Affective User Interfaces

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Abstract Affective user interfaces are interfaces that are capable of eliciting, conveying, modeling, enhancing, or influencing emotions in their user. This chapter summarizes the role user affect plays in interface design, including how it can best be understood and represented, and the variety of methods pertaining to its analysis and display. Drawing on the state of the art and history of affective interfaces, we highlight how such interfaces can be used to enhance existing computer-mediated communication to make them more engaging and more natural, as well as to enable new interaction possibilities. Specifically, we focus on: (1) Augmenting computer-mediated communication with affect, (2) Digital emotion regulation and support, (3) Affective immersive experiences, (4) Affective haptics, and (5) Persuasive interfaces. Finally, we consider the risks of these technologies, including ethical aspects (e.g., emotion surveillance, ground truth reliability and bias), as well as the opportunities for such interfaces, from affective embodied agents designed for health and positive behavior changes, to affective learning and education, and to artistic creations.[1]

Introduction

Human emotions are changes in brain and bodily functions that have measurable outcomes in cognitions, physiological responses, and behaviors (Kemp et al., 2015). Their role in the design of intelligent systems has been recognized for a long time.

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Rosalind Picard (1997), in her seminal book on affective computing, argued that computers need affective abilities “to function with intelligence and sensitivity toward humans”. For a large range of systems, interactions with humans is impacted by the affective state and perceptions of the user, and including considerations about these aspects in the design of such systems is beneficial, if not necessary.

Since all cognition is tinted with emotions, any designed artifact or system, digital or not, will involve some emotional aspects. User experience gained importance in understanding the usability of technology in the last two decades, and affective responses were an important part of that. But our subject matter goes beyond affective responses and value judgments given by users, which are critical for assessing user experience and acceptance.

We use affect as a general term to denote emotion, mood, feelings, and more permanent traits like personality. Emotions are physical responses, whereas mood is more of a disposition, and denotes a longer period. Personality denotes general traits that underlie a large range of behavior, and can be assumed to be permanent for all practical purposes. While emotions are subjective, their expressions can function as social signals. Subsequently, humans also learn to exhibit these signals in the absence of emotions; a smile can be a genuine indicator of happiness, or a social indicator to signal approval. On the one hand, this is a source of ambiguity when we create artifacts that try to recognize a user’s affect, but on the other hand, we use this mechanism to create artifacts that can “express” a certain affect. For example, if flinching is one of the indicators of fearful behavior in a particular cultural context, an interface that flinches away from the touch of the user may appear fearful in a similar context. Senseable behaviors on both side of the interface are the design handles of affect.

In an affective interface, affect can be considered as a variable that represents the state of a user. This can be followed by selecting a compensatory strategy to improve the interface (Hudlicka and Mcneese, 2002). But this is a simplification, and the full potential of emotions appears in interactions as “dynamic, culturally mediated, and socially constructed and experienced” (Boehner et al., 2005). We define affective user interfaces to be those that are capable of eliciting, conveying, modeling, enhancing, or influencing emotions in their users. We include in our definition systems for which emotional aspects are central in the design, those that can exhibit signs that will be interpreted by humans as affective, as well as systems that can analyze and respond to their users’ various affective states. Each of these aspects requires a different design and analysis approach. We will first discuss how affect can be represented, affective data acquisition and analysis. Then we will cover five representative areas where affect can enhance human computer interaction. Finally, we will discuss the risks and challenges, as well as the opportunities of affective user interfaces.

Representing Affect

Designing an affective user interface requires consideration of what affect precisely signifies, and how it can be represented. Appraisal theories of emotions have been influential in linking emotions to states and behaviors in response to perceptions. These theories can help the designer systematically assess whether at a certain moment an avoidance or approach behavior is elicited, or whether the individual is empowered in terms of agency or coping with a particular situation (Moors et al., 2013). Systems-based approaches to appraisal mechanisms assume that events in the external world are first checked for relevance (including novelty effects that trigger bottom-up attention processes), then for their implications for the goals of the agent, next for coping strategies (including control and adjustment parameters), and finally, how they agree with the self image of the agent (i.e. normative significance) (Sander et al., 2005). These theories have also influenced research in affective computing, as they provide systematic ways of representing affect in a computer system. Affective computing approaches often simplify and operationalize the affective state, and are sometimes criticized for this (Boehner et al., 2005).

If an explicit representation of user's affect is required, the most common solution is to adopt a categorical or dimensional representation that is established via self-report or through multimodal observations of the user. These are simpler compared to appraisal models, as they do not include any causal reasoning. A popular categorical framework posits the existence of "basic emotions", such as happiness, sadness, anger, fear, disgust, and surprise (Tomkins, 1962; Ekman, 1999). These categories may not be a robust and valid way of representing affect in humans, as there are significant cultural, individual, and contextual differences in their expression and perception. However, they will result in a set of indicators, such as particular facial expressions, and these indicators can be detected to infer such states statistically. Newer approaches, such as the theory of constructed emotion (Barrett, 2017) are in favor of context-dependent and more loosely connected bodily systems, but in practice, categorical representations of affect, basic or otherwise, are still ubiquitous in human-computer interaction (D'Mello and Kory, 2015).

Dimensional approaches use continuous representations in a small number of dimensions instead of a discrete number of categories to represent the user's state. The most popular dimensional approach is based on Russell's (1980)'s Circumplex Model of affect, where the affective state is mapped to a two-dimensional, real-valued space, represented by "Valence" and "Arousal" (VA), denoting the energy and pleasure/displeasure dimensions of the affect, respectively. This model (and similar dimensional approaches) are obtained by estimating distances between pairs of emotional words, and using multidimensional scaling to map them onto a sub-space of two dimensions, which are then empirically labeled. Arousal and valence have found wide acceptance as a good set of basis vectors to span this space. The extension of the model to a third dimension gives us "Dominance," (D) which plays a central role in appraisal theories by accounting for power and control (Russell and Mehrabian, 1977). The resulting three dimensional space is often denoted as the VAD-space. Figure 1 shows a few examples from the Affective Norms for English

Words (ANEW) corpus, where each word is tagged with VAD values, making them representable in this 3D space.

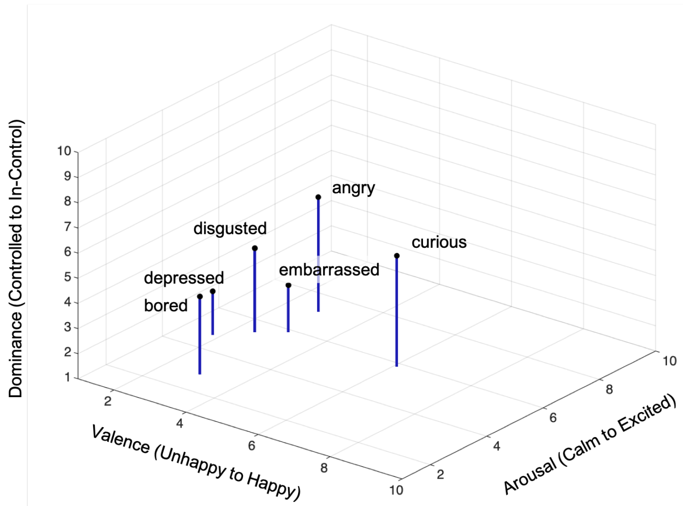


Fig. 1 Several words from the ANEW corpus represented as points in the VAD-space. Note that some concepts, such as ”depressed” and ”bored” are very close numerically. It is clearly difficult to annotate emotions using a purely numeric or visual representation; language makes nuances much more prominent.

