Artificial Intelligence for Emotion Regulation at Work

Uichin Lee, Duri Lee, Eunji Park*, Heejeong Lim

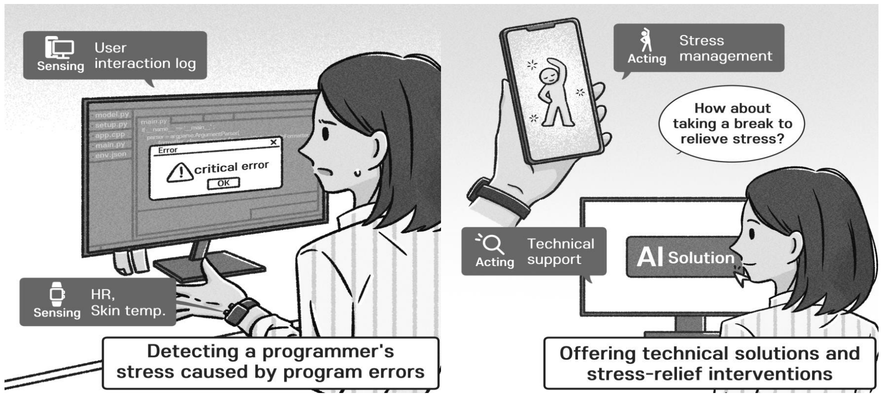
KAIST, *Chung-Ang University

December 3, 2025

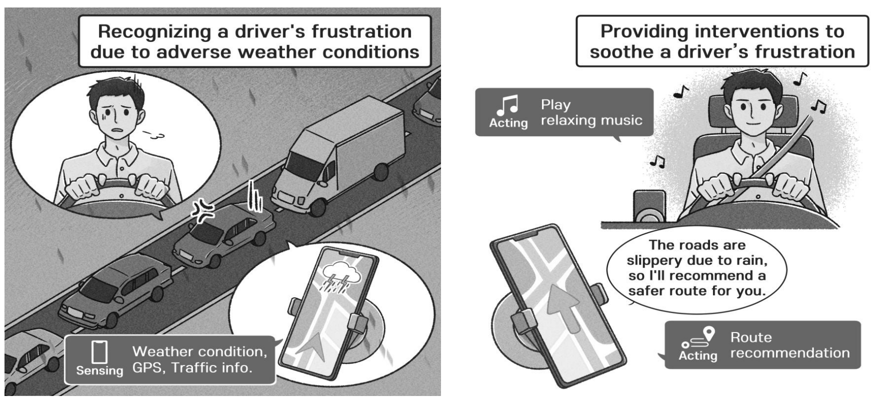
Artificial intelligence (AI) technologies refer to systems that mimic human intelligence by perceiving their environment and making decisions to achieve specific goals (Nilsson, 1998; Russell & Norvig, 2016). AI technologies have the potential to play a pivotal role in enhancing employee health and well-being—addressing issues such as stress/anxiety, sleep disturbances, and mood fluctuations—and improving productivity through task automation and productivity tracking (Nepal et al., 2024). Workers are set to coexist with AI in a manner that augments their capabilities across major domains of human intelligence (Zirar et al., 2023). This chapter explores the role of AI in enhancing workplace health, well-being, and productivity, focusing in particular on how AI can be used to augment human capabilities in emotion regulation.

