial expression [4]. Alarcao et al. surveyed the literature of emotion recognition using electroencephalogram (EEG) signals [5]. Salawu et al. reviewed research progress of applying affective computing in the domain of cyberbullying detection [6]. Paiva et al. summarized the projects working on building empathetic virtual agents and robots [7]. These in-depth surveys provide important technical blueprints on how to collect, process, and analyze data from various modalities, how to model and simulate affect in robots, how to apply AC in different domains, etc. However, these surveys did not review theoretical underpinnings of AC.

Research in AC is colored by investigators' viewpoints, concepts, and theories of affect. These *a priori* beliefs and assumptions are rarely discussed and reviewed. A thorough conceptual analysis will be fruitful to the community. First, it can help accommodate different understandings of affect and facilitate dialogues among people from diverse disciplines and backgrounds. Second, it can help organize the literature, make theoretical comparisons across studies, and identify research gaps. Third, it can inform the design and development of AC systems and provide road maps for future research. Therefore, our survey aims to provide a thorough conceptual analysis that is missing in previous surveys. We propose the function-component-representation (FCR) framework to summarize different conceptions of affect along three dimensions that each address an important theoretical question: function of affect addressing why compute affect, component of affect addressing how to compute affect, and representation of affect addressing what affect to compute. Applying this framework to all the surveyed papers, we answer our first research question:

- *RQ1. What are conceptions of affect in AC in terms of three dimensions: function of affect (why compute affect), component of affect (how to compute affect), and representation of affect (what affect to compute)?*

Answers to why compute affect, how to compute affect, and what affect to compute may not be independent from each other. For example, a certain component may be more

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manifested or actively involved in one function of affect over the other (objective reality). A certain representation may be more suited for computing affect using one component over the other (ease of analysis). A certain representation may have always been adopted for a certain function (convention). Reflections on reasons behind the coupling of certain conceptions may point to advantages of certain combinations of conceptions or opportunities for engaging with less frequent combinations. Examining the frequency distribution of different combinations of conceptions, we answer our second research question:

- *RQ2. What are common and uncommon combinations of conceptions in AC?*

We collected 2,126 papers from ACM DL and IEEE Xplore databases up to October 1, 2017. Following Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guideline to exclude papers [8], we had a final pool of 1,110 papers. We developed our initial coding scheme from the psychology literature and revised it to include conceptions in the data that were not captured. We coded each paper by its theoretical underpinnings and computed frequency distributions of individual conceptions and combinations of conceptions. We reported our findings and discussed implications for future research. We hope our survey can facilitate discussions on theoretical challenges faced by the community, facilitate comparisons across different studies, and provide road maps for conceptualization.

In this paper, we take the scientific instrumentalism philosophy rather than the realism philosophy and stay neutral to different theoretical assumptions about emotion, because each of them faces issues and judging which one is better is beyond the scope of our paper. Our conceptual analysis looks at current conceptions of affect and evaluates the extent to which each conception has contributed to the advancement of empirical research (i.e., frequency/quantity), but not the extent to which each conception corresponds to reality (i.e., validity/quality). We present the diversity of theoretical views in AC and leave decisions of which ones make sense or should be explored to readers.

2 Previous Surveys

We found 90 previous surveys during our systematic review. Most surveys focused on technologies specific to certain modalities, application domains, or overlapping fields with AC. Only two surveys discussed emotion theories underlying AC research. However, they did not fully address the diversity of theoretical perspectives in AC or provide the frequency distribution of papers holding each viewpoint. We also discussed other resources (e.g., psychology or AC books) that inspired our framework [1].

2.1 Surveys of Specific Modalities

Forty four papers reviewed technology development related to a specific data type or modality. Among them, sixteen papers explained the methodology of recognizing emotions from various behavioral channels and simulating emotional expressions in agents and robots using these modalities. These behavioral channels include facial expressions [4], speech [9], body posture, gesture, and movements [10], and touch or haptic input to keyboard, mouse, and touch screen [11]. Nine papers discussed labeling and predicting emotions from various physiological signals, including skeletal muscle signals [12], brain signals [5], and autonomic nervous system signals [13]. Five papers described the methodology of analyzing affect and simulating affective expressions through various content forms, such as text [14] and color [15]. One paper reviewed progress in eye-tracking technologies for emotion recognition [16] and another in response-time measurements to quantify affect and its influence [17]. There are also 12 papers that surveyed multimodal approaches to emotion recognition and expression [18]. They found multimodal approaches were able to increase performance such as accuracy of detecting emotions and realness of simulating emotional expressions [18]. These surveys mainly focused on technical solutions to challenges such as data collection, feature extraction, machine learning models, and fusion of distinct data types.

2.2 Surveys of Specific Domains

Thirty five papers reviewed application domains of AC. Among them, eleven papers described affect-aware systems in education and learning, which can recognize and respond to students' emotions, support personalized learning experience, and improve the learning outcomes [19]. Eight papers introduced various applications of AC technologies in health and medicine, including self-tracking systems to monitor and improve physical, mental, and emotional health [20], automatic assessments of physical and mental symptoms (i.e., depression, etc.) [21], and treatment of disorders related to affective incompetence (i.e., autism, etc.) [22]. Six papers discussed computational models of emotions in agents or robots that can understand users' emotions, show empathy and other expressions, and be social companions [7]. Three papers considered applications of AC in collaborative work, where employees' emotions are monitored and regulated [23]. The remaining seven papers examined the application of AC techniques in content analysis and retrieval [6], [24], game experience [25], tourism experience [26], and public or driving safety protection [27], [28]. These surveys mainly focused on development of AC systems that could resolve technical requirements and restrictions posed by different application scenarios.

2.3 Surveys of Overlapping Fields

Nine surveys reviewed research progress in related fields including social signal processing [29], pervasive computing [30], physiological computing [31], and personality computing [32]. Technologies reviewed in these surveys can potentially benefit research in AC.

2.4 Surveys that Included Emotion Theories

Only two surveys reviewed emotion theories underlying AC research. Calvo et al. summarized six emotion theories viewing emotions as expressions, embodiments, cognitive

1. Lists of related surveys, books, and other resources can be found in related_surveys.xlsx in https://hdl.handle.net/11299/219454

appraisals, social constructs, neural circuitry, and psychological constructs, which informed different design and technical choices of affect detection systems [33]. Gunes et al. provided a brief summary of discrete, dimensional, and appraisal-based representations and reviewed affect detection systems that used the dimensional representation [34]. These reviews were important first attempts to organize differing models of affect, but they did not fully address the issue. They overlooked research that focused on other functions of affect than affect detection and lacked a theoretical framework to decompose affect from multiple angles. Moreover, the qualitative nature prevented them from answering questions such as which emotion theories were more influential and which were less explored. To respond to the need for a deeper conceptual analysis [35], we propose a conceptual framework to analyze papers and summarize different conceptions of affect.

2.5 Other Resources

Several psychology books examined functions of emotion in behavioral and cognitive processes, social interactions, and cultures [36], components of emotion involved in emotion communication and measurement [37], and representations of emotion in the body, mind, and language [38]. Our framework is derived from these discussions in specific functions, components, and representations. Several AC books discussed affect generation and detection technologies and underlying emotion theories [39]. Our coding scheme is inspired by these discussions. However, these books only focused on representative works selected by chapter authors. In our survey, we include a larger sample of papers and thus are able to identify different theoretical perspectives missing from previous books and compute their frequencies.

3 METHODS

3.1 Search Process

We conducted our search in ACM and IEEE Xplore digital libraries, because most computing work is published in these two databases. We explored searching with a number of keywords, including emotion, emotion recognition, affect detection, emotion modeling, and affective computing. We found that "affective computing" was the best term, because it returned sufficient (several thousand) but not too many (tens of thousand) or too few (a few hundred) results for a reasonable analysis. Besides, "affective computing" has been widely acknowledged by scientists in the field. The limitation of the search process is discussed in Section 5.4.

3.2 Inclusion/Exclusion Criteria

We filtered out papers according to relevance and quality criteria through two passes. The inclusion criteria is:

- **Relevance Criteria:** The paper involves the use and development of "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" and is written in English.
- **Quality Criteria:** The paper is a full journal/conference paper that is peer-reviewed.