In the rest of this article, we will mention systems and interfaces where a user is assigned to either a categorical or dimensional state vector. While we know that such simplified representations are fundamentally incomplete and often socio-culturally biased, they can still be a source of significant improvement over systems that completely ignore the user’s emotional state.

Affective Data Acquisition

Acquisition of affective state or response of a user can rely on self-report including explicit tagging (such as emoticons used to respond to social media content), or on automatic analysis approaches. We briefly discuss both possibilities.

Self-reported affect

Self-report is important in applications where the user provides explicit input for the affective state, which is communicated to an agent or to other users. It is also a major aspect of user evaluations, more so for affective user interfaces.

The most direct form of self report is via explicit querying of emotions with an emotional state questionnaire, where subjects evaluate their felt emotions via Likert scales. The popular Positive and Negative Affect Schedule (PANAS) scale uses 5-point Likert scales and evaluates affect along 20 dimensions (Watson et al., 1988), and is generally deemed a reliable and valid instrument in the assessment of affective states. These dimensions are either positive (Attentive, Active, Alert, Excited, Enthusiastic, Determined, Inspired, Proud, Interested, Strong) or negative (Hostile, Irritable, Ashamed, Guilty, Distressed, Upset, Scared, Afraid, Jittery, Nervous) affects. The total score is calculated by finding the sum of the 10 positive items, and then the 10 negative items. PANAS has multiple versions, with the PANAS-SF being the most common and widely available version[2]. While the temporal window of the query (e.g. the moment, the session, a day, a week, a month, etc.) can be adjusted through the wording of the questions, Feldman Barrett (2004) notes that with passing time, self-reported emotions will become less accurate.

Similar reporting approaches can also be employed with observer evaluations of the subject's affective state. For instance, the ECHOS mobile phone platform was developed for caregivers to annotate affective (and communicative) states of individuals with minimally verbal autism spectrum disorder (Johnson et al., 2020). States like "frustrated", "crying", or "glee" can be marked with a button click on a phone application as they happen during the observation by the caregiver, while a wearable device on the cared person collected additional audio-visual data.

Numeric scales can be made more accurate with visual aids like the Self-Assessment Mannikin (SAM) (Bradley and Lang, 1994), which makes the differences between the grades more tangible and interpretable. Desmet (2018) extended this idea with Product Emotion Measurement instrument (PrEmo), which uses animated cartoon characters for 14 discrete emotions. Visual aids are particularly important for crowdsourced 'observer' annotations (e.g. via Amazon's Mechanical Turk), where annotators may come from a variety of cultural backgrounds, or may have less experience in annotating such data.

For dimensional approaches, the Affect Grid is a common choice of asking the user how they feel Russell et al. (1989), where the user marks their state on a 9×9 grid with labels, discretizing the continuous circumplex space. The Feeltrace tool allows the user to mark points on the 2D valence-arousal space continuously using a controller, thereby allowing a more efficient representation of temporal changes (Cowie et al., 2000) (see Fig. 2).

Self-report relies on the users to discern and report their emotional states, and this can be a difficult task at times. There will also be subjective differences in how

[2] From The Ohio State University: https://ogg.osu.edu/media/documents/MB%20Stream/PANAS.pdf, Accessed 19 November 2024.

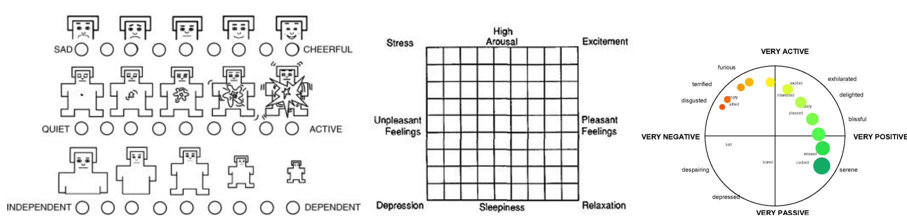
good the users are in self-assessment. Furthermore, self-report is prone to social desirability bias, where the user will refrain from reporting a state that does not agree with the image they would like to project to others. To partially avoid such biases, one can assess the user via indirect questions. An alternative to asking the user about their feelings is to observe the user's behavior during product use, and quantify the affect - manually or automatically. We discuss such monitoring in the next subsection.

Automatic affect recognition

The advantages of automatic assessment are the possibility of long term monitoring with much less effort, and the observation of dynamic changes in the affect during an interaction, which is not easy to measure with a questionnaire provided at the end of a session. The latter also empowers interfaces that can adjust their behavior to the user. Depending on the application setting, the choice of modaliti(es) to detect the affective state of the user is a key decision.

The second important decision is which labels and levels of affect are required for the particular setting. Sentiment analysis can be used to map affect into positive, neutral, and negative classes. More granular approaches could implement regression functions that continuously measure affect along several directions or categories, customized for the specific application.

Finally, the temporal resolution of the measurements is an important design decision. Ambady and Rosenthal's (1993) research on thin slices of behavior has shown that short segments of behavior may be sufficient to predict subjective evaluation results. In their seminal study, they used 30 seconds of behavior to predict teacher evaluations. However, signals from different modalities are sampled and processed at different resolutions. Speech signals, for instance, are sampled at a high frequency, and can provide labels at a level of seconds, whereas text-based affect assessment requires longer data segments to provide reliable assessments. Subsequently, text analysis may be more useful for session-level analyses. This difference in resolution



(a) (b) (c)

Fig. 2 (a) Self Assessment Manikin, adopted from (Bradley and Lang, 1994), figure reprinted with permission from Elsevier (b) The Affect Grid (Russell et al., 1989) (c) Feeltrace (Cowie et al., 2000).

brings unique challenges in alignment and combination of evidence from multiple modalities (D'Mello and Kory, 2015).

The literature on automatic affect recognition is vast, and there are dedicated conferences (e.g. Affective Computing and Intelligent Interaction - ACII) and journals (e.g. IEEE Transactions on Affective Computing) which feature research in these areas regularly. We will provide a very brief discussion of the main issues for different modalities here, including facial expression recognition, vocal analysis, text analysis, body pose analysis, haptics, biometric sensors, and virtual sensing. We will restrict ourselves to more established approaches, but this is a fast-paced field with new and improved tools being made available every year, and any static snapshot of it is bound to become out of date very rapidly.

Face analysis. Face analysis software has been often used to infer users' affective states. This area has a long history of research, both for categorical and dimensional analysis of affect. Open source and commercial tools are available for face analysis, based on deep learning and more traditional pattern recognition approaches, providing real-time detection of facial landmarks (or anchor points), facial action units and their intensity (Ekman and Friesen, 1978), as well as facial expression recognition (Baltrušaitis et al., 2016; Chang et al., 2024). Furthermore, head pose and gaze estimation are also enabled, which allow for the detection of a user's visual focus of attention.

While earlier approaches struggled with estimation tasks under realistic pose and illumination conditions (the so called "in the wild" setting), more recent approaches have vastly increased numbers of parameters and are trained with very large datasets. Subsequently, they are more robust to such variations. Nonetheless, there may be age, race, and sex related biases in the training conditions, and commercial solutions should be checked carefully against these.

For interface design, sensing the user's satisfaction and frustration are the two most important analysis tasks. Yet, people do not necessarily smile when they are happy about using a product. Basic emotional expressions are rarely expressed in daily life, and their interpretation depends on the context. On the other hand, observing a person's facial affect over longer periods and accumulating the findings can provide a more robust estimation of the general state of the person and can be used for instance in extracting mental health indicators.