1 Envisioning AI-assisted Emotion Regulation in Work Contexts

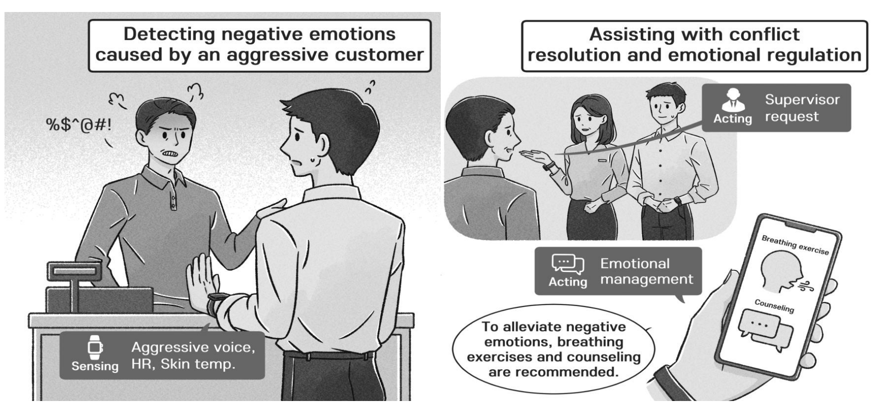
Effectively managing one's emotions in the workplace, such as refraining from yelling during frustrating situations, is an essential skill across numerous professions. This is particularly important in roles characterized by high stress, unpredictability, and significant emotional labor. Below are insights into how AI can support emotion recognition and regulation in specific work scenarios.



a) Knowledge work scenario



b) Driving work scenario



c) Interpersonally-oriented work scenario

Figure 1: AI-assisted emotion regulation scenarios in different work contexts.

In the context of *knowledge work* (e.g., occupations like programmers and researchers), stressful situations, such as encountering a critical bug during programming or facing challenges in solving a problem, demand immediate attention and can lead to high stress. AI models can predict emotional responding in these situations through various inputs, such as physiological signals and interaction patterns (Fritz & Müller, 2016; Müller & Fritz, 2015). AI can then provide personalized coping strategies, such as suggesting a short mindfulness exercise or a problem-solving technique tailored to the programmer's past successful experiences. Deadlines approaching for software releases can escalate tension and anxiety. AI could assist by breaking down remaining development tasks into manageable chunks with realistic timelines and possibly automating simpler tasks to reduce workload and stress. Researchers facing unexpected experimental results or waiting periods during experiments might experience boredom or frustration. AI could detect changes in affective states and suggest engaging in a brief, related educational video or a mental exercise to keep the researcher's mind stimulated yet relaxed, ensuring they remain productive and manage their emotional state effectively.

In driving work professions (e.g., delivery, taxi, and bus drivers), situations like unexpected severe traffic jams, aggressive driving encounters, or extreme weather conditions can induce frustration, stress, and surprise. AI can help by providing real-time traffic updates and suggesting alternate routes, offering calming music or guided breathing exercises during high-stress moments, and even adjusting the vehicle's internal environment to reduce discomfort from extreme weather conditions.

Finally, interpersonally-oriented work in both face-to-face roles (e.g., department store sales and in-person counseling) and remote roles (e.g., call center and online chat support) involves a high degree of emotional labor demand (i.e., emotional display rules and difficult or rude customers) which can induce high stress and the potential for negative emotion contagion. AI can also be useful in such contexts. For example, sales personnel facing severe complaints due to product flaws can benefit from AI-assisted coaching modules that provide strategies for handling difficult customers and maintaining emotional composure. In situations where service workers face prolonged demands or complaints over the phone or online (e.g., for those working in call centers), AI can offer real-time suggestions to de-escalate situations, manage the worker's stress levels, and prevent burnout.