Fig 1 shows the process of filtering papers. Searching for the term "affective computing" in the two databases returned 2,126 results (completed on Oct 1st) and 2,118 remained after removing duplicates. The first pass of screening based on titles, keywords, and number of pages yielded 1,680 results. Papers whose titles and keywords were clearly irrelevant to AC or not original contributions (e.g., proposals, talks, keynotes, conference introductions, editorials, reflection papers, surveys, and reviews) and papers with only 1 or 2 pages were excluded. The second round of screening based on full text yielded 1,110 results. Papers that were irrelevant in content, not original contributions, not peer-reviewed journal/conference papers (e.g., extended abstracts, posters, books or book chapters, demos, theses, and revision drafts), or not in English were excluded. The final pool had 1,110 papers published between 2000 and 2017.

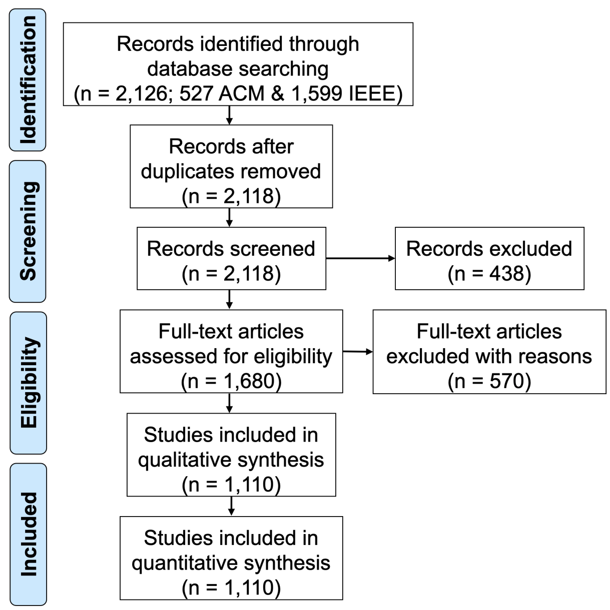

Fig. 1: PRISMA flow diagram.

3.3 Review and Coding Process

We went through all the papers examining why investigators computed affect, how they computed affect, and what affect they computed. We formed basic ideas about different ways researchers conceptualized affect. For example, some researchers pursued future technologies to recognize and respond to human emotions, while others sought to design humanoid robots. Some used facial expression for emotion recognition, while others used physiological signals. Some studied specific classes of emotions like joy and anger, while others studied more general affective concepts such as valence and arousal. With these impressions in mind, we turned to the psychology literature for a more formal categorization of different perspectives and developed the initial coding scheme. We went through all the papers the second time to code each paper and marked papers that did not fit into the coding scheme. We revised the coding scheme to include conceptions of those marked papers. The finalized coding scheme is presented below. The limitation of the coding process is discussed in Section 5.4.

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3.3.1 Why Compute Affect: Function of Affect

Emotion has many important functions. Generation of emotion is found to direct attention, prepare the body for immediate action, and assist complex decision-making [36]. Regulation of emotion manages negative effects of emotion and prioritizes other behavioral and cognitive processes over emotion [40]. In addition to intrapersonal functions, expression and recognition of emotion are important interpersonal functions [36]. AC can thus improve individuals' affective experiences or machines' emotional intelligence by supporting these functions. We labeled papers into one of the four categories based on the primary function of affect they studied: 1) affect generation (eliciting emotional responses in individuals or modeling emotion in agents and robots), 2) affect regulation (assisting regulation or providing intervention), 3) affect expression (enhancing communication of emotions between individuals or simulating emotion expression in agents, robots, and content), and 4) affect detection (collecting valid emotional signals or designing algorithms to recognize human emotion).

3.3.2 How to Compute Affect: Component of Affect

Emotion involves changes in feeling, cognitive, motivational, physiological, behavioral, and social components, like syndromes characterized by a set of associated symptoms [37]. There are debates in psychology on which components cause or precede the others and are thus central. For example, neo-Jamesian theorists maintain that bodily responses are central [41]. Appraisal theorists believe that appraisals are central [42]. Social constructionists posit that social mechanisms are central [43]. However, it is generally acknowledged that each component carries some emotional information. Although papers in AC may not explicitly mention any emotion theory, they inevitably utilize one or more modalities to approach and compute affect, which can be mapped into different components formalized in psychology. This choice of modality reflects implicit conception of emotion, even if researchers may be unaware of it. We labeled papers into one of the seven categories based on the modality used for studying the primary function and the matched component: 1) feeling component for modalities revealing inner feelings, 2) cognitive component for modalities revealing thoughts and reasoning, 3) motivational component for modalities revealing motivations, 4) somatic or physiological component for modalities revealing physiological signals, 5) motor or behavioral component for modalities revealing expressive behaviors, 6) social component for modalities revealing social dynamics, and 7) multiple components for modalities revealing different sources of emotional information (i.e., across different components).

3.3.3 What Affect to Compute: Representation of Affect

We experience and recognize different emotions. How to represent or classify emotions is under debates. There are two major theories: basic emotion theory and core affect theory. In basic emotion theory, emotion is categorized into distinct classes. Several emotions that are believed to be universally recognized and biologically distinguished are basic emotions (e.g., anger, sadness). Other emotions are non-basic in that they are mixtures of basic emotions and other mental states (e.g., guilt, frustration) [44]. In contrast, core affect theory states that emotions are distributed in a dimensional space (e.g., valence and arousal as dimensions) and that discrete categories are constructed concepts without biological basis [45]. Core affect theorists do not believe different emotions are biologically distinct from each other. In addition, biomarkers (e.g., facial muscle movements, heart rate variability) can be directly used to specify different affective experiences without naming them. A hybrid of categorical and dimensional models by mapping between them can also be used. Therefore, we labeled papers into one of the four categories based on the representation of affect they mainly adopted: 1) biomarker, 2) discrete or categorical, 3) dimensional, and 4) hybrid. Note that the representation system is independent from the measurement scale. Studies using discrete representations may adopt ordinal or continuous ratings (which indicates intensity) of discrete emotions, whereas studies using dimensional representations may collapse continuous dimensions into discrete categories (e.g., positive vs. negative valence).

Function	Component	Representation
Generation	Feeling	Biomarker
Regulation	Cognition	Category
Expression	Motivation	Dimension
Detection	Physiology	Hybrid
	Behavior	
	Social	
	Multiple	

TABLE 1: Current conceptions regarding FCR dimensions.

3.3.4 Final Coding

We coded papers according to the finalized coding scheme. We went through all the papers a third time to code papers into subcategories to further capture the granularity and diversity of AC studies. For example, affect detection was further divided into subtopics of "improving data quality" and "improving algorithm design". The behavioral component was further divided into different modalities, including facial, vocal, and other behavioral expressions. The discrete representation was further divided into basic and nonbasic emotions. These subtopics were generated from common themes identified for each conceptual category [2].

4 Conceptualization of Affect: FCR Framework and Findings

Table 1 lists current conceptions of affect for each dimension of FCR framework found in our paper pool. Each paper explicitly or implicitly adopts a perspective under each dimension to form its distinct theoretical underpinning [3].

2. Final codes of all the 1,110 papers can be found in final_codes.xlsx in https://hdl.handle.net/11299/219454

3. Tables of frequency distributions of papers over different conceptions and years can be found in results.xlsx in https://hdl.handle.net/11299/219454

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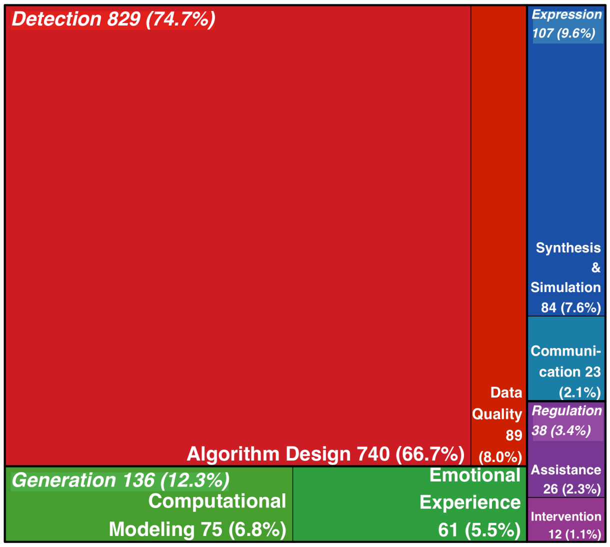

Fig. 2: Paper distribution over function and subtopic.