Voice analysis. Like face analysis, voice analysis can be performed by non-intrusive sensors, such as a microphone equipped on a mobile phone or a social robot. The analysis of voice encompasses both speech emotion recognition and voice paralinguistics, the latter for the non-verbal signals with socially relevant information. Schuller (2011) classifies paralinguistics into *speaker states*, *speaker traits* and *vocal behaviors*. Speaker states deal with states changing over time, such as affection, emotion, stress, sleepiness, and intoxication, while speaker traits are more about speaker characteristics like age, gender, and personality. Furthermore, vocal behaviors such as laughs, cries, coughs, hesitation and consent indicating backchannel signals can be detected from the voice.

Historically, research in signal processing has produced powerful features to analyze voice content, initially for speech and speaker recognition purposes. Mel

Frequency Cepstral Coefficients (MFCC), for example, have been instrumental in analyzing human voice. Loudness and fundamental frequency were used in estimating affect (Trigeorgis et al., 2016). Publicly available tools like OpenSMILE (Eyben et al., 2010) allowed the extraction of many acoustic features, such as spectral features, intonation, intensity, and formants.

Since the voice modality is sampled with high frequency, the amount of features can grow very quickly for even a small voice segment. Low level statistical descriptors (LLDs) are used to summarize these features. To standardize comparisons, the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) was introduced (Eyben et al., 2015). While these features have been shown to be robust for different speech domains, later convolutional deep neural networks were used for both feature extraction and classification. In particular, long short-term memory (LSTM) has been used to model the temporal aspect of the collected signals (Trigeorgis et al., 2016; Rouast et al., 2019). After the rise of large language models (LLMs), voice based emotion recognition is improved by joint embeddings of multimodal information (see Fig. 3).

Text analysis. Natural language processing tools are used for affect assessment at different levels. The text to analyze is obtained from the interactions of the user, either spoken (and transcribed) or created in written form directly.

The Linguistic Inquiry and Word Count (LIWC) approach counts word frequencies for specific groups, such as positive and negative emotion words, or discrepancy words (Tausczik and Pennebaker, 2010). This produces highly interpretable results.

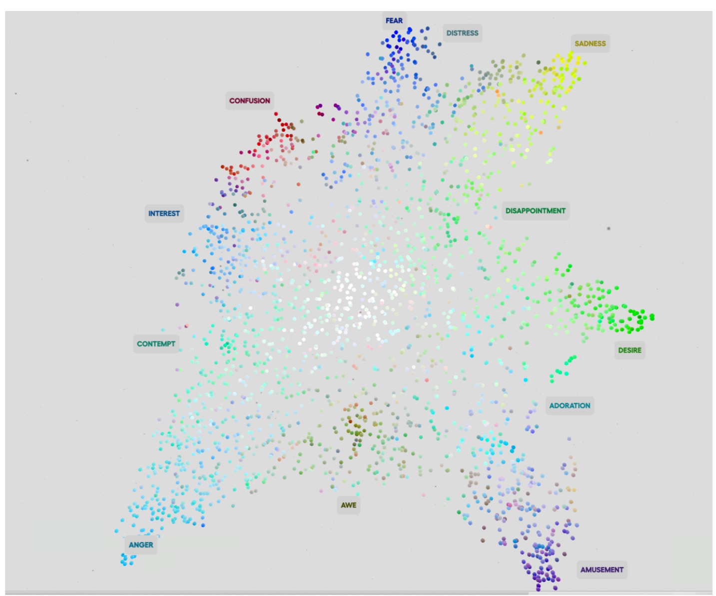


Fig. 3 A 2D visualization of the embedding space for voice affect. Adopted from Hume.AI's interactive EVI documentation.

Another word-based approach would be to use an affect dictionary, where emotional scores are given for specific words. For example, the Dictionary of Affect contains over 4000 words scored along valence and arousal dimensions (Whissell, 1989). The Affective Norms for English Words (ANEW) is a similar tool (Bradley and Lang, 1999). VADER is a rule based tool that targets social media texts (Hutto and Gilbert, 2014).

More complex approaches use supervised and semi-supervised learning and implement functions that can map text to emotional labels or sentiments (Calvo and D'Mello, 2010). SentiWordNet uses semi-supervised learning to annotate all WordNet synonym groups (called synsets) as positive, negative, or neutral (Baccianella et al., 2010). Recent advances in deep learning and large language models offer boosts in accuracy in this task, at the cost of increased model complexity and computational cost, and often reduced interpretability. Through machine learning, word embeddings, such as Word2Vec or Glove vectors, can be learned from huge corpora to represent semantic relations between words (Bordoloi and Biswas, 2023).

All these approaches are language-specific, and there are limited resources for non-English languages. For affect dictionaries, corpus studies are conducted in specific languages. In cases where these studies are limited or non-existent, automatic translation tools can be used to use existing dictionaries or models from high-resource languages (Halfon et al., 2016).

Body pose and gesture analysis. Both cameras and wearable sensors can be used to detect body movements and poses. Since mobile phones are equipped with accelerometers and gyroscopes, they provide additional sensing capabilities for such purposes. However, feature extraction and modeling is both very context-dependent, and not well-established for this modality (Kleinsmith and Bianchi-Berthouze, 2012). Computer vision-based detection of the pose of the human body and hand gestures has rapidly progressed in the last ten years, allowing image-based fit of a skeleton representation to both the body and the hands (Cao et al., 2021; Sun et al., 2019). In addition to such contactless gesture sensing, contact-based interaction (such as in smartphones, smart screens, and smart watches) has progressed to enable gestures and touch patterns to serve as input to different systems (we discuss haptics next). However, these are used primarily for input selection in human-computer interaction, and their affect sensing potential is not fully used (Vatavu, 2023).

Annotated datasets for affective body poses typically employ actors, and the foremost settings involve artistic expressions, such as dancing. Acted emotions, while easier to recognize for an observer, do not possess the richness of the genuine emotional expressions. However, certain patterns, such as low energy and slow movements, sagging and bowed body and head, stretched arms, relaxed shoulders, etc. have been consistently associated with different emotional expressions (see Kleinsmith and Bianchi-Berthouze (2012) for a review). Lim and Okuno (2014) proposed that high-level features like speed, intensity, regularity, and extent can be used to recognize affect across modalities. Sadness, for example, is associated with lower speed across modalities, such as gait and speech.

The most important body cue for detecting affect is in hand gestures, both in conjunction with speech and as a stand-alone modality. Yet, emotions do not have clear, simple, and unambiguous expressions in this modality. For instance, Noroozi et al. (2018) describes the bodily expression of anger as follows: “Body spread. Hands on hips or waist. Closed hands or clenched fists. Palm-down posture. Lift the right or left hand up. Finger point with right or left hand. Finger or hand shaky. Arms crossing.” We do not expect that all these signs of are present for a particular case. Furthermore, the idiosyncratic and cultural variability is high, and the context contributes significantly to what can be expressed at any given moment.

Haptics. The haptic modality acquires affect via detection of certain touch styles (e.g. hitting, patting, pushing, rubbing, squeezing, stroking, tapping, etc.), detected via specific sensors, which provide different affordances. Earlier sensors relied on small servos, whereas more recent technology uses shape memory alloys (SMA), which can produce controllable compressions, and vibration sensors (Zhou et al., 2023). Touch is often highly ambiguous, so this modality is highly contextual and subjective.