2 A New AI-assisted Emotion Regulation Framework

2.1 Brief Theoretical Backgrounds

2.1.1 Emotion regulation process model

In the field of psychology, numerous studies have been conducted on emotion regulation. The previous studies have been focused on understanding how individuals regulate their emotions in terms of how, why, and with what consequences (Davidson, 1998; Grandey, 2000; Gross, 1998b, 2015; Webb et al., 2012). Representatively, Gross (1998b) proposed a process-oriented model of emotion regulation that distinguishes between antecedent-focused regulation, which occurs before the emotion is generated, and response-focused regulation, which occurs after the emotion is generated. The process-oriented model proposes that emotions can be regulated by either adjusting the inputs that influence them (known as antecedent-focused emotion regulation) or by modifying their outcomes (known as response-focused emotion regulation). For instance, individuals have the option to interact with or avoid particular individuals or situations based on how they expect it will affect their emotions (referred to as situation selection). Additionally, they can direct their focus towards or away from certain things to influence their emotions (known as attention deployment). Differences in characteristics between these two classes of emotion regulation can lead to varying strategies for regulating emotions. Antecedent-focused emotion regulation may involve reassessing the situation to diminish its emotional significance, a process known as reappraisal. Conversely, response-focused emotion regulation aims to alter response tendencies once emotions are already underway, with suppression being a common strategy for regulating one's expression. Depending on the chosen strategy, the methods through which AI supports emotion regulation can also vary.

2.1.2 Interpersonal emotion regulation

Emotion regulation can also take on a social nature. While research on emotion regulation has primarily focused on the intrapersonal process perspective, emotion regulation can also have interpersonal aspects (Zaki & Williams, 2013). In intrapersonal regulation, the emotion regulator and the target are the same individual, whereas in interpersonal regulation, they are different. For instance, a service worker may need to engage in conversation with a dissatisfied and angry customer. This type of conversational interaction naturally involves "interpersonal aspects of emotion regulation," where the service worker aims to regulate the emotions of the customer. AI can assist in interpersonal emotion regulation through various communication channels. In situations where the regulator and target directly interact (face-to-face), AI can intervene by using interactive agents to analyze emotions in real-time and mediate the target's emotions during conversations, for example, by delivering push notifications or adjusting ambient lighting (Hwang et al., 2014; Snyder et al., 2015). Online scenarios naturally involve computer-mediated interactions; for example, service workers interact with supporting computing systems that provide contextual information (e.g., models, previous similar questions, conversation history). Their capabilities could be augmented via AI-assisted features, such as automatically responding to customers' inquiries and displaying a customer's emotions in real-time.

2.1.3 Emotion modeling

Several well-known emotion theories, namely basic emotion theories, appraisal theories, and the theory of constructed emotion, offer foundations for building representational models for machine learning approaches (Barrett & Westlin, 2021). Basic emotion theories (Anderson & Adolphs, 2014; Ekman, 1971) and appraisal theories (Moors et al., 2013) posit that emotions are innate and recognizable, with each emotion tied to specific biological or psychological mechanisms. For instance, anger is attributed to an "anger" mechanism, while fear is linked to a "fear" mechanism. These mechanisms suggest that specific emotions are supported by dedicated neurons or appraisal processes, implying a form of essentialism where each emotion has a distinct "fingerprint" or ideal prototype. For example, as illustrated in Figure 2.a), when a person experiences anger in response to a stressful stimulus, this can be identified through specific autonomic markers (e.g., increased heart rate) and behavioral markers (e.g., yelling). This implies that emotions can be inferred based on reliable biological and behavioral indicators. Contrastingly, the theory of constructed emotion (Barrett, 2009) argues that emotions are not innate but are constructed by the brain based on past experiences via emotion concepts to make sense of and respond to the world (as "the remembered present" (Edelman, 1989)). According to this theory, the brain models bodily sensations within the context, constructing emotions from these interpretations. This approach shifts away from the notion of fixed emotional mechanisms towards a more fluid and dynamic understanding of emotions as products of the brain's interpretative processes under a given context. In Figure 2.b), a person's brain uses emotion concepts to categorize contextualized sensations to construct an instance of "anger" emotion via autonomic changes and facial, vocal, and behavioral expressions. The theory of constructed emotion offers new insights for machine learning by enabling machines to learn from past experiences—specifically, how a user experienced emotions within complex, real-life contextual fingerprints (e.g., time, location, social, and work contexts), beyond simplified, universal fingerprints (e.g., heart rate variability)—to infer a user's current emotional state under similar or new contexts (e.g., feeling stressed while engaging in a particular task at work with customers). Note that the fluid and dynamic nature of human emotions poses a significant challenge, as AI must adapt to ever-evolving emotional experiences.