4.1 Function

We identified four functions of affect as AC researchers' answers to why compute affect: generation, regulation, expression, and detection. Figure 2 shows the frequency distribution of papers for each function and subtopic. Most AC studies focused on affect detection. Fewest focused on affect regulation. The number of studies concerning affect generation and the number of studies concerning affect expression fall in the middle. This pattern did not change over time.

4.1.1 Affect Generation

Affect generation refers to the production of affective responses to external or internal conditions, which in turn influence action, thoughts, and behavior [46]. Some affect generation mechanisms are pre-wired and heritable [47], but most are learned and shaped by social and cultural factors [48]. Several stimuli databases were constructed to reliably elicit subjects' emotions for research, such as International Affective Picture System [49], Geneva Affective Picture Database [50], International Affective Digitized Sounds [51], and Montreal Affective Voices [52].

One hundred thirty six papers (12.3% of the 1,110 papers) focused on affect generation. Among them, sixty one papers (5.5% of the 1,110 papers) studied individuals' emotional experiences with novel stimuli, technologies, and systems. For example, researchers tested the emotional effects of visual features [53], sound or music characteristics [54], haptic and thermal stimuli or tactile objects [55], virtual reality [56], game, product, artifact, or user interface design [57], and interaction with intelligent agents [58]. Researchers also investigated how individual differences and social factors influenced emotional reactions to the same stimulus, technology, and system [59]. Elicitation of emotions could be used to improve user experience and evaluate product design [60], facilitate desired mental activities [61], and help with diagnosis and treatment of emotional disorders [62].

Seventy five papers (6.8% of the 1,110 papers) implemented computational models of emotions to enhance believability and intelligence of agents and robots. Appraisal models were dominant, where emotions are generated from appraisals of the environment that can be computed in symbolic form [42]. Researchers used Ortony, Clore, & Collins-inspired [63], Lazarus-inspired [64], or Scherer-inspired [65] appraisal variables to generate artificial emotions. The mapping from appraisals to emotions could be predefined [63] or learned from human data and subsequent interactions with the world [66], [67]. Several studies considered decay and transition process [68], anticipation of future stimuli [69], mental models of others [70], coping strategies [71], and influence of mood and personality when generating emotions [63]. Besides, researchers modeled and tested effects of emotions on attention [72], social interactions [73], and decision-making [74]. Biophysical models, where emotions are generated from neurophysiological responses (e.g., activities of artificial neural circuits [75], neurotransmitter system [76], or endocrine system [77]) and social construction models, where emotions are generated from social mechanisms (e.g., emotional contagion [78]) were also explored.

4.1.2 Affect Regulation

Affect regulation refers to the extrinsic and intrinsic process that monitors, evaluates, and modifies affective reactions, which can be controlled or autonomic, conscious or unconscious [79], [80]. Different forms of regulation include emotion regulation, coping, mood regulation, and psychological defense. Although these constructs can be differentiated, we combine them under the umbrella of affect regulation, because they are highly correlated and overlapping with each other [40]. Regulation strategies can be classified along different dimensions: cognitive vs. behavioral, engagement vs. diversionary, antecedent-focused vs. response-focused, minimizing negative affect vs. maximizing positive affect, and self-regulation vs. interpersonal regulation [81], [82]. Common regulation strategies include suppression, reappraisal, rumination, and problem solving [83], [84].

Thirty eight papers (3.4% of the 1,110 papers) focused on affect regulation. Among them, twenty six papers (2.3% of the 1,110 papers) built technologies to track individuals' emotions and assist emotion management. Researchers often used wearable devices to track neurophysiological signals (e.g., brain waves, breathing, heart rate, muscle contraction, sweat gland activity) and provided biofeedback through games, lights, visual displays, and vibration to help individuals practice arousal control [85]. Researchers also built systems to track collective emotions at work through self-reports [86], applications for social sharing of emotions and exchanging of social support [82], [87], and prototypes for expressive painting, photography, and writing [88].

Twelve papers (1.1% of the 1,110 papers) built intervention technologies to handle users' emotions and improve their emotional health. For example, intelligent tutoring agents were developed to respond to students' frustration or boredom by encouraging students, providing personalized instructions, and re-engaging students with learning [89]. Researchers also built toy robots simulating pet behaviors to calm down anxious users [90], systems to track users' diet, alcohol use, exercise, sleep, and stress levels and provide advice or intervention for behavior change [91], and affective agents to accompany older adults [92].

4.1.3 Affect Expression

Affect expression refers to the manifestation and communication of affect to other individuals and intelligent systems through various signals [93]. Possible channels, media, and modalities to signal affect include facial, vocal, or bodily expressions, neurophysiological responses, and text, music, or other content. It is conceptually useful to differentiate expression from generation, because expressed affect often does not match experienced affect. Cultural differences and individuals' voluntary control both contribute to this dissociation [94], [95]. Therefore, researchers usually study affect expression without modeling internal affective processes.

One hundred and seven papers (9.6% of the 1,110 papers) focused on affect expression. Among them, twenty three papers (2.1% of the 1,110 papers) designed technologies to enhance emotion communication. Researchers augmented communication technologies with emotional clues using pictures [96], typeface [97], geometric figures [98], facial expressions [99], and emoticons [100]. They also designed "embodied" communication systems that could transmit heartbeat [101], muscle contraction [102], temperature [103], touch [104], and goosebumps (multimodal transmission of heart rate, respiration, and electrodermal activity) [105]. These emotional clues increased closeness between users [106], but might lead to miscommunication due to varying interpretations [107]. In addition to remote communication, researchers also built eyeglasses with outward-facing displays of emoticons for people with disability in facial expressions to express emotions in face-to-face communication [108] and a tablet-based authoring system to help children create emotionally engaging stories [109].

Eighty four papers (7.6% of the 1,110 papers) simulated affect expression in agents, robots, contents, or other non-life forms. Researchers emulated facial expressions [110], body movements [111], gaits [112], walking sounds [113], speech [114], gaze [115], touch [116], and multimodal expressions [117] in humanoids. They used sounds [118], motifs [119], movements [120], breathing-like behaviors [121], and touch [122] to simulate emotion expressions on non-humanoids. Display of expressive behaviors can also convey personality, interpersonal stances, and cultural backgrounds [123]. In addition to emotion synthesis and simulation, researchers designed algorithms to generate emotional content such as text [124], music [125], pictures [126], and painting [127]. Affect expression was found to increase believability and realness of agents [69], improve users' satisfaction and bonds with agents [128], and influence people's emotional experiences and decision-making [129].

4.1.4 Affect Detection

Affect detection refers to recognition of affect or affective information from various signals, which is the reverse process of affect expression. Possible channels, media, and modalities to detect affect include expressive behaviors, physiological signals, and contents like text, music, and pictures. There are three types of expression datasets for affect detection research: posed or acted expressions [130], induced expressions [131], and natural or spontaneous expressions [132]. Although posed expressions might elicit emotions to some degree [133], they are generally considered different from genuine expressions [134]. Induced expressions by sensory stimuli [135], recollection of past emotional events [136], or imagery of emotional scenarios [137] are genuine expressions, but they are context-insensitive. Natural expressions generated from real interactions, conversations, or scenarios [132], have the highest ecological validity, but are more difficult to collect and more noisy.

Eight hundred twenty nine papers (74.7% of the 1,110 papers) focused on affect detection. Among them, eighty nine papers (8.0% of the 1,110 papers) worked on sensing, annotating, and validating affective datasets. Researchers usually used readily available sensing devices to collect affective data, such as cameras and EEG caps, but they sometimes had their own specific needs that were not met by these options [138], or had a better arrangement of sensors to improve precision [139]. Traditional annotations of affect like self-reports or observers' ratings take time and effort. To speed up the process, researchers crowdsourced the annotation tasks [140] and built active learning algorithms [141]. Researchers further proposed using ranking instead of rating [142], using iterative approach [143], modeling annotators' reaction lags or distortions [144], and monitoring annotators' accuracy and fatigue [145] to improve data quality. Researchers continued to construct new databases with different expression methods [146], modalities [147], emotions or personalities [148], and cultures [149].