Biometric Sensors. Physiological signals like the heart rate, skin conductivity (galvanic skin response), and brain activity can provide objective information about a person’s changing arousal and engagement levels. While there is some research in camera-based, unobtrusive sensing of signals such as the heart rate (Wu et al., 2012), most scenarios use contact-based sensors for this modality. Acquiring brain signals in particular requires good signal amplification, extensive filtering, and long setup times (Wu et al., 2023; Hu et al., 2019).

Virtual sensors. A person’s behavior and interactions in a virtual space, just as their behavior in a physical space, can indicate their affective state. It is possible to sense affect from behaviors in online games, from social media interactions and shared content, and from reactions to situations created in virtual reality. The latter setting is particularly suitable, as more immersive experiences can elicit stronger emotional responses.

Multimodal analysis. Combining multiple modalities for affect detection requires solving several challenges in addition to modality-specific issues, but it can be rewarding. D’Mello and Kory (2015) reviewed close to a hundred multimodal affect analysis systems, and established that while multimodal systems brought improvements over unimodal systems, the improvements were less significant for non-acted, more naturalistic stimuli. The most frequently combined modalities were face and voice. Speech, as an additional modality that we have not explicitly mentioned here, can be conceived of as a combination of voice paralinguistics and textual content. For different approaches on designing multimodal machine learning models for affect recognition, we refer the reader to (Baltrušaitis et al., 2018). Table 1 summarizes the pros and cons of different modalities discussed in this section, as well as a few key application areas of each.

Modality	Advantages	Disadvantages	Application Areas
Facial expression recognition	Well-established analysis pipeline; Cheap sensor solutions; Open source software available; Unobtrusive.	Privacy concerns; Idiosyncratic and cultural variations in expressions; Most tools focus on a limited set of emotions	Affect-sensitive virtual agents, social robotics
Voice analysis	Mature signal processing approaches; Strong models already available; Unobtrusive.	Language and culture specific processing; Temporal processing required; Cross-corpus challenges.	Health indicators, affective chatbots and customer service
Text analysis	Very rich semantic space; Arbitrary label complexity; Wide tool availability.	Language-specific analysis; Low-resource languages and dialects.	Sentiment and affect analysis of healthcare reports, customer service logs, e-mails
Body pose and gesture analysis	Good complementary modality; Can reveal subtle emotions; Particularly good for arousal estimation.	Large idiosyncratic and cultural variations.	Public speaking training, empathic social agents
Haptics	Allows rich representations and wide interaction affordances; Touch sensors can instrument mobile devices and physical objects	Can be ambiguous, contextual and subjective; Few large-scale datasets.	Game and playful interactions, behavioral biometrics
Biometric sensors	Not sensitive to cultural variations; Objective.	Intrusive sensing; Too low level; Too slow variations - depending on the application.	Healthcare and monitoring tools, innovative gaming experiences
Virtual Reality sensors	Sensors embedded in the Head-Mounted Display; Great control over user environment and stimuli	Biometric privacy and security; Sensors differ widely amongst headsets	Improved presence, gaming applications
Multimodal analysis	Modalities can complement each other, and fill in data gaps. Cross-modality supervision.	More complex and costly processing; Diminishing returns for naturalistic settings.	Affect-related feedback for self-regulation

Table 1 Main modalities of observing affective signals, their advantages and disadvantages, and some of their key application areas.

Ground Truth

Automatic affect analysis tools require training samples with affective ground truth annotations. Objective measurements, such as physiological responses, can provide such labels. In the design phase, these labels can be collected with additional sensors, and models can be trained. Then, during the operation of the product, more unobtrusive modalities will be used to monitor the users.

One issue to pay attention to will be to keep the ecological validity of data collection high. This refers to the resemblence of the experimental conditions to the real world settings, and a high ecological validity implies that the findings are more generalizable.

After objective measurements, affect labels given by domain experts can be the second most reliable ground truth indicator. However, the expert labels are typically costly. For example, a trained facial action coder takes 50 to 60 minutes to score a single minute of facial video. Furthermore, expert coding relies on measurable behavioral indicators, and not on subjective report of the user. Consequently, if is limited in the estimation of the user's state.

This is followed by crowdsourced or novice annotations, using services such as Amazon's Mechanical Turk. This is a cheaper alternative for expert annotations, and requires some basic (but short) training to the annotators. There are known approaches to increase the reliability of such annotations, such as seeking agreement from multiple annotators. One should keep in mind that crowdsourced annotators typically have access to Internet resources (and can automate some of their work), and have low incentive to spend long periods of time. In all cases, inter-rater reliability needs to be checked for annotation quality assessment.

Augmenting interactions with affect

How are affective user interfaces redefining the nature of experiences and interactions? A growing body of work within affective user interfaces concerns augmenting human-computer interactions with affect. Such augmentations can manifest in several ways, depending on the display device, type of interaction, and context of use. Affective interfaces can be used to enhance existing computer-mediated communication with affective or emotional cues, which could involve adding facial expressions, body language, or verbal tone to virtual assistants or chatbots to make them more engaging or more natural. One could also see such augmentations as a means of capturing user affect and utilizing such affect data in interactive systems. This could involve using physiological sensors or facial expression recognition to gauge user affect and adapt the interaction accordingly. Alternatively, it is possible to design interactions that deliberately evoke specific emotions or affective states. Example applications include creating therapeutic VR experiences to address anxiety or phobias, or using persuasive design techniques to influence user behavior in a positive manner.

Embodied interaction approaches typically encompass both analysis and synthesis of affective cues. The body of the agent, be it virtual or physical, will be used to display social and affective signals to create augmented interactions with humans. In this context, a robot may express hesitation and confusion to improve the naturalness of the interaction, even if there is no real confusion or a true need for hesitation (Bohus and Horvitz, 2014). Some embodied interaction approaches, such as Höök's (2018) Somaesthetic Appreciation Design practices, are characterized by a subtleness in how they encourage bodily interaction through the choice of modalities offered, their requirement in making space to insulate oneself from the outside world so as to allow attention inwards, and in their intimate correspondence between movement and interaction.

A number of applications benefit clearly from affective displays. Social robotics is the first one we should mention. Social robots may use facial expressions, voice and paralinguistics, body posture and gestures to express an affective state. Furthermore, face detection and facial landmarking can be used to orient the robots "gaze" towards the user's face to provide a more natural interaction. Even though there are cultural display rules for certain emotional expressions, it is often not so difficult to select a display that will be widely recognized for a particular emotion, and multimodality can be of great benefit. Particularly for companion robots, expressing warmth and empathy is important, and affective responses can increase acceptance and adoption of the robot (Breazeal et al., 2016).

Virtual agents, like robots, use a mixture of verbal and nonverbal cues to give a sense of affective states. Such agents find increasing use in customer service and training programs, where engagement, rapport, and empathy are valuable (Paiva et al., 2017). With the development of large language models, such software agents have gained immense abilities in holding natural conversations with users, whereas previously, they could be trained only on very specific domains. Clearly, we will see more use for automated agents across the board, and representation of affect will be crucial to combat the dehumanization that may come with such widespread use of technology in everyday interactions.

Adding emotional tones to synthesized voice can increase the realism and naturalness of a computer agent's voice communication, and depending on the task, users may prefer a more realistic voice in the agent. This can be achieved by adding emotional vocal bursts, or by suitably transforming the spoken utterance prosody. For this latter, an input text can be first encoded in linguistic features, then enhanced with emotional features, and finally processed for synthesizing an appropriately colored voice. Triantafyllopoulos et al. (2023) summarize recent advances in affective speech synthesis and note that current paradigms are data driven, and rely on large scale machine learning, including end-to-end deep learning models. In particular, adversarial learning is adopted for this task, where a generator learns to add a certain emotion to the voice, and a discriminator assesses the realism of the emotion via classification. They also identify "disentanglement" as the holy grail of emotional speech synthesis, where a signal can be decomposed to all its relevant factors of variation (such as content, identity, affect).

