Beyond the Basic Emotions: What Should Affective Computing Compute?

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Abstract
One of the primary goals of Affective Computing (AC) is to develop computer interfaces that automatically detect and respond to users' emotions. Despite significant progress, "basic emotions" (e.g., anger, disgust, sadness) have been emphasized in AC at the expense of other non-basic emotions. The present paper questions this emphasis by analyzing data from five studies that systematically tracked both basic and non-basic emotions. The results indicate that engagement, boredom, confusion, and frustration (all non-basic emotions) occurred at five times the rate of basic emotions after generalizing across tasks, interfaces, and methodologies. Implications of these findings for AC are discussed.

Author Keywords
Affective computing, basic-emotions, non-basic emotions

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Experimentation, Human Factors.

Introduction

Until the mid '90s, interface design was primarily concerned with the cognitive constraints of the user [1]. Affective experiences (emotions, moods, feelings) of the user were not on the radar of mainstream HCI. The realizations that (a) humans are more than mere cognitive machines, (b) emotions are an inextricable part of our everyday experience, and (c) the continual and complex interplay between cognition and emotion is the hallmark of information processing in humans, led to the *affective revolution* and the field of *Affective Computing* (AC) [2]. Broadly, AC focuses on creating technologies that can monitor and appropriately respond to the affective states of the user in an attempt to bridge the communicative gap between the emotionally expressive human and the emotionally deficit computer. An interface that is sensitive to a user's affective state is expected to be more usable, useful, naturalistic, social, and enjoyable - all factors that guarantee wide use and acceptance.

The field of AC is now more than a decade old, its flagship journal, *IEEE Transactions in Affective Computing*, has been launched, and remarkable progress has been made along a number of fronts. These include basic research on emotions during interactions with computers, fully automated systems that detect naturalistic expressions of affect with modest accuracy (see [3, 4] for reviews), systems that synthesize emotions (see [5] for a survey), and prototypes of affect-sensitive interfaces that detect and respond to users' affective states in addition to their cognitive states [6]. Research in some areas, such as audio-visual affect detection, has advanced to the point that review articles are being published [3, 4, 7], while other areas such as affective brain-computer interfaces are in their infancy. Needless to say, sufficient research has been accrued to warrant a critical examination of some of the underlying assumptions and common trends in the field. Along these lines, the present examines one of the most basic issues in the field of AC. Specifically, what emotions should affective interfaces be responsive to? Simply put, what *should* affective computing compute? To address this question we begin by looking at what affective computing currently *does* compute.

What Does Affective Computing Compute?

Researchers in the affective sciences (primarily psychologists) have proposed a number of taxonomies to categorize the emotions that occur in everyday experiences [8-10]. Broadly, the emotions can be divided into *basic* and *non-basic* emotions. Emotions such as anger, surprise, happiness, disgust, sadness, and fear typically make the list of basic emotions [9]. Emotions such as boredom, confusion, frustration, engagement, and curiosity share some, but not all, of the features commonly attributed to basic emotions (e.g., presence in primates, coherence in response systems; see [9] for full list). Consequently, these emotions are labeled as *non-basic* emotions. It should be noted that the term "emotion" is being used broadly in this paper to include both bona fide emotions (e.g., anger) and cognitive-affective blends such as engagement and confusion.

This crisp distinction of basic vs. non-basic emotions, which was propagated in the 1960's, has had a lasting influence on scientific inquiry to the present day. While the basic emotions have enjoyed a privileged status by being on the forefront of research, the non-basic emotions have been relegated to the sidelines.

Studies analyzed

Type: 5 studies on different HCI applications: 1) interaction with an Intelligent Tutoring System 2) interaction with online courseware 3) practice session with standardized testing 4) writing (2 studies).

Methodologies: emote-aloud, online self-reports, cued-recall.

Total data: 14,359 emotion reports from 131 participants over the course of 5,545 minutes (or 92 hours) of interactions.

Findings: (1) There was a 5:1 affect: neutral ratio; (2) There was a 5:1 non-basic: basic emotion ratio; (3) Engagement, boredom, confusion, and frustration were the most frequent emotions.

Conclusion. Affect computing researchers should consider non-basic emotions in addition to the basic emotions.

Irrespective of the fact that there is considerable debate over the very existence of basic emotions [11, 12], researchers have still emphasized these six emotions at the expense of overlooking other non-basic emotions [13].