Seven hundred forty papers (66.7% of the 1,110 papers) worked on feature engineering, algorithm design, and visualization methods to better harvest data. These works covered all kinds of features [150], machine learning models [151], and emotions [152] (see Section 2.1 for reviews). Standard libraries and toolkits were constructed to benefit the community [153]. There exists cultural specificity of emotion recognition [48]. Researchers thus explored cross-culture and cross-corpus affect recognition using transfer learning or other techniques [154] and built culture-dependent affect detection systems [155]. In addition to accuracy improvements, researchers studied how to visualize recognized affect [156], how to respond to recognized affect [157], and how to recognize affect in real-time [158].

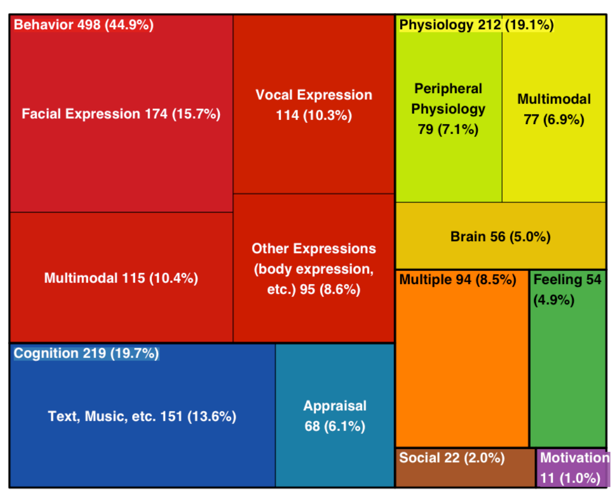

Fig. 3: Paper distribution over component and modality.

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4.2 Component

We identified six components of affect as AC researchers' answers to how to compute affect: feeling, cognition, motivation, physiology, behavior, and social. Researchers also combined multiple components, which forms the seventh category. Figure 3 shows the frequency distribution of papers for each component and modality. Most AC studies used the behavioral component, followed by cognitive and physiological components. Fewest used the social or motivational component. This pattern did not change over time.

4.2.1 Feeling Component

The feeling component refers to the subjective experience of affect [159]. The term "feeling" is often used interchangeably with "affect" or "emotion", but it only refers to the phenomenological aspect of affect in this paper (i.e., part-whole relationship). The feeling component directly and explicitly reflects affect and is thus commonly used as ground truth for other components. The most common way to measure feelings is self-reports. There are many validated questionnaires in psychology, including assessments of a particular emotional state [160], measurements of multiple discrete emotions [161], and measures of affect dimensions [162].

Fifty four papers (4.9% of the 1,110 papers) mainly used the feeling component. Feelings towards interactions with technologies are crucial to user experience, so researchers gathered self-reports to understand emotional effects of different stimuli, user interfaces, products, and systems [60]. Self-reports were often sampled right after the experiment in the lab or multiple times throughout the study in the field (e.g., experience sampling method) [163], but researchers developed a physical slider for users to continuously input their feelings when interacting with technologies [164]. Historic feeling logs were used to predict longer-lasting moods or current feelings [165]. Observers' labeling is another way to infer feelings. Researchers utilized crowdsourcing to quickly collect a mass of annotations with different mechanisms to ensure the quality of labels [143], which helped creation of large affective datasets. Finally, several studies used pictures [96], typefaces [97], geometric figures [98], and emoticons [100] to communicate individuals' feelings.

4.2.2 Cognitive Component

The cognitive component refers to the cognitive process involved in emotion, such as appraisal of internal and external stimuli [42]. Appraisal theories believe the appraisal process activates other components and thus put the cognitive component as central [42]. They only differ in their choices of appraisal variables and mapping rules from appraisals to emotions. Cognitive therapies are often used to help manage affect and treat affective disorders [166], [167]. The cognitive component is also related to information retrieval [168].

Two hundred nineteen papers (19.7% of the 1,110 papers) mainly used the cognitive component. Among them, sixty eight papers (6.1% of the 1,110 papers) utilized the appraisal mechanism to generate and regulate affect. Use of the cognitive component makes it possible to incorporate affect into artificial intelligence [64], [65], [74]. In these studies, computational models of affect were built based on different appraisal theories, where artificial emotions were generated from computation of appraisal variables [63], [64], [65]. Inference rules to derive emotions could be hardwired [63], or learned from human data and interactions with the world [66], [67]. The generated emotion could in turn influence attention [72], social perceptions [73], and decision-making of agents and robots [64], [65], [74]. The cognitive component is also important to emotion regulation. Several applications were designed to facilitate cognitive reappraisal through expressive writing or painting [88].

One hundred fifty one papers (13.6% of the 1,110 papers) utilized the cognitive process of encoding and decoding of affective information in different types of contents. Algorithms were designed to encode affective information in text [124], music [125], pictures [126], scribblings [127], sounds [118], and motifs [119], which emulated the composition and creation process of humans. Researchers also designed algorithms to recognize affective properties of text [169], pictures [170], paintings [171], music [172], videos [173], and textures [174]. Affective clues in these contents could help predict emotion of content producers or consumers [175] and help index the content for retrieval [176].

4.2.3 Motivational Component

The motivational component refers to the action and inaction tendencies prioritized by emotion [177]. Motivation is important for a person to move forward in life and make achievements [178]. Affect can change individuals' intrinsic and extrinsic motivation [179]. For example, depression reduces motivation to initiate and complete goal-directed tasks [180]. Empathy leads to altruistic motivation [181]. It is thus possible to use affect to guide and regulate motivation.

Eleven papers (1.0% of the 1,110 papers) mainly used the motivational component. Education and health are the two domains that were studied in these papers. For example, researchers developed tutoring systems to keep students motivated by responding to their negative emotions, providing helpful feedback and instructions, and showing empathetic reactions [89]. Researchers also built systems to track users' diet, alcohol use, exercise, sleep, and stress levels, and provide intervention for behavior change [91].

4.2.4 Somatic/Physiological Component

The somatic/physiological component refers to the physiological changes accompanying affect [182]. In James-Lange theory, bodily responses are the primary causes of feelings and prepare our body for subsequent actions like fight or flight, so the somatic component is regarded as central [41]. Although the causality is under debates, the theory highlights the close link between the somatic component and the feeling component, which motivates the use of somatic responses as objective measurements of affect. In situations where people are intended to fake their emotions, unaware of their emotions (subliminally induced emotions), or unable to articulate their emotions [183], physiological measurements are best alternatives to self-reports. Although bodily responses cannot be acted, they may be regulated for affect management (arousal control and meditation) [184].

Two hundred twelve papers (19.1% of the 1,110 papers) mainly used the physiological component. Among them, fifty six papers (5.0% of the 1,110 papers) collected and analyzed brain activities. Brain activities can be sensed from a

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variety of noninvasive technologies such as functional magnetic resonance imaging (fMRI) [185], functional near infrared spectroscopy (fNIRS) [186], and EEG [187]. However, EEG is the dominant approach in AC, probably because it is more affordable and accessible than other methods. EEG was used to predict various emotions, such as engagement vs. boredom [187], positive vs. negative emotions [188], and six basic emotions [189]. Common features extracted from EEG for emotion recognition include time domain features (e.g., event related potential, fractal dimension, higher order crossings), frequency domain features (e.g., band power, higher order spectra), and time-frequency domain features (e.g., discrete wavelet transform) [190]. A variety of machine learning models were built for EEG-based emotion recognition [188]. The traditional EEG caps are quite expensive and cumbersome, so researchers explored the feasibility of more affordable and lightweight EEG headsets like Epoc [191]. Brain signals are also tracked in biofeedback systems to help individuals practice affect regulation [192].

Seventy nine papers (7.1% of the 1,110 papers) collected and analyzed physiological activities in the peripheral nervous system that controls skeletal muscles, smooth muscles, cardiac muscles, and glands [193]. Three types of measures are widely used: cardiovascular measures, electrodermal measures, and respiratory measures. Cardiovascular measures include heart rate and heart rate variability extracted from electrocardiography (ECG) signals, blood volume pressure extracted from photoplethysmogram (PPG) signals, and skin temperature [194]. Electrodermal measures include skin conductance level and skin conductance variability from galvanic skin responses [195]. Respiratory measures include respiration rate and respiratory variability collected from breath rate sensors [196]. We also classified surface electromyography (EMG) signals [197], thermal or hyperspectral imaging data [198], hormones [199], pupil diameter, and blink rate [200] as physiological measures rather than behavioral measures. Unlike expressive behaviors, people cannot directly use these signals to convey and recognize emotions. Finally, physiological signals could be monitored in biofeedback systems to help individuals practice affect regulation [85], or transmitted in embodied communication to increase intimacy and closeness [101], [106]. The advantage of peripheral physiological measures is their affordability, lightweight, and user-friendliness [201].