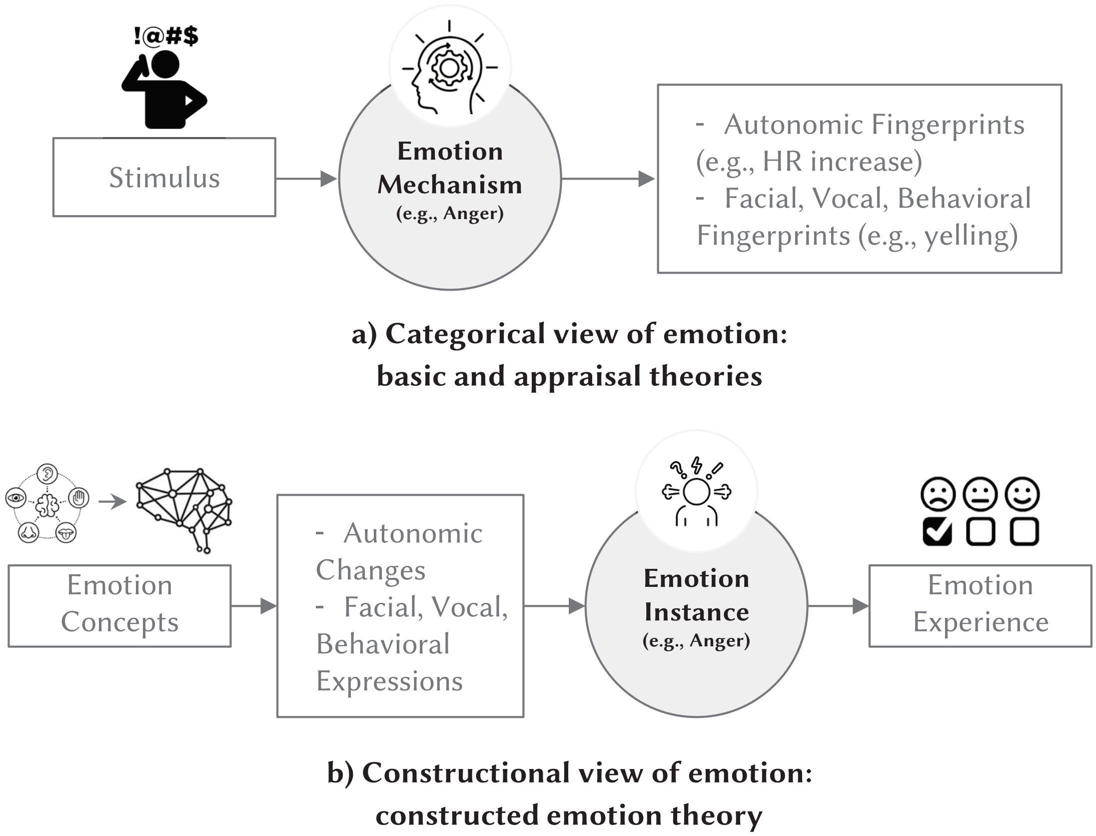


Figure 2: Emotion measurement models.

2.2 Multimodal Sensing in Prior Emotion Regulation Research

Emotion regulation research commonly employs a variety of scenarios that elicit specific emotions and acquire data in controlled laboratory environments. These scenarios range from viewing emotional images and videos to performing speech tasks. Each study aims to explore how different types of emotions are regulated in various contexts or the different effects of emotion regulation strategies like reappraisal and suppression. This prior research provides crucial insights into the potential for quantitative assessment of emotion regulation and mechanisms for applying AI technologies for automatic sensing and mapping in developing AI-assisted emotion regulation strategies. For instance, Gross (1998a) investigated the behavioral and physiological responses (e.g., interbeat intervals, skin conductance, and respiration activation) to various emotional stimuli such as sad, neutral, and amusing emotions, which require different emotional regulation strategies (i.e., reappraisal, suppression). In the following, we present the primary data types used in previous research and describe example studies to illustrate the applications of multimodal data in research.