A third major application domain is interactive and expressive artifacts created in the digital arts domain. Affective displays are used to increase audience engagement, to stimulate new expressions of ideas and sentiments, and to evoke emotional reactions from the audience. One can argue that affect is ever-present in interactions and is ever manipulated. The very large canvas of Rembrandt's "The Night Watch" painting in the Rijksmuseum (Amsterdam) may be perceived as a device that invokes awe in its viewer, and seen as a design targeting a particular affective experience. Artists have throughout history played with light and shadows, or sound and colors to invoke emotions in viewers. Many artistic installations were created to sense affect through various modalities and to interactively use these sensations in the synthesis of some form of output (Paul, 2023). The lack of complexity and underlying semantic connections that we find in human emotions often makes these interfaces superficial, and user's attention and engagement cannot be maintained for longer periods once the novelty effect is exhausted. Subsequently, we see large scale installations that use sound and color exuberantly to amplify the said novelty effect (e.g. the *Machine Hallucinations: Sphere* installation of Refik Anadol Studio[3]).

We now move on to more detailed description of specific areas where affective data can enrich human-computer interactions, and focus on five cases to a provide more in-depth view of the field: (1) Augmenting computer-mediated communication with affect, (2) Digital emotion regulation and support, (3) Affective immersive experiences, (4) Affective haptics, and (5) Persuasive interfaces.

Augmenting communication with affect

Social connection plays a critical role in promoting physical health, mental well-being, and cognitive function. However, the pervasiveness of automation, often lauded for its convenience, may inadvertently curtail opportunities for meaningful social engagement, to the extent of eliminating the human entirely from our daily routines. This calls for means by which technology can best mediate genuine feelings of connection, rather than isolate us, and the incorporation of social cues and affect in design helps mitigate these effects. For example, Terzioğlu et al. (2020) added a few simple behaviors inspired by animations to robot arms on a factory floor, including a breathing-like secondary action that enhanced the life-likeness of the robot, and managed to improve their perception by the factory workers.

Such augmentation with affect is particularly important for computer-mediated communication, to bridge the gap between the limited expressivity of text- or video-based communication and the richness of face-to-face interactions. An emerging means of achieving this is through biosensing (measuring one's physiological activity) and the sharing of such physiological signals (or biosignals). While applications of physiological computing are typically designed for individual use cases, research has explored how biofeedback can be socially shared between multiple users to augment communication (Feijt et al., 2021; Moge et al., 2022). Indeed, Moge et al.'s (2022) review of such shared physiological interfaces highlights the importance of considering the physio-temporal and social contextual factors in sharing biosignals, and how it can promote social-emotional competences across the intrapersonal, interpersonal, and task-focus levels.

A notable example is HeartChat by Hassib et al. (2017), which integrates heart rate in a mobile chat application as a cue to increase awareness and empathy, particularly if they are close friends or partners. More generally, sharing heart rate helps users

[3] https://www.fastcompany.com/90948807/refik-anadol-just-turned-the-las-vegas-sphere-into-the-worlds-largest-ai-artwork, Accessed 19 November 2024.

to implicitly understand each other's context (e.g., physical activity levels) and emotional states. Relatedly, Liu et al. (2021) created Significant Otter, a smartwatch and smartphone app that allows romantic partners to share and respond to one another's heart rate signals, where these are presented as animated otter avatars.

Such biosensing enables easier and more authentic communication, which helps foster social connection. The intimate nature of biosignals, their non-conscious and effortless production, and the fact that they are normally only available to another party in physically close communication are the advantages (Feijt et al., 2021). On the other hand, their usage can cause feelings of vulnerability and unease due to surveillance and privacy related issues. Subsequently, using these approaches requires careful consideration of context and social setting.

As a special case of augmenting communication with affect, we consider small group and team interactions. Managing emotions is important for the success of such interactions, both for creating and maintaining group cohesion, as well as for fostering group creativity (To et al., 2017). A range of interfaces have been designed to address monitoring and guiding affect in group and team interactions. In addition to sensing individuals, interactions between group members is also used for this task. For example, Zhang et al. (2018) introduced TeamSense, which used wearable sensors on individual group members to record continuous behavioral features during individual activities and interactions, and aggregating these to estimate the team member's affective states and group cohesion.

An important scenario in this area is an embodied agent, such as a social robot, to act as a group member and to help the group in their goals. In such cases, the expressed affect of the agent will influence the group dynamics, teammate preferences, and the distribution of trust within the team (Sebo et al., 2020). Aragon and Williams (2011) suggest ease of use, simple access, and intuitive processes as the main design guidelines for such interfaces. Improving group communication by enabling the communication of affect can lead to increased engagement of individual members, and facilitation of the resonance of ideas to promote creativity.

Digital emotion regulation and support

Digital emotion regulation refers to applications and systems that are geared towards conscious efforts of users to use digital technology to modulate their affective states, by evaluating their current state and contrasting it to a goal state. Such technology can help increasing positive (or decreasing negative) affect, and typically draws on psychological studies for its mechanisms. The regulation mechanisms may rely on explicit feedback, to be cognitively evaluated, or on implicit feedback, via peripheral or experience-based stimuli Slovak et al. (2023). Examples of these mechanisms include breathing regulation via sensory feedback, affective gaming using bio-feedback, and awareness systems that provide notifications upon detecting a target affective state.

A safety-critical use case is automotive user interfaces, where built-in Driver Monitoring Systems (DMS) monitor a car driver's state of drowsiness and distraction, typically using face analysis and eye tracking, and safe driving behavior is promoted via feedback. In scenarios where the driver's emotional state is monitored, additional features can be enabled. High arousal and anger emotion are associated with aggressive driving states and with risky driving behaviors. Once such a state is detected, regulation mechanisms may be used to defuse it Braun et al. (2021). Selecting a calming music, using soft ambient light, empathic speech-based feedback are suggested and tested in the literature. However, such interventions themselves may be distracting or patronizing, and need to be carefully tested under real-life conditions. For explicit feedback, breathing exercises and bio-feedback may be used for drivers who actively seek to calm themselves.

Another important application area concerns older adults, who have an increasing need for socio-emotional support. Affective interfaces can provide some limited support or mediate such support from distant relatives. A prime example in this category is the pet seal robot PARO, which senses touch and produces affective noises and movements. It may not be possible for an older adult to feed and take out a dog for a walk regularly. The advantage of the robotic pet as opposed to a real one is in its low maintenance requirements. Such interactions are known to create positive affect in the users, correlated with the active engagement frequency in the usage period McGlynn et al. (2017). Furthermore, people may form intimate bonds with such affect-displaying technologies, even to the point of engaging in ritualistic displays of grief and separation following the disfunction of the robotic pet[4].