Seventy seven papers (6.9% of the 1,110 papers) collected and analyzed multimodal physiological signals. Different types of sensors are usually integrated to a single device, so cardiovascular measures, electrodermal measures, and respiratory measures were often collected at the same time [201]. Researchers also combined signals of peripheral nervous systems with brain signals [202], facial muscle signals [203], pupil size, and blink rate [200].

4.2.5 Motor/Behavioral Component

The motor/behavioral component refers to the expressive behaviors accompanying affect [44]. Emotions exert influence on others and environment through action and behavior [47]. As a result, expressions in face, body, speech, and other behavioral modalities have long and widely been used to communicate emotions [47]. Using behavioral signals to measure emotions becomes a natural choice [4]. They are also easier to collect and interpret than physiological signals. However, expressive behaviors may be acted. Psychology research suggests acted expressions are different from natural or induced expressions [134]. Expressive behaviors are often regulated for social norms or affect management [204].

Four hundred ninety nine papers (45.0% of the 1,110 papers) used the behavioral component. Among them, one hundred seventy four (15.7% of the 1,110 papers) analyzed facial expressions. A very influential method is Facial Action Coding System (FACS), which encodes movements of individual facial muscles for different emotions [205]. FACS provides manually engineered features for emotion recognition and synthesis [152]. Other features, such as optical flow, Gabor wavelets, multistate models, and generative model fitting, were used for facial expression analysis [206]. Eye gaze and head movements were sometimes used as part of facial features for emotion recognition [207]. Neural networks that could automatically learn useful features were also developed for facial expressions [208]. Databases of acted expressions were mostly used for training and evaluation, but spontaneous and micro expressions that have greater ecological validity and are hard to be disguised were also explored [206], [209]. Besides, researchers tried to improve the robustness of facial expression analysis against aging, pose changes, and mouth movements [210]. Facial expressions were commonly simulated in humanoids [110].

One hundred fourteen papers (10.3% of the 1,110 papers) analyzed vocal/paralinguistic expressions. Commonly used acoustic features include frequency related parameters (e.g., pitch, jitter), amplitude related parameters (e.g., shimmer, loudness, harmonics-to-noise ratio), spectral features (e.g., alpha ratio, hammarberg index, Mel-frequency cepstral coefficients), and temporal features (e.g., the number of loudness peaks per second) [150]. Neural networks were also adopted to automatically learn useful acoustic features from data [211]. Both acted and spontaneous vocal expression databases were constructed and analyzed [212].

Ninety six papers (8.6% of the 1,110 papers) analyzed other behavioral expressions, including walking styles [213], postures, gestures, body movements [214], head movements [215], touch inputs [216], gaze, fixation, eye movement [217], and online behaviors [218]. Postures, movements, gaze, and gaits were simulated in agents and robots for affect expression [115], [121]. Touch was used as emotional cues for embodied communication [104]. Daily activities and behaviors were tracked to provide advice or intervention for emotion management [91]. These other behavioral expressions are less studied than facial and vocal expressions and lack standard feature sets or validated affective databases.

One hundred fifteen papers (10.4% of the 1,110 papers) combined multiple behavioral modalities. Cameras and microphones are often used together to collect audiovisual data for emotion recognition [219]. Use of audio data could help recognize spontaneous facial expressions distorted by speech [210]. Researchers explored a variety of fusion strategies to combine different modalities for affect detection, such as feature-level fusion [220], model-level fusion [219], prediction-level fusion [221], and decision-level fusion [222]. Several studies simulated multiple behavioral expressions in agents and robots to convey emotions [117], [123].

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4.2.6 Social Component

The social component refers to the social dynamics of affect [43]. Affect influences both intrapersonal and interpersonal functioning. The social component can be used to probe affect in a broader context like crowds, groups, organizations, and societies. The social process is important to the development and learning of emotions [223] and mediates emotions like love and guilt [224]. The social and cultural context is also believed to specify details of affect that are not specified by the natural, biological process [43].

Twenty two papers (2.0% of the 1,110 papers) used the social component. Social and cultural factors that could change individuals' emotional experiences with technologies were investigated [59], [128]. Emotional contagion were modeled to understand the dynamics of emotions in the crowd [78]. Platforms were designed to facilitate social sharing of emotions and exchanging of social support [87]. Agents and robots were built to provide social support and companionship [90], [92]. Social networks were utilized to predict users' emotional states [225] and make friend recommendations [226]. Several systems were built to track collective emotions at work [86], or to facilitate team building through online collaborative drawing [227].

4.2.7 Multiple Components

Researchers combined modalities not only within a single component, but also across different components. Ninety six papers (8.6% of the 1,110 papers) used multiple components. Most studies combined physiological and behavioral modalities to recognize different emotions [148]. Some studies also combined affective qualities in content (e.g., text, music) and biophysical signals for affective information retrieval or emotion recognition of consumers [228]. Different fusion strategies were explored to improve the performance of multimodal systems [228]. Researchers also studied to what extent different channels influenced perception of emotions in different contexts [229].

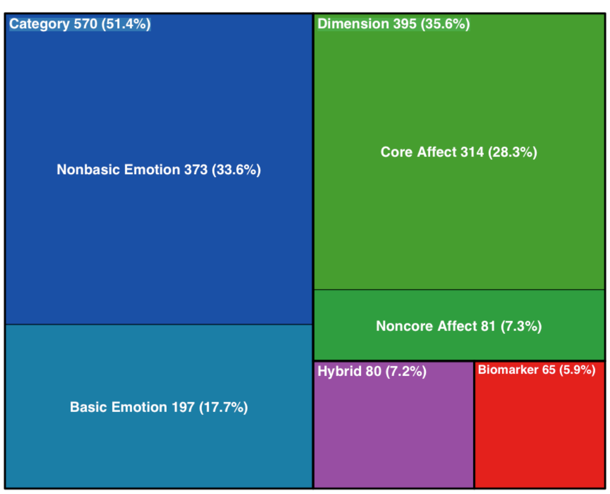

Fig. 4: Paper distribution over representation and type.

4.3 Representation

We identified four representations of affect as AC researchers' answers to what affect to compute: biomarker, discrete, dimensional, and hybrid. Figure 4 shows the frequency distribution of papers for each representation and type. Most AC studies adopted discrete representations, followed by dimensional representations. Fewest adopted biomarker or hybrid representations. Papers using dimensional representations significantly increased from 2008 to 2009 and then maintained at around 35%.

4.3.1 Biomarker

Biomarker representations characterize different affective experiences directly with biomarkers (e.g., muscle contraction, heart rate), which are used as intermediate features in other types of representations [38]. Papers using biomarker representations used low-level feature profiles to specify affective experiences without naming them. Sixty five papers (5.9% of the 1,110 papers) adopted biomarker representations. For example, some researchers only predicted action units (contraction or relaxation of every facial muscle) in the facial action coding system (FACS) [209]. Some only visualized physiological signals and body movements over time to users without providing a label of their affective experiences [156]. Using biomarker representations provide users with detailed feature profiles of their affective experiences and allow them to interpret the data in their own way. However, only providing features without a label is likely to confuse users about what emotion they are experiencing and confuse readers about what emotion the paper is studying.

4.3.2 Discrete/Categorical Representation

Discrete/Categorical representations organize emotion into discrete categories such as anger and surprise [44]. In basic emotion theory, several emotions that are believed to be universally recognized and biologically distinguished are basic emotions. Other emotions are seen as blends of basic emotions and thus, are non-basic [44]. Evidence supporting this view includes the findings that certain emotions seem to be universally recognized [47] and that certain emotion clusters stably emerge from hierarchical cluster analysis of the emotion words across languages [230]. However, there is also evidence supporting opposite views that there are no universal emotions but only cultural products constructed from core affect (i.e., dimensional representation). Supporters of basic emotion theory disagree on which emotions are basic and propose different emotion models, including Ekman's model (later expanded to include social-moral emotions) [44], Ortony, Clore, & Collins's model [231], Tomkins' model [232], Plutchik's emotion wheel [233], and the Geneva emotion wheel [234]. Ekman's model of six basic emotions (happiness, sadness, surprise, anger, disgust, and fear, sometimes plus neutral and contempt) is most widely adopted in AC, so we regard Ekman's categories as basic and other less common categories as non-basic.