Heart activity: The heart is a classic indicator of the autonomic nervous system's response, making heart rate, interbeat interval, and heart rate variability, which can be extracted based on the data acquired via electrocardiogram (ECG or EKG) or photoplethysmogram (PPG) sensors. Heart rate is defined as the number of heartbeats per minute, which indicates overall cardiovascular activity (Shaffer & Ginsberg, 2017). Interbeat interval refers to the time elapsed between consecutive heartbeats, and heart rate variability is the metric that represents the variability of interbeat intervals. Higher variability generally reflects increased parasympathetic activity associated with a relaxed state, while lower variability typically indicates increased sympathetic activity associated with stress or arousal. Given that the autonomic nerve system plays an essential role in emotion, data acquired from the heart has been used as representative metrics in emotion regulation research. Gross and Levenson (1997) collected physiological data such as cardiovascular interbeat intervals in situations where subjects suppressed emotions of amusement or sadness. This study revealed that suppressing amusing emotions results in greater changes compared to not suppressing emotions, highlighting the physiological impact of emotional suppression.

Skin conductance: Skin conductance, also known as electrodermal activity (EDA), is instrumental in assessing sympathetic activation behaviors with physiological responses, such as sweating when stressed. S. H. Kim and Hamann (2012) analyzed skin conductance responses while participants viewed negative or neutral images and were instructed to modulate the intensity of felt emotion (i.e., watch, decrease, increase). The results show that emotion regulation to increase the intensity led to a significant increase in skin conductance response (SCR) across all genders. However, notable gender differences in SCR emerged in the condition of emotion regulation to decrease emotion. These findings underscore the importance of using SCR as an indicator of emotion regulation influenced by the type of emotion (e.g., negative, positive), the type of modulation direction (e.g., increase, decrease), and gender.

Cortisol: As a hormone that increases with sympathetic activity, cortisol levels provide insight into the effects of emotion regulation on the autonomic nervous system. Lam et al. (2009) measured participants' cortisol responses after performing a speaking task, a well-known Trier social stress test that required emotion regulation. The study assessed how cortisol levels varied depending on the participants' trait-level emotion regulation strategies. The results showed that participants with high levels of these traits had significantly higher cortisol levels than those with low levels, suggesting that the intensity of these traits may predict cortisol reactivity.

Video (coded behavioral data): The changes in emotion-related behavioral characteristics observed in videos serve as vital indicators for assessing emotion regulation. People's behaviors differ when expressing natural emotions compared to regulated emotions. For example, when people try to act happy despite feeling unhappy, their behavior differs from when they genuinely feel happy. Previous studies have quantitatively measured specific behaviors—for example, capturing data on their frequency, duration, and intensity—

although the reliance on observer-coded data means that accuracy often requires averaging across multiple coders (Gross, 1998a; Gross & Levenson, 1997).

Brain activity: Approaching emotion regulation as a cognitive process, researchers explore the brain's active regions during emotion regulation tasks using electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) data. Ochsner et al. (2002) utilized fMRI to identify the neural system facilitating reappraisal, finding activation in the prefrontal cortex areas. Goldin et al. (2008) investigated the neural differences when performing suppression and reappraisal, demonstrating that the chosen strategy affects prefrontal cortex activation over time.

2.3 A New AI Framework for Emotion Regulation

A typical AI pipeline for affective computing consists of sensing, mapping, and acting stages. Sensing involves sensor data collection of physiological and/or behavioral markers such as those reviewed above, along with ground truth data (known as labels). In application to intrapersonal emotion regulation, because antecedent-focused emotion regulation (e.g., situation selection and modification) mostly involves situational awareness as a first step, computers can track a user's dynamically changing situations to offer context-aware interventions. Meanwhile, response-focused emotion regulation would involve tracking an individual's emotional responses via experiential, behavioral, and physiological forms, which can be captured via mobile, wearable, and Internet of Things (IoT) sensors (including motion and temperature sensors).