Breathing is an emerging key modality of emotion regulation and support. It provides unique opportunities for human-computer interaction due to its dual nature: it acts as an autonomic physiological process, yet is easily controlled by paying attention to it. As such, a substantial body of work within HCI, art, and design has explored the utilization of breathing as an interaction modality. Notably, Prpa et al. (2020) propose four frameworks to categorize breath-responsive systems: breathing regulation, mindfulness, somaesthetics, and social. Breathing regulation systems support mental and physical health by helping users ensure a beneficial breathing rate. Mindfulness systems leverage the inherent ability of breath to cultivate attentiveness. The somaesthetics approach, pioneered by Höök (2018), prioritizes the embodied experience of one's own breathing sensations. Lastly, social systems utilize breathing to augment communication, fostering empathy and connection. For example, *BreatheWithMe* by El Ali et al. (2023b), capitalizes on (synchronized) breathing input presented visually (LED matrix) or as vibrotactile feedback on the arm (see Fig. 4), to stimulate social connectedness or provide insight into others' affective state.

Obviously, cultural factors play a role in the effectiveness of such interactions, and substituting actual human affect with technology that mimics it is not without its risks. In a study conducted in an eldery care facility with a robotic exercise coach, Görer et al. (2017) observed that a major concern among the residents was the

[4] https://www.popsci.com/worlds-saddest-funeral-robot-dogs-held-japan/, Accessed 19 November 2024.

replacement of a social function with a more cost-effective, but purely technology-mediated solution. On the other hand, these works also highlight the potential of digital emotion regulation and support tools in many domains, including during smartphone use, while driving, for breathing regulation and mindfulness, or even as a means of emotional support in the form of friendly robot interactions during older age.

Immersive Affective Experiences

Immersion is an important property of visual display systems. Increasing immersion, from non-immersive systems like simple laptop screens to semi-immersive systems like the cave automatic virtual environment (CAVE) with all-around projections, and to fully immersive systems like head-mounted displays (HMDs) that completely isolate their users from the external world and substitute their visual and auditory perception with designed and integrated stimuli, provide us with new, powerful and engaging experiences that can stimulate our senses and emotions in rich ways (Marin-Morales et al., 2020).

Before the introduction of HMDs, more immersive and enhanced viewing experiences combined motion pictures with synchronized physical effects that occur in the theater, including motion, vibration, scent, rain, etc, complementing the traditional role of sound and music for emotional modulation. In 1984, the world's first commercial 4D film "The Sensorium" was screened, and it was followed by many enhanced viewing experiences that were created for theme parks all over the world. For example, the "Soarin' Over California" show in Disney California Adventure

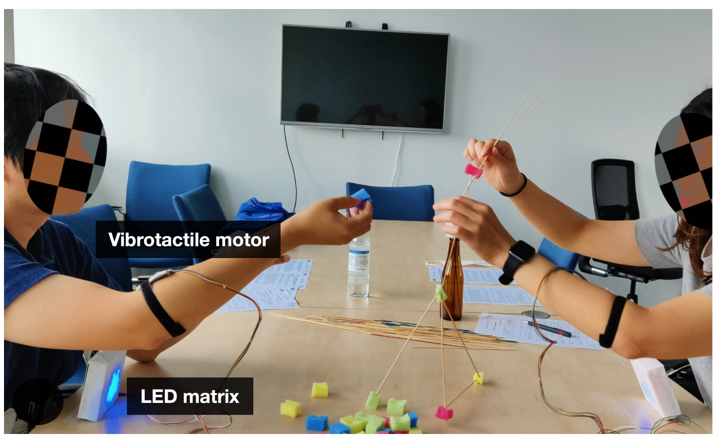


Fig. 4 BreatheWithMe prototype. Two participants each wearing a stretch sensor and playing the Mikado sticks game, where their sensed breathe signals are visualized on an LED matrix or actuated on a vibrotactile motor placed on the other person's arm.

included motion of the seats (which were lifted into a hemispheric screen and simulated the movements experienced on a small plane), scents sprayed on the audience (such as grass, sea breeze, roses and oranges), and wind effects. One downside is that the equipment for this ride contained about 454 tonnes of steel infrastructure for a capacity of 87 guests, and was therefore quite expensive[5].

Recently, the wide availability of consumer HMDs has made immersive virtual reality (VR) systems a feasible alternative to expensive physical environment setups, and particularly suitable for designing tailored affective interactions that afford greater control and understanding of the virtual experience. VR offers several unique advantages, including much reduced hardware cost per user (compared to special effect theatres), providing experiences with high immersion and presence with enhanced emotional responses, enabling more natural multimodal communication (e.g., using haptic feedback and spatial audio), and providing greater control and experimentation by allowing researchers and designers to create specific scenarios and test their impact on user emotion, as well as to allow users to create their own emotional expressions.

For emotion elicitation, VR offers a strong alternative to image and video stimuli that are typically used, and is linked to emotion regulation. Subsequently, VR is also used in arts to provide immersive and affective experiences into important societal issues. Alejandro G. Iñárritu's Academy Award-winning VR experience "CARNE y ARENA (Virtually present, Physically invisible)" is a narrative on irregular migrants and refugees crossing a border, and puts the viewer in the shoes of the refugee to experience the difficulties more deeply and emotionally, forcing the viewer from a passive observer position to a more active, role-playing position[6]. Such an experience may have profound implications for empathy and awareness of others.

Beyond immersive affective cinema or VR experiences, a growing body of research delves into the potential of harnessing affective visualizations and biosignals within immersive settings, where evidence shows the potential of combining VR and biofeedback to foster empathic abilities in humans. Combining VR and neuroresponsive Brain-Computer Interfaces (BCI) can be a powerful paradigm for emotional regulation (Semertzidis et al., 2020). For therapeutic purposes, VR is used to provide highly controlled stimuli to help with emotion regulation, for instance in combatting phobias and anxieties (Van Rooij et al., 2016).

In all these cases, immersion is used as a way to have a stronger affective response from the user, and most of these systems are designed as interoceptive systems, i.e. systems related to the perception of internal bodily states. For such systems, the choice of visualization of the feedback signal to the user is an important design decision. Signals from the body, in raw or processed form, can be incorporated into the visual elements of the VR construct (such as anxiety mapped to the ambient light level in the scene), or some property of the real-world process or artifact can be used to represent the signal (such as a beating heart visualization for representing the heart rate), which is called *skeuomorphism* in graphical user interface design.

[5] https://en.wikipedia.org/wiki/Soarin', Accessed 19 November 2024.

[6] https://phi.ca/en/carne-y-arena/, Accessed 19 November 2024.

The sense of presence is an important indicator of how immersive the experience is. To give an example, in a study on interoceptive cardiac recognition, El Ali et al. (2023a) found that participants systematically underestimated their heart rates, and found a significant inverse correlation between participants' performance on the cardiac recognition task (i.e., how well they could recognize their own heartbeats when visualized as visual, audio, or audio-visual) and their reported sense of presence. The relation between presence and embodiment is important in these scenarios and having a visible body in the form of an avatar may increase interoceptive sensing for the users.

Affective Haptics

Affective haptics (Tsetserukou et al., 2009) is defined as a field that studies and designs haptic systems capable of eliciting, enhancing, or influencing human emotions. Pressure, temperature, wetness, rhythm, contact area, and velocity can be used as modulators of affect in haptics, but most scenarios require specific actuators to create and modulate affective sensations (Raisamo et al., 2022). These limitations push designers to incorporate innovative mechanisms such as the phantom illusion, which can evoke affective touch in VR environments (Kirchner et al., 2024). There are many applications of affective haptics, such as those involving body awareness, bio sensing, emotion communication, and emotion regulation support (Vyas et al., 2023). Below we focus on two well-studied affective haptic displays: thermal and vibrotactile.