Five hundred seventy papers (51.4% of the 1,110 papers) adopted discrete representations. Among them, one hundred ninety seven papers (17.7% of the 1,110 papers) only studied basic emotions (happiness, sadness, surprise, anger, disgust, fear, contempt, and neutral). Three hundred seventy three papers (33.6% of the 1,110 papers) studied non-basic emotions besides basic ones, such as academic emotions (boredom, frustration, engagement, fatigue, and flow) [235], distressing emotions (depression, stress, anxiety, and pain)

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[220], social emotions (conflict, guilt, love, etc.) [215], and emotions defined in Ortony, Clore, & Collins's model [57].

4.3.3 Dimensional Representation

Dimensional representations define emotions in a dimensional space [45]. Psycholinguistic research that represents similarities between emotion words as distances between points in a geometrical space through multidimensional scaling consistently identifies a two or three dimensional representation [45]. Different dimensional models proposed from these research are demonstrated to be rotations of the same dimensional representation, which includes the valence (or pleasantness), arousal (or intensity) dimension for the two-dimensional representation plus dominance (or power) dimension for the three-dimensional representation (called core affect) [236]. A few researchers propose other dimensions such as expectancy [228], liking [152], and dimensions of personality and traits [218]. In this survey, valence, arousal, and dominance are regarded as core affect and other dimensions as non-core, because this three-dimensional representation is widely acknowledged [237].

Three hundred ninety five papers (35.6% of the 1,110 papers) adopted dimensional representations. Among them, three hundred and fourteen papers (28.3% of the 1,110 papers) studied core affect (valence, arousal, and dominance). Eighty one papers (7.3% of the 1,110 papers) studied non-core affect, such as liking [187], power and expectancy [228], personality [218], and attitudes [151]. Most studies collapsed continuous dimensions into categories (e.g., high vs. medium vs. low for arousal and positive vs. neutral vs. negative for valence) and used classification instead of regression approaches [147]. Only a few works predicted continuous values in the dimensional space using regression methods [238]. Dimensional representations can cover a wide range of emotions with only a few dimensions and support better replicability and reproducibility due to convergence of different dimensional models.

4.3.4 Hybrid Representation

Both discrete and dimensional approaches are influential in affective computing. Eighty papers (7.2% of the 1,110 papers) combined both representation systems, where one representation can be converted and mapped to the other. Most studies mapped basic and nonbasic emotions to the dimensional space of core affect [239]. A few studies mapped discrete emotions to noncore affect [240]. Biomarkers are intermediate features to predict discrete categories or continuous dimensions, so combining biomarkers with discrete or dimensional representations is not considered hybrid. The hybrid representation faces the representation mapping problem (i.e., conversion from one measurement scale to another, like reducing continuous to discrete) [241].

4.4 Combinations of Conceptions

Although each conceptual dimension can individually classify literature, they may not be fully independent from each other. Researchers need to combine their answers to why, how, and what questions for a complete view. Certain combinations of conceptions may be preferred due to objective reality, ease of analysis, or convention. To test whether such coupling actually exists, we computed the frequency distribution of papers for each possible pairing between function, component, and representation and used Chi-squared test to see whether proportions of papers for one conceptual dimension are significantly different among values of the other dimension in a contingency table [242]. Chi-squared test results suggest that certain combinations of conceptions are significantly more popular than others.

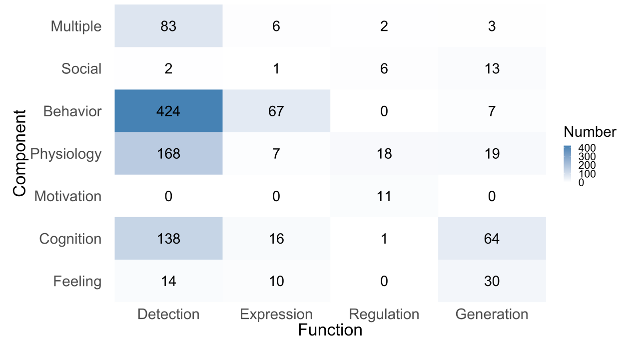

Fig. 5: The frequency distribution of papers for different pairs of functions and components.

4.4.1 Function and Component

Figure 5 shows the frequency distribution of papers for different pairs of functions and components. We find that the behavioral component is preferred in affect expression and detection studies. There are 67 (62.6%) of the 107 affect expression papers and 424 (51.1%) of the 829 affect detection papers that used the behavioral component. The probable reason is that behavioral modalities are easy to access and straightforward to use. There are a plenty of behavioral databases for emotion recognition and synthesis [212]. Cameras and microphones that are typically used for behavioral signal collection are often readily available. It is also natural to simulate and synthesis behavioral expressions in agents and robots, which often come with a human-like shape. However, the dissociation between expressive behaviors and internal affective processes makes it less useful in affect generation and regulation, which is also reflected in our data. For example, expressive suppression is considered a maladaptive regulation strategy in most cases, because it only changes external expressions but not inner feelings [243]. Compared to these short-term behavioral changes, long-term behavioral changes (e.g., exercise, sleep, diet) may be more useful in affect generation and regulation research.

We find that the physiological component is often used in affect regulation and detection. There are 18 (47.4%) of the 38 affect regulation papers and 168 (20.3%) of the 829 affect detection papers that used the physiological component. Although physiological signals are harder to collect and interpret, they are still commonly used, probably because they reveal genuine emotions that are often not visible to others and sometimes even not known to self [183]. This objectivity of the physiological component is crucial to not only affect detection, but also affect regulation. Arousal control and meditation are adaptive regulation strategies, as changes in physiological responses genuinely reflect changes in inner feelings [184]. Physiological systems are

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hard to be reasonably simulated in robots and agents, which limits its use in affect generation. Compared to behavioral modalities, physiological modalities are less useful in signaling emotion in normal interactions. However, they are very useful for intimate interactions. Transmission of heartbeat, touch and other biophysical cues can enable "embodied" communication and increase closeness [101], [103]. There are great opportunities of using the physiological component in affect generation and expression research.

We find that the cognitive component is preferred for affect generation and detection. There are 64 (47.1%) of the 136 affect generation papers and 138 (16.6%) of the 829 affect detection papers that used the cognitive component. The cognitive component has a strong influence on affect and can be represented and computed in symbolic forms. These advantages make it suitable for computationally modeling affect and integrating it to existing AI framework [63]. Besides, the cognitive process needs to be emulated in algorithms in order to recognize affective qualities in contents, organize them for retrieval, and create emotional content [125], [172]. Surprisingly, although cognitive therapies are common methods to manage individuals' affect and treat affective disorders [166], [167], they are not well explored in AC. Since text and language are already used as a major way to convey affect in remote and face-to-face communication respectively, there are fewer opportunities of using the cognitive component in affect expression. However, several studies tried other forms of content for affect expression, such as music [125], pictures [126], and painting [127].

We also find 83 (10.0%) of the 829 affect detection papers combined multiple components. There are already a lot of multimodal systems that combine modalities within a single component. However, fewer multimodal studies combined modalities across components. Such multicomponent recognition approaches face higher challenges on data collection and fusion due to larger variation in sensors and data types, but may be worthy to explore, because modalities of different components are more likely to complement each other than modalities of the same component.

Although not many studies mainly used the feeling component, it is the hidden cornerstone of many AC studies, because it provides the valuable ground truth for testing and using other components. When measuring users' affective experiences with different stimuli, technologies, and systems, self-reports are usually the first choice. In affect detection, self-reports or observers' ratings provide the labels for evaluating different classification algorithms. We also find there lacks research in the motivational and social components. Currently, the motivational component is only studied for affect regulation in the education and health domains [89], [91] and the social component is mainly studied for affect generation, including modeling emotional contagion [78] and testing social and cultural influences on emotional experiences [59], [128]. Future research could explore using these components in other functions of affect.