In affective computing (Tian et al., 2022), the mapping stage learns the associations between sensor data and labels, using either simple machine-learning techniques like decision trees or more complex techniques such as convoluted neural networks. Machine learning models can similarly be trained to infer what kinds of emotion regulation strategies are employed (E. Park et al., 2024). This kind of sensing and mapping can also be extended to interpersonal emotion regulation. For example, context sensing can capture a user's

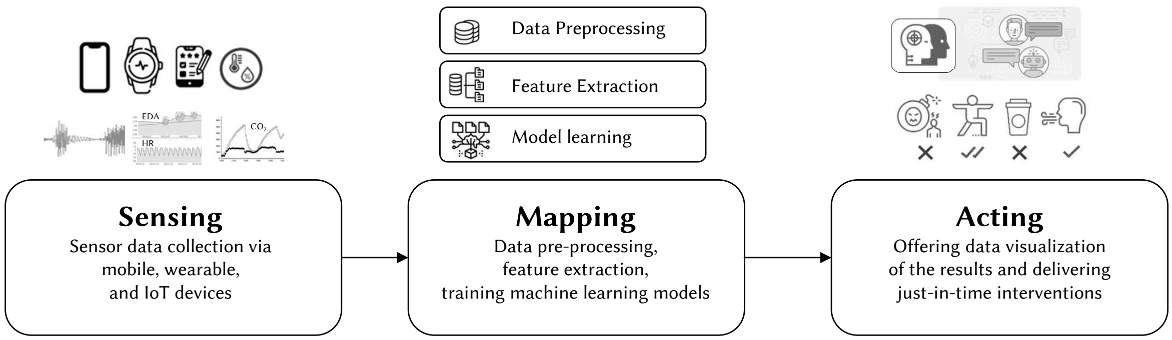


Figure 3: Affective computing framework: sensing, mapping, and acting.

conversational interactions (e.g., a customer's voice), and such data can then be used to train machine learning models specifically designed to deal with interpersonal interactions.

The sensing and then mapping facilitate appropriate responses in the acting stage, enabling automated systems to intervene when specific emotions are detected. For example, whenever an event is detected (e.g., a customer's anger), a computer system can automatically trigger some interventions (e.g., displaying warning signs or changing a customer's voice for soothed delivery). This concept of context-triggered action (Schilit et al., 1994) is also known as just-in-time context-adaptive intervention (W. Choi et al., 2019; Nahum-Shani et al., 2018) where intervention is delivered to a user based on a user's varying contexts.

Existing measurement models of emotion in affective computing mostly relied on a categorical view of emotion in that training data are collected from participants in a laboratory setting by eliciting an emotion category via a stimulus (e.g., stressor) (C. Y. Park et al., 2020; Sharma et al., 2019). If data are collected "in the wild," existing measurement models of emotion rely on a constructional view of emotion. In this case, ecological momentary assessment via mobile devices is typically used to capture a user's self-reported emotional experience (e.g., anger, happiness, or stress) in situ, along with passive sensor data (e.g., heart rates, location, phone usage, or social interactions) (Kang et al., 2023). Machine learning algorithms are then used to find the mapping between a user's self-reported emotional experience and passive sensor data of behavioral and physiological states. This process is similar to how our brain builds emotion concepts based on past emotional experience, and such concepts are then used for recognizing constructed emotion.

3 AI for Emotion Regulation: Sensing and Mapping

Affective computing is a broader topic that can cover topics related to AI and emotion regulation. Existing affective computing research, however, is mostly focused on automatic emotion and stress recognition using multimodal sensors (ranging from skin conductance and heart rate to brain waves and facial images). Luckily, existing affective computing research can be easily transferred to emotion regulation. This section covers the core pipeline for affective computing: data collection (sensor data and labels), machine learning model training, and model performance evaluation. Since each data type requires different treatments, four major sources which include speech data, images/videos, physiological signals, and behavioral/environmental data are overviewed separately. We then provide an overview of how such affective computing approaches can be applied to emotion regulation. For example, we consider how we can automatically quantify emotion regulation strategies (e.g., suppression) and use them for AI-assisted emotion regulation services (e.g., offering relaxation content to a call center worker who has a stressful call).