Taking heed from the psychological community, the AC community has also focused on the basic emotions. To illustrate this point, a recent review of 29 state-of-the-art vision-based affect detection methods by [4] indicated that most systems were concerned with detecting the six basic emotions. A similar conclusion can also be applied of the audio-based affect detection community, although they sometimes also focus on stress, irritation, and frustration. Finally, a recent meta-analysis of 30 multimodal affect detection systems also indicated that a majority of the systems focused on detecting the basic emotions [14].

The emphasis of basic emotions in AC research raises the questions of whether these emotions warrant such a privileged status. Do basic emotions dominate the affective landscape when people perform personally-relevant tasks with computer interfaces? Do computer experiences resonate with anger, sadness, fear, disgust, happiness, and surprise? Or is a different set of non-basic emotions more relevant? For example, is a computer user more likely to be bored and confused vs. sad and fearful? If the non-basic emotions are more relevant, then it might be equally or more important for AC systems to focus on detecting and responding to non-basic emotions, such as boredom and confusion, instead of sadness and fear.

The present paper analyses the relative importance of basic and non-basic emotions by looking at the emotions that are prominent during interactions with computer interfaces. We do this in the tradition of meta-analysis, but with fewer (k = 5) studies analyzed. The small number of studies analyzed and the fact that they are all from a single research group limit the scope of the conclusions and these limitations are discussed in the last section.

Descriptions of Studies Analyzed

The present analysis focused on studies that monitored both basic and non-basic emotions while participants interacted with different computer interfaces. We selected a set of five studies that were conducted in our research lab from 2004 to 2010. Although the choice of studies may limit the generalizability of the analysis, the chosen studies span a wide set of interfaces, and data collection techniques, which is similar to the current AC literature. The studies involved different tasks, computer interfaces, and methodologies to monitor emotions. The tasks and interfaces included:

(Study 1) Learning computer literacy with an Intelligent Tutoring System (ITS) [15]. The study used an emote-aloud protocol in which seven undergraduate participants verbalized their affective states as they occurred while interacting with a conversational ITS called AutoTutor [16] for approximately 90 minutes.

(Study 2) Completing an online course on statistics (unpublished). In this study, 3 students enrolled in an online statistics class with the Aleks computer tutor [17]. Each student completed eight 45 minute sessions with the tutor. Students self-reported their affective states every 3 minutes by selecting one emotion from a list of basic and non-basic emotions.

(Study 3) Completing a practice session of a standardized test with a computer interface [18]. The emotions of 41 undergraduate students were tracked while they solved difficult analytical reasoning problems from the Law School Admission Test (LSAT). A cued-recall approach was used for the annotation of emotions: participants viewed videos of their faces and screen captures and judged their emotions from a set of 14 states (basic emotions, non-basic emotions, and neutral). The annotation was performed at relevant points in the problem solving process (after new problem was displayed, in the midst of problem solving, after feedback was received).

(Studies 4 and 5) Writing argumentative essays. In two studies, 86 participants used a computer interface to write argumentative essays on a diverse set of topics ranging from socially-charged issues, such as abortion and the death penalty, to academic topics that typically appear on standardized tests in the U.S. (e.g., whether high-school should be extended to five years) [19, 20]. The hypothesis tested in this study was that writing triggers a host of affective states, some of which are tied to the topic of the essays (topic affective states), while others are more closely related to the cognitive processes involved in writing (process affective states). Participants self-reported emotions after the completing the writing session via a cued-recall procedure similar to Study 3.

The brief descriptions of these studies illustrate the diverse tasks, interfaces, and methodologies used to track emotions in each study. Task and interface diversity included learning with a conversational tutor (Study 1), learning with a point-and-click tutor (Study 2), solving difficult problems (Study 3), and creative writing (Studies 4 and 4). Methodological diversity included: emote-alouds (Study 1 - participants verbally express their emotions as the emotions are experienced), online self-reports (Study 2 - participants are periodically asked to fill out a questionnaire on their emotions), and cued-recall protocols (Studies 3, 4, and 5 participants provided judgments of their emotions from videos recorded during the session).