4.4.2 Function and Representation

Figure 6 shows the frequency distribution of papers for different pairs of functions and representations. We find that discrete representations are slightly preferred over dimensional representations in most AC studies except for affect

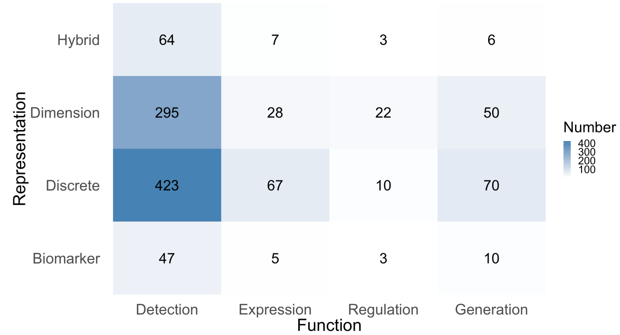

Fig. 6: The frequency distribution of papers for different pairs of functions and representations.

regulation. There are 70 (51.5%) of the 136 affect generation papers, 67 (62.6%) of the 107 affect expression papers, and 423 (51.0%) of the 829 affect detection papers that adopted discrete representations. Although basic emotions alone are not sufficient to portray the diversity of emotions, discrete representations give researchers the freedom to study a wide range of non-basic categories, including academic emotions, social emotions, distressing emotions, and aesthetic emotions. They can even create a new category for a certain type of affective experience and study it [6], [235].

There are 22 (57.9%) of the 38 affect regulation papers that adopted dimensional representations. For many regulation strategies, arousal is an important core affect to regulate [184]. That's probably why dimensional representations are preferred over discrete representations in affect regulation. Dimensional representations can represent different emotions by only a few dimensions and help improve the replicability and reproducibility of AC studies. However, it is less straightforward and harder to apply to new domains, where there lacks knowledge about how to specify a new affective phenomenon in the dimensional space. Besides, most studies that adopted dimensional representations collapsed continuous dimensions into discrete categories (positive vs. neutral vs. negative valence and high vs. medium vs. low arousal), probably due to ease of computation using classification instead of regression methods. Only a few studies computed continuous values in the dimensional space [238]. We do not find many studies using hybrid representations. Use of continuous values for dimensional representations and hybrid representations may be explored in the future.

4.4.3 Component and Representation

Figure 7 shows the frequency distribution of papers for different pairs of components and representations. We find that discrete representations are preferred over dimensional representations when researchers studied the behavioral component and cognitive component. There are 321 (64.5%) of the 498 behavioral-focused papers and 110 (50.2%) of the 219 cognitive-focused papers that adopted discrete representations. This is not surprising, because expressive behaviors and cognitive appraisals are distinguishable among different emotions. Besides, common feature sets of behavioral expressions such as Facial Action Coding System (FACS) are often mapped to discrete representations and common

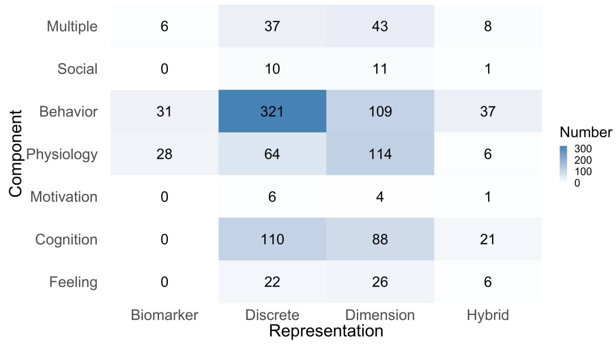

Fig. 7: The frequency distribution of papers for different pairs of components and representations.

behavioral expression databases like Cohn-Kanade database are mostly labeled in discrete categories [244].

We also find dimensional representations are preferred over discrete representations when researchers used the physiological component. There are 114 (53.8%) of the 212 physiological-focused papers that adopted dimensional representations. Physiological signals are naturally suited for regulation, communication, and recognition of arousal [101], [194]. Some physiological channels like EEG are also suited for detection of valence [188]. It is more convenient to use dimensional representations for the physiological component. The coupling between component and representation poses the need for representation mapping for future research.

5 Discussion

5.1 Addressing the Research Questions

Our first research question is what are different conceptions of affect in terms of function, component, and representation. By using psychology theories to guide our coding process, we identified four functions (generation, regulation, expression, and detection), six components (feeling, cognition, motivation, physiology, behavior, and social) plus multiple components, and four representations (biomarker, discrete, dimension, and hybrid). This reflects the huge diversity of AC researchers' theoretical standpoints. Despite the diversity, the community as a whole had an inclination towards computing emotions for affect detection, using the behavioral channels to compute emotions, and adopting discrete representations. This suggests opportunities to explore less studied areas, especially technologies for emotion regulation, use of the motivational or social components, and adoption of hybrid representations.

Our second research question concerns the common and uncommon combinations of conceptions. Although in theory conceptual dimensions should be independent from each other, in practice they may be not due to objective reality, ease of computation, and convention. Indeed, we find coupling between certain pairs of conceptions. For example, the behavioral component is often preferred in affect detection, while the cognitive component is preferred in affect generation and regulation. Studies using the behavioral component often adopted discrete representations, whereas those using the physiological component often adopted dimensional representations. Following these choices may give you access to many resources and enable incremental progress. However, since no consensus has been reached regarding what is the central component and what is the right representation, less frequent combinations may be explored. For example, researchers may try modeling physiological systems in agents and robots to study mind-body relationships and test James-Lange theory that claims physiological responses cause feelings.

Our conceptual analysis uncovers hidden theoretical assumptions behind AC and organizes these different viewpoints along three dimensions: function, component, and representation. It also reveals what individual conceptions and what combinations of conceptions are more common than others. Following the instrumentalism philosophy, these findings provide us with different ways to compute affect and their popularity in AC research. Our analysis is a first step towards a better understanding of affect, because it does not answer realism questions such as whether these conceptions are valid, to what extent they correspond to reality and perform well, and why some conceptions are more common than others. We encourage future research to elucidate and justify conceptual choices regarding function, component, and representation and to collaborate with psychologists to strengthen the theoretical foundation. We also encourage more work to explore the less frequent intersections of FCR and evaluate their usefulness and validity. This type of research will help figure out why they are less used (e.g., whether they are less promising research avenues, whether they are hard to study, and whether they are incompatible with each other) and decide whether we should move towards those less explored areas.

5.2 Using the Framework

There are several benefits from using the FCR framework. First, the FCR framework can organize the messy research space of AC into different niches and demonstrate the similarities and differences of theoretical stances across papers. It thus can help researchers position their own works in a particular research niche and find the most related works from that space. Suppose we have a new idea on generating artificial "emotions" in robots and want to know whether similar ideas have been tested and how they have been carried out. Without the framework, we will likely be overwhelmed by the vast literature of AC. By using the framework, we see our research is in the niche of emotion generation, so we can restrict our search to those papers and quickly filter out papers on emotion regulation, expression, or detection. If our idea is to simulate physiological systems in robots for generating arousal and valence, we can further position our research in the niche of physiological component and dimensional representation. Previous studies in the same niche are likely to be the most relevant. Other studies on emotion generation that used different components or representations (such as the cognitive component and categorical representation) can complement or contrast with our idea.

Second, the FCR framework can serve as a blueprint for conceptualizing affect and help turn a rough idea into a more concrete project. Suppose we want to test the possibility of using virtual reality (VR) for AC research. The FCR framework informs that we need to think about what affect to compute, how to compute affect, and why compute affect and presents us with different answers to these questions. For what affect to compute, we may think about a particular emotion we are interested in (e.g., pain) and choose which representation we want to use (e.g., pain and no pain as two categories vs. continuous pain scale). For how to compute affect, we may think about a particular component that carries information about the target emotion (e.g., feeling vs. physiology) and choose which modality or channel to use for that component (e.g., questionnaire vs. wearable sensors). For why compute affect, we may think about a particular function of emotion that VR can contribute to (e.g., generation vs. regulation) and choose the corresponding experimental protocol (e.g., using VR to evoke desired emotional states vs. using VR for meditation practice). Our answers to the three questions highlighted by the FCR framework may influence each other. For example, if we choose to implement meditation protocols in VR, we may choose the physiological component to measure pain, because meditation has direct physiological effects [245]. The FCR framework also reminds us that we need to provide justifications for our choices regarding the three dimensions, which will just be our thinking process that turns our initial idea to the current project. For instance, we choose to use continuous pain scale, because we target patients who suffer from chronic pain and need to measure their pain ratings over time when using VR. We choose to use VR for emotion regulation, because previous studies show movies and music are non-pharmacological alternatives for pain reduction and VR also provides an immersive environment. We choose to measure physiological responses, because mediation has direct physiological effects and we don't want participants to be interrupted by pain questionnaires. If the project is very large (e.g., build a social humanoid robot), we may want to break down the project by different functions of emotion we want to study and then decide on the component and representation for each function.