3.1 Sensing in Affective Computing

Emotion recognition can leverage various sensor data, such as speech data, images/videos, physiological signals, and behavioral/environmental data, which can be captured via mobile, wearable, and IoT devices, as shown in Figure 4. The dataset involves actors performing emotions provided by researchers (emotion acting) or using stimuli (e.g., sad movies or photos) that can elicit specific emotions in participants. In this case, the elicited emotions are used as labels for machine learning. While there is the advantage of being able to collect data on pre-defined emotion categories in a laboratory setting (e.g., stress and sadness), there is a limitation in that it may differ from emotions people feel in their everyday environment. An

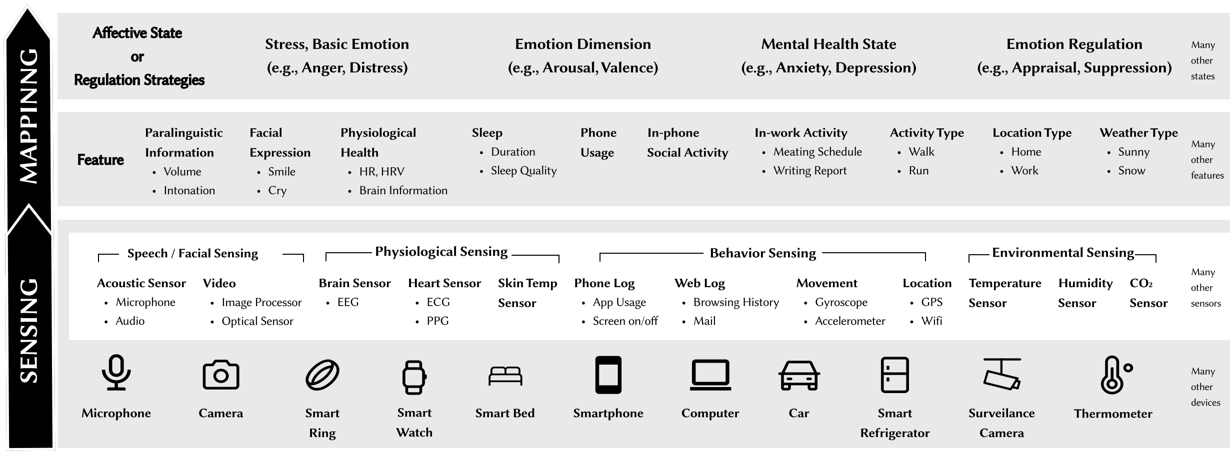


Figure 4: Emotion recognition: from sensors to features and states.

alternative strategy is to leverage the experience sampling method or ecological momentary assessments, where users self-report their emotional states experienced during their daily lives. In this case, the self-reported states are used as labels for machine learning. For the ecological validity of machine learning models, it would be essential to collect the datasets from everyday contexts beyond laboratory contexts via emotion acting or elicitation. Existing datasets are mostly collected in laboratory settings, and a few recent datasets consider everyday settings, e.g., K-EmoPhone (Kang et al., 2023).

3.2 Mapping in Affective Computing

In emotion recognition, the process typically involves three main steps: pre-processing, feature extraction, and classification of sensor signals, as illustrated in Figure 5. While deep learning techniques can eliminate the need for manual pre-processing and feature extraction, these steps can still be beneficial in certain situations.

3.2.1 Vocal expressions (speech emotion recognition)

In speech emotion recognition, speech signals are first pre-processed for feature extraction, and then the extracted features are used for model training and classification (Akçay & Oğuz, 2020; Zhao et al., 2019). Time-series voice data are first segmented into smaller