The five studies that were selected adhered to the following criteria. First, all studies involved interactions with a computer interface. Second, all studies involved a non-trivial task so that the participants were sufficiently challenged and could experience both positive and negative emotions. Third, there was sufficient variability in the tasks, so any generalizable patterns could not be simply attributed to task effects. Fourth, the interaction sessions were sufficiently long (between 30 minutes to 1.5 hours) to allow a diverse set of emotional responses to unfold. Fifth, the emotions were tracked at multiple points during the interaction session so that a fine-grained sampling of emotions could be obtained. Sixth, both basic and non-basic emotions (about 7 each with small differences across studies) were monitored in order to afford meaningful comparisons between emotion categories. Seventh, multiple methodologies were used to track emotions in order to avoid methodological artifacts.

The data of interest were reports of discrete emotions collected in each study. Taken together, a total of 14,359 emotion reports were collected from 131 participants over the course of 5,545 minutes (or 92 hours) of interaction.

Results and Discussion

The analyses proceeded by computing the proportional occurrence (p_{ijk}) of emotion (i) for participant (j) in study (k). For an individual participant, the sum of proportions of e emotions is 1. The key measure for emotion i in study k, is the mean proportional occurrence (MPO) of emotion i across the s participants in study k.

Descriptive statistics (mean and standard deviation) for MPOs across studies are presented in Table 1. The number of emotions varies across studies because there were small differences in the set of emotions considered in each study. This is also the reason why the sum of MPOs across emotions does not equal 1.

The results were illuminating in a number of respects. There was a 5:1 affect vs. neutral ratio, which indicates that interactions with computers are indeed affectively charged since neutral in these studies was defined as “a state with no apparent emotion or feeling.” Additionally, the difference between the sum of emotions in each study (M = .83) compared to neutral (M = .17) was significant, $t(4) = 6.1$, $p = .004$ d = 5.44 sigma, so this finding generalizes across studies and is consistent with a very large effect [21].

There was also a 5:1 non-basic to basic emotion ratio. The difference between the sum of the non-basic emotions in each study (M = .88) was significantly higher than the sum of the basic emotions (M = .17), $t(4) = 5.8$, $p = .004$, $d = 4.47$. This indicates that the non-basic emotions were significantly and substantially more prevalent than the basic emotions.

Basic	**N**	**M (SD)**	**Non-basic**	**N**	**M (SD)**
Angry	5	.02 (.02)	**Bored**	5	**.12 (.09)**
Anxious	4	.04 (.02)	**Confused**	5	**.10 (.05)**
Contempt	5	.03 (.02)	Curious	5	.05 (.05)
Disgust	5	.02 (.01)	Delighted	2	.02 (.00)
Fearful	3	.00 (.00)	Eureka	3	.05 (.05)
Happy	4	.03 (.02)	**Engaged**	3	**.42 (.12)**
Sad	3	.01 (.00)	**Frustrated**	5	**.12 (.11)**
Surprised	4	.01 (.01)			
Neutral	4	.21 (.09)			

Table 1. Mean proportional occurrence of emotions across studies with standard deviations in parentheses.

Two criteria were adopted to identify the most frequent emotions that users reported across studies. First, the mean (across studies) occurrence of a *frequent* emotion should be greater than .067 (1/16 since there are 16 emotions). Second, in order to determine if an emotion consistently occurred across studies, its signal to noise ratio (SNR), computed as the ratio of the mean to the standard deviation, should be greater than 1. It provides a measure of signal strength (MPO across studies) to noise (between-study variance in MPO). Engagement, boredom, frustration, and confusion were the only four emotions that met these two criteria. Importantly, these are all non-basic emotions.

There is the concern that the present emphasis on mean effects across studies might bias the results because a basic emotion might be very frequent in one study but not in other studies. To address this issue, we examined the maximum MPO associated with the 8 basic emotions across the five studies. The maximum occurrence of a basic emotion never exceeded .07, while the maximum for the four frequent non-basic emotions (engagement, boredom, frustration, and confusion) ranged from .17 to .57.

General Discussion

The present analysis was based on five studies that systematically monitored emotions while users performed conceptually difficult tasks with computer interfaces. Although this analysis was preliminary, it yielded three important insights. First, computer experiences are affectively charged. This highlights the importance of building emotionally-aware interfaces, which is a major thesis of affective computing. Second, it was the often-neglected non-basic emotions, instead of the basic-emotions, that were more prevalent. This raises some concerns about AC's focus on the basic emotions. Third, engagement, boredom, confusion, and frustration were the most frequent emotions experienced, suggesting that these emotions might be good candidates for AC research.