Thermal. For thermal displays, prior research has shown that higher temperatures are often perceived to be comfortable and enjoyable, while also capable of fostering social closeness (IJzerman and Semin, 2009). Similarly, much research has demonstrated an association between warmth and positive emotions, and coldness with negative emotions, when participants are exposed to mild to moderate changes in temperature (El Ali et al., 2020). Salminen et al. (2013) found that a temperature change of 6°C, especially when transitioning to warmer stimuli, was experienced as unpleasant, stimulating, and dominant. By contrast, a slightly lower 4°C increase still evoked dominance and stimulation, but was deemed pleasant.

Vibrotactile. For vibrotactile displays, Yoo et al. (2015) found that keeping a consistent vibration frequency on the hand can impact valence ratings positively. In contrast, Wilson and Brewster (2017) reported no correlation between valence ratings and vibrations in isolation when including thermal stimuli. Macdonald et al. (2020) noted that emotional resonance was a common perception for vibrations, making them generally perceived as positive due to familiarity. Seifi and MacLean (2013) identified that on-hand vibrations characterized by smooth and rhythmic patterns were perceived positively, while rough and intense vibrations elicited negative or alarming responses. Lastly, Jones and Singhal (2018) identified that warming the skin can impact one's ability to distinguish vibration patterns.

Persuasive Interfaces

Almost 30 years ago, Reeves and Nass (1996) showed that interfaces which enhance users' affective state are viewed as more intelligent and likable. Similarly, Fogg (1998) showed in "charismatic computers" that an interface that helped establish a safe and trusting relationship with users ultimately lead to more effective and co-operative interactions. These interfaces play on the fact that affective states can influence persuasive communication. Indeed, emotions viewed as a mental status can greatly shape people's attitudes, guide decision-making, and activate subsequent behaviors (Gratch and Marsella, 2004). Viewed in this manner, Rafaeli and Vilnai-Yavetz (2004) found that technological artifacts and features can elicit emotional reactions when they interrupt people's normal routine in work or life.

Considering such influences, Thaler and Sunstein (2008) introduced the concept of "nudging", which refers to how subtle changes in the "choice architecture" can influence people's behaviors in predictable ways. People's initial responses to stimuli can often be emotional, and have a strong impact on decision making. Empathy nudges, for example, use emotionally charged representations to elicit feelings of compassion in users.

A classic example is Laschke et al.'s (2011) "Never Hungry Caterpillar" energy monitoring system, which engages users in sustainable behaviors through a living animal representation that breathes and twists in pain, in response to ideal energy consumption and deviations from it, respectively. By raising the awareness of the user, the desired behavior is facilitated.

Such nudges, however, can be considered manipulations of the user, which can raise ethical concerns in cases where the user is not fully aware of the mechanism of persuasion. In the context of a new mobile application or service launch, nudges and manipulations can evoke an emotional responses of creepiness, along with fear, anxiety and strangeness, and ultimately influence users' judgments about the application (Zhang and Xu, 2016). When the manipulative aspect is hidden from the user, these mechanisms are dubbed as *dark patterns* (Gray et al., 2018). Coined by Harry Brignull, this term denotes approaches that are used in applications that essentially make users do things they did not mean to, such as purchasing an item or unknowingly signing for a newsletter.

Risks and Challenges

As we have so far seen, affective user interfaces can confer a multitude of benefits to users: from designing affective technology for health and wellbeing, to augmenting computer-mediated communication with affect to increase social connectedness and empathy. Before discussing the opportunities in this area, we briefly summarize the main challenges and risks for individuals and the society.

Emotion surveillance and the AI Act. While adding emotion estimation capabilities to AI systems can be a powerful tool, helping the creating of better digital assistants, safer cars, or health aids through wearables, they can be used a means of surveillance in spaces like workplace, classroom, hospitals, prisons, and such. This kind of application is highly risky in terms of user privacy and wellbeing. It is of course possible to design AI systems that do not identify users explicitly. There is a great need for regulations to ensure retaining the benefits of affect estimation without creating privacy and ethical risks.

Recently, the European Union adopted the AI Act, which is a draft of a law to regulate the development, deployment, and use of AI in the EU or when it will affect people in the EU[7]. The draft adopts a risk-based approach, and defines some AI techologies as having unacceptable risk (including biometric identification), high risk (use of AI in educational and workplace settings), and limited or minimal risk. While there are provisions made 'for medical and safety reasons', the AI Act means significant oversight and regulation for any emotion-aware software and systems that are designed to enhance the workplace and educational spaces (Häuselmann et al., 2023). The assessment of such systems will include their development, but also will continue into their product lifecycle. Furthermore, there will be designated national authorities to deal with legal complaints.

Risks due to biases and inaccurate claims. The history of AI systems is full of unrealistic claims about the capabilities of AI systems, as well as cases where AI systems have been shown to function poorly for specific demographic subgroups, due to data or algorithm biases (Buolamwini and Gebru, 2018). In the former case, the systems may have been trained with data that do not include sufficient variance to classify a particular sub-group correctly. In the latter case, the algorithm may have certain in-built assumptions that may prevent it from operating correctly, when those assumptions fail.

In affective computing, an example application is deception detection, where computer systems are trained to pick up subtle facial and bodily cues that arise from emotional responses, increased cognitive load and attempted behavioral control during deception (Poppe et al., 2024). These systems are shown to perform better than some humans under some conditions, but are far from perfect in detecting deception automatically. Consequently, using such technology in critical decision making tasks, such as lie detection used on asylum seekers at the border, poses significant risks, and should be avoided.

Ground truth reliability. For emotion measurement research, there are clear issues with ecological validity: while there is evidence that suggests that people sometimes smile when happy, frown when sad, and so on, how people communicate such emotions (e.g., anger, disgust, etc.) can vary substantially across cultures, situations, as well as across people within a single situation Feldman Barrett et al. (2019). Furthermore, facial expressions can indicate more than one emotion (so-called compound expressions), or be altogether misleading about the underlying emotional state (Du and Martinez, 2015). For affective computing, Picard (2003) highlighted several challenges, including how to sense and recognize emotion, affect modeling, emotion expression, ethical considerations, and the utility of considering

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[7] https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence, Accessed 19 November 2024.

affect in HCI. Such issues can be especially prevalent when the target user group consists of children and adolescents (Zeman et al., 2007).

Design recommendations for dealing with ground truth issues include ensuring robust experimental designs, reaching sufficient data quantity for modeling, appropriate emotion elicitation for data collection (which may not be possible for all emotions due to ethical reasons), committing to an emotion model and corresponding annotation method, choosing the right sensor modalities, and choosing the right machine learning setup for recognition (Bota et al., 2019).

Frustration and emotion dependence. One of the earlier systems of adaptive user interfaces is Mozer's (1998) "Neural Network House", which was a computerized home that can program itself (i.e., adapt) by observing the lifestyle and desires of the inhabitants. It demonstrated how easily humans got frustrated with mistakes of a smart technology. Since then, there have been many such adaptive user interfaces. When it comes to affect, however, there are challenges to incorporating these as key interaction elements. Affective user interfaces can improve user experience and adaptivity, but typically trade off usability. It remains a challenge to strike the right balance between these aspects: should the adaptation go wrong, especially when drawing on affective signals, the users' experience can be severely affected, which can further threaten their sense of agency by prompting undesired or poorly timed actions from the system. Furthermore, excessive reliance on affective elements can also have detrimental effects.

To give an example, the Paro seal robot we mentioned earlier can function as an effective therapy aid for diverse user groups like older people and people with dementia, alleviating stress and instilling feelings of affection. However, it should not be seen as a substitute for human contact, and should not cause more isolation through its placeholder role.