Third, the FCR framework can help generate new ideas and inspire new research directions. Suppose we have been doing research in facial expression recognition of basic emotions, which involves detection as the primary function, behavior as the primary component, and categorical model as the primary representation. By using the framework, we can clearly see other possibilities. For example, we may have reached a high accuracy on classifying facial expressions into discrete categories. We can then try predicting continuous values in the dimensional space. We may add other modalities such as physiological signals to improve the accuracy. We can also utilize facial expressions for emotion expression in humanoids or test expressive suppression for emotion regulation. There exist paradigms or conventions to combine certain functions, components, or representations, but the FCR framework provides other possibilities by pointing out less common combinations. We can start with two conceptual dimensions decided (such as function and component) and look for different flavors of the third one (such as representation).

Lastly, the FCR framework can deconstruct the complexity and clear the confusion associated with affect in computing. Affect is an ill-defined concept. There is no consensus of what emotion is. Differing theoretical views in psychology and AC may puzzle scientists in computing, especially new researchers. The FCR framework addresses this issue by emphasizing three core questions to think about (why compute affect, how to compute affect, and what affect to compute) and providing an overview of existing answers to these questions. Although it does not capture all possible conceptions of affect, the framework can be easily modified to add other important dimensions such as the measurement scale (nominal vs. ordinal vs. interval) or incorporate changes to current functions, components, and representations of affect. The plasticity of the FCR framework gives it potential to evolve with the new understanding of affect in the future.

5.3 Tradeoffs in AC

In the review process, we find several tradeoffs in AC research. The first is universality vs. specificity, which originates from psychology debates on whether facial expressions of emotions are universally recognized or culture specific. No consensus has been reached so far [44], [48]. Similar tradeoffs may exist in AC research, such as whether affect detection classifiers should be person-independent or person dependent, whether improvements of algorithms should be made on a single dataset or across datasets, whether emotional expressions should be context-free (acted and induced expressions) or context-sensitive (natural expressions), whether certain component and modality should be regarded as central and used for all research or the value of different components and modalities varies, and whether emotions should be represented in a universal dimensional space or in specific categories. We need more careful rationales for our decisions concerning these tradeoffs. Unfortunately, few studies in the literature discussed the reasoning behind their decisions and it is unclear whether it is objective reality, ease of computation, or convention that resulted in the popularity of certain conceptions and approaches. Therefore, we are calling for more research validating the most common or convenient approaches, more clear explanations of rationales behind different choices in papers, and more explicit discussions in papers about the implications and consequences of these choices (e.g., the generalizability, reliability, and validity of findings).

The second is data vs. algorithms. Technological advancements were major contributions of most studies and only a few focused on improving the data. AC systems are built with assumptions that certain emotions will be experienced or expressed by users, but this may not always be true. Different emotions may be experienced in different contexts (e.g., academic emotions in classes and aesthetic emotions in museums). Even if emotions are experienced, users may not express them, especially when they interact with machines rather than people. Similarly, we may start developing applications for emotion regulation without knowing what regulation strategies people actually adopt and prefer in advance. We thought meditation would be great, but it might not work for most people. The importance of acquiring real user data should be emphasized in AC and more research should be encouraged to work on the collection of high quality, authentic user data.

The third is categorical (nominal form or unordered classes) vs. ordinal (rankings or ordered classes) vs. con-

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tinuous (intervals) measurement scales. Many AC studies that adopted dimensional representations ended up collapsing continuous dimensions into discrete categories and applying classification instead of preference learning or regression approaches. Although commonly done, there are statistical reasons not to do this. For example, DeCoster et al. studied the common practice of dichotomizing continuous measures in psychology and obtained justifications from 66 researchers for dichotomization. They found that many justifications could not stand scrutiny and that dichotomization led to less powerful and less accurate statistical tests [246]. Another paper by Yannakakis et al. also discussed the advantages of ordinal annotation with respect to both reliability and validity and supported the thesis that emotions are ordinal by both theoretical arguments and evidence [241]. Although nominal annotation may lead to easier computation and analysis and has been a convention, we encourage future work to use measurement scales compatible with the representation such as ordinal or continuous annotation for dimensional models. By using compatible measurement scales, we can then fully understand the effectiveness and usefulness of different representation models.

5.4 Limitations and Future Work

This survey has several limitations. First, it does not cover all papers related to AC. Publications after October 2017, publications in other academic databases (e.g., social science papers), publications only using terms "emotion" or specific types like "pain" rather than "affective computing", and publications without original contributions (e.g., chapters, reflections) are not covered. Inclusion of these papers may change our results. For example, publications after Oct. 2017 may start concentrating on other functions of affect than detection. Social science papers may prefer feeling rather than somatic or motor components as the major component, because it is more suited for qualitative and ethnographic studies. Unlike affect detection or expression publications, papers that study affect generation or regulation may not self-identify as AC that commonly. Book chapters, reflections, proposals, and other non-original works may mention papers that are not in the present paper pool. However, this sampling bias is inevitable, because it is difficult to find all relevant studies and review a paper pool that is even several times larger than the 2,126 papers we reviewed. Besides, although the specific frequency distributions may change, the framework along with the coding scheme and categories are likely to remain stable, because they are derived mostly from psychology research and only partially from the data. Even the specific frequency distributions are still meaningful, because it at least reflects conventions and preferences of studies that self-identify as AC. Future work may incorporate these overlooked papers to the framework and compute more precise frequency distributions.

Second, our coding process has subjectivity in it . Papers may be assigned into multiple categories instead of exclusive categories. For example, papers may use the feeling component as hidden cornerstones in addition to their primary component. Some affect regulation studies may also use affect detection systems. Different functions, components, and representations of affect are in fact interrelated rather than independent. However, we made the tradeoff to code papers into exclusive categories, because taxonomy results based on primary focus are easier to interpret than results mixing primary and secondary focuses. Assigning a paper into multiple categories gives equal weights to applied categories and smooths actual preferences. Besides, unlike primary systems that are original work, secondary systems used in adjunct with primary systems are usually borrowed or adapted from previous studies, which are probably already counted. Another source of subjectivity originates from the fact that the majority of papers were coded by the first author. We only had the first author code the majority of the papers, because other coders' participation could not continue due to their time constraints compared to the long time span of this project. However, the codebook was guided by previous psychology research and revised by multiple coders after reviewing a set of papers and resolving disagreements. In addition, we did not include several other codes that are also important, such as predefined conditions vs. self-reports vs. observers' ratings as ground truth, posed vs. induced vs. spontaneous expressions, and use of categorical vs. ordinal vs. interval measurement scales (i.e., classification vs. preference learning vs. regression). Future work may improve our review by iterative codebook development based on inter-rater reliability scores, categorization in terms of functions, components, and representations for secondary focus, and inclusion of other useful codes.

Third, there is a lack of technical depth in our survey. We focus on the breadth rather than the depth of AC research to complement the significant body of in-depth technical surveys for different modalities and contexts that provide guidelines regarding specific techniques. However, broader perspectives of affective computing are still valuable, as a specific avenue may be a dead end at one point but become worth pursuing as (e.g., sensing) technologies advance. In our work, we focus on the broader perspective of current conceptions of affect, pointing out both well-explored and largely uninvestigated areas. We point readers to those in-depth surveys summarized in Section 2, if they look for detailed comparisons of different technologies, technical guidelines, or directions for technical advancement. Future work should focus more on which theoretical assumptions about emotion are valid, generalizable to broad contexts, or lead to better performance.

6 Conclusion

In this survey, we proposed the function-component-representation framework to organize differing theoretical viewpoints in AC and provided a thorough conceptual analysis of the literature. We coded 1,110 papers according to the coding scheme inspired by psychology theories and computed the frequency distribution of papers for each individual conception and each possible pair between function, component, and representation. We found preferences towards affect detection, behavioral component, and discrete representations. We also found certain pairs of conceptions were more common than others. We discussed the implications of our findings, explained the benefits of our framework, and examined the limitations of our survey.

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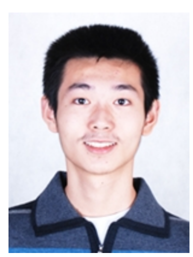

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