It is important to acknowledge three limitations with this analysis. First, one might object to drawing major generalizations from the small number of studies analyzed. Although this is a valid concern, it should be noted that the major claims were backed by statistically significant results, indicating that the patterns generalize across studies. Furthermore, the studies tracked emotions at a fine-grained level (there were almost 15,000 emotion reports), so there is substantial data to warrant the claims.

There is also the concern that the present set of studies focused on users performing *academic tasks* with PCs (learning from computer tutors, solving problems, writing essays). This raises the question of whether the findings will generalize to a different set of work tasks (e.g., editing a word document or reading an article online) and computer platforms (e.g., tablets or smart phones). Although this is certainly a valid concern, it is important to note that there is considerable overlap between the present tasks and other work-related computer activities. In particular, the tasks in the studies we analyzed can be decomposed into primitive subtasks, such as reading text, providing responses, receiving feedback on actions, making decisions, and composing written text. These primitive subtasks are expected to be observed in a number of similar work-related activities and the four non-basic emotions emerge over the course of performing these subtasks. Specifically, engagement is prevalent when the user focuses on the superordinate goal of completing an important task. Boredom occurs when the user abandons the superordinate goal and disengages. Confusion is triggered by unexpected feedback, anomalies, contradictions, and when the user is unsure about how to proceed. Frustration occurs when important goals are blocked and users get stuck. To summarize, we have some confidence in the generalizability of the findings to other work-related tasks, although the findings are presumably less applicable to leisurely activities such as gaming, blogging, and online shopping. Nevertheless, this is entirely an empirical question and future research is needed to resolve this issue.

The third limitation pertains to the studies themselves, namely that they were (a) laboratory studies involving a rather homogeneous population of undergraduate students (b) conducted by our research group and (c) used self-reports to measure affect. These are all valid criticisms that make the present findings more tentative rather than conclusive. What is needed is a replication of the present analysis with a larger set of studies featuring substantially greater diversity in student populations, computer interfaces, research groups, and methodologies used to monitor emotions. This is precisely what we have done albeit in the context of academic tasks. Specifically, we have conducted a meta-analysis of 24 studies that utilized a mixture of methodologies (online self-reports, online observations, emote-aloud protocols, cued-recall) and affect judges (students themselves, untrained peers, trained judges) for fine-grained monitoring of 14 discrete affective states of 1740 middle-school, high-school, college, and adult students in five countries over the course of interactions with a range of learning technologies, including intelligent tutoring systems, serious games, simulations environments, and simple computer interfaces [22]. Indeed, preliminary analyses have indicated that boredom, confusion, and engagement were once again the major emotions, along with curiosity and happiness, while contempt, anger, disgust, sadness, anxiety, delight, fear, and surprise were comparatively rare (five of these are basic emotions).

It is important to emphasize two points about the present claims about basic and non-basic emotions in order to avoid any unintended overgeneralizations. First, this paper does *not* claim that AC *only* focuses on basic emotions. There are definite examples of AC systems that also consider non-basic emotions. For example, researchers working on the emotional aspects of games have always considered boredom to be of importance (e.g., [23]). The claim is simply that AC researchers, particularly those focusing on affect detection, have emphasized basic over non-basic emotions, and there is adequate data to support this assertion as noted by recent reviews on affect detection [3, 4, 14].

Second, the claim is also *not* that AC should avoid studying basic emotions. On the contrary, one can conceive of a number of AC applications where basic emotions are very relevant. For example, it is perfectly reasonable for an agent demonstrating the harmful effects of bullying to synthesize *fear* and *sadness* [24]. Similarly, it is important for an automated call center monitoring system to detect when a customer is *angry*. Again, the claim is that *both* basic and non-basic emotions deserve equal focus. It might also be interesting to consider blends of basic and non-basic emotions or instances when they occur in close succession (e.g., surprise followed by confusion).

In conclusion, one can always make the case that a particular emotion, basic or non-basic, might be relevant in a particular domain. However, the results of the present study suggest that AC should expand its scope to include important non-basic emotions such as engagement, boredom, confusion, and frustration. At the very least, these and other non-basic emotions should receive more attention in AC if creating functional affect-sensitive user interfaces is an important goal.

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