Biosignal interpretation and privacy. While there may be clear benefits to digitally manifesting and sharing of human biosignals within affective user interfaces, for example to increase engagement and reduce stress, to influence social behavior and trust, or to increase intimacy and enable more authentic communication, these come with their own sets of challenges. The sensing modality (e.g., ECG), the context where biosignals are used (e.g, self or other), and how they are visualized (e.g., heart icon) can impact their interpretation by users. In this regard, Howell et al. (2016) have shown that such biosignals are inherently ambiguous and open to multiple interpretations, and this should be taken into account in deciding how (i.e. which modality) and when they are shared. Depending on the context, individuals may draw different conclusions, aligned with their expectations. Subsequently, an adversarial context may elicit more unfavorable conclusions.

Sharing and receiving biosignals has consistently raised privacy concerns for end users, for example with respect to the disclosure of HR data (Liu et al., 2017). This also ties with the recurring finding that whereas participants are willing to see others' biosignals, they are reluctant to share their own (El Ali et al., 2023b).

Opportunities

In this section, we provide properties of representative applications in affective user interfaces (see Table 2), and then discuss the opportunities presented in several application areas. Selection of the appropriate modality for a given application depends on several factors, such as noise conditions for the modality in the expected usage scenario, hardware requirements, convenience and accuracy trade-offs. Multiple modalities can be considered, if they can improve robustness or accuracy, and the increased cost and complexity are justified.

Domain	Purpose	Technology
Health and wellbeing	ECAs for early detection of symptoms of depression and stress; ECAs as empathic friends	Facial expressions, body movements and voice, for both analysis and synthesis; Texting style adaptation
Education	Measurement of student interest, boredom, engagement	Facial expression analysis and sound level measurement
Automotive	Driver drowsiness and distraction monitoring; affective in-car assistant to change vehicle's ambiance and recommend content for safety and personalization	Face, eye gaze, and gesture tracking for driver state recognition; Prompt engineering and generative AI for empathetic voice synthesis
Customer service	ECAs and automated voice-based customer service agents with affective skills, both seeking to improve perception of trust and empathy	LLM for semantic analysis; Text, facial expression, voice, and gaze synthesis for the agent, face and voice analysis of the customer
Retail and marketing	Emotion analysis to test the effectiveness of advertisements; Analysis of customer motivation from social media messages	Facial expression and gaze analysis for customer reactions, text emotion and emoji analysis for social media
Gaming and entertainment	Biofeedback to help emotion control or reduce stress and anxiety; Ambient game adaptation	Biosensors for heart rate, breathing, and brain signals; Facial expressions
Social robotics	Empathic responses and natural interactions	Face and voice analysis
Arts and creativity	Creation of user-responsive and immersive digital artworks; Participatory arts	All possible sensing and synthesis approaches can be used

Table 2 Applications of affective user interfaces

Affective embodied conversational agents. There is little doubt now on the importance of developing, evaluating, and testing the limits of conversational agents for different applications, such as health and behavior change and for customer services. More than a decade ago, Lisetti et al. (2013) presented a multimodal Embodied Conversational Agent (ECA) that empathically delivers an evidence-based behavior change intervention through real-time adaption of verbal and non-verbal message to users. The ECAs with empathic abilities showed promise in helping reduce alcohol consumption in problem drinkers. Yang et al. (2019) examined affective experiences associated with Conversational Agents such as Siri or Alexa, and found that affective responses differed depending on the scenarios, but in general both pragmatic and hedonic qualities influenced affect. Specifically, for the factors underlying pragmatic quality, these comprised of helpfulness, proactivity, fluidity, seamlessness and responsiveness of the agent.

More recently, the field of Artificial Intelligence has undergone a transformative shift with the introduction of so-called “foundation models”. These models, developed on the basis of deep neural networks and self-supervised learning, are gaining widespread acceptance, especially as they led to the emergence of advanced models of Generative AI for image and video synthesis (such as Midjourney or Stable Diffusion), large language models (LLMs, such as ChatGPT or Claude), and ‘empathic’ LLMs (such as EVI). These tools are exhibiting impressive proficiency in analyzing multimodal affect and producing content that is nearly indistinguishable from human-generated content, including text, images, audio, and video. We see that affective LLMs are increasingly integrated into more skilled ECAs and chatbots, and play a role in new application domains such as automotive applications. The expectations and acceptance of users will also change with more widespread usage of these tools.

Affective learning and education. Incorporating affect-aware feedback can be important to improve engagement and enhance learning outcomes. The main usage of affective interfaces in this domain is the assessment of the students’ state (Yadegaridehkordi et al., 2019).

In a seminal study that looked at cognitive-affective states during interactions with three different computer-based learning environments (dialogue tutor system, problem-solving game, problem-solving-based Intelligent Tutoring System), Baker et al. (2010) found that confusion and engaged concentration were among the most common states within all environments, and experiences of delight and surprise were surprisingly rare. Given this, they emphasized the need for better detecting and responding to boredom and confusion during learning. Grawemeyer et al. (2017) looked at how to adapt formative feedback based on students’ affective states – specifically, what type of adaptation should be included, and how this feedback should be presented. Their findings showed that affect-aware support helped contribute to reducing boredom states and off-task behavior switching, which can have a positive effect on learning.

Health and wellbeing. Much evidence, dating back already to the 20th century, suggests that emotion, stress, motivation and other affective states are crucial for decision making and behavior. As such, significant amount work within affective computing has been geared toward the development of automatic stress detection or depression monitoring through multiple modalities (Greene et al., 2016). In addition to automated diagnosis and self-tracking, tangible interfaces, such as affective haptics, are explored for this application area (Sanches et al., 2019). Any technology in this domain requires thorough user testing and validation, as application mistakes can have human costs. Subsequently, applications in this area often target pre-diagnosis, rather than actual diagnosis (which requires qualified and certified experts), and are geared towards self-help and self-improvement.

Commercialization. Despite significant scientific and technological progress in affective computing research, commercialization is limited (Novak et al., 2017). The summary given in Table 2 comes from actual commercial applications, but some of these applications are just becoming financially viable, thanks to improved accuracy of computational tools and LLM-driven progress in chatbot and ECAs.

D'Mello and Kory (2015) note that most affect detectors are created to detect basic emotions, whereas real-world interactions rarely involve these. While the low amount of commercial examples partly stems from the core limitations in affective interfaces (see Sec. Risks and Challenges) such as generalizing to situations outside the laboratory, in other situations it remains unclear how to adapt to recognized affective states, and to what extent this infringes upon the user's sense of agency.

Summary

We have extensively discussed the trade-offs in designing affective interfaces, and presented the state of the art technologies that are used for such systems with their advantages and drawbacks. Equipping systems with affect sensing capabilities can make them more engaging, responsive, and more natural. Drawing on the state of the art and history of affective interfaces, we explored what new interaction possibilities are afforded by this type of interfaces. New possibilities and use cases will certainly be created as these interfaces become more ubiquitous, and there are ample opportunities to create better systems.

On the other hand, there are issues related to privacy, agency, cost and complexity of systems, and risks associated with relying on automatic systems for tasks where mistakes may have human costs. We have covered issues like emotion surveillance, ground truth reliability and bias. These aspect are some of the most urgent issues in affective user interfaces. Raising awareness about both the capabilities and risks is undoubtedly the first step in this direction. New regulation frameworks, such as the AI Act in Europe, are seeking to mitigate the risks associated with rapid deployment of these applications, and will ultimately benefit commercialization by establishing safeguards and trust.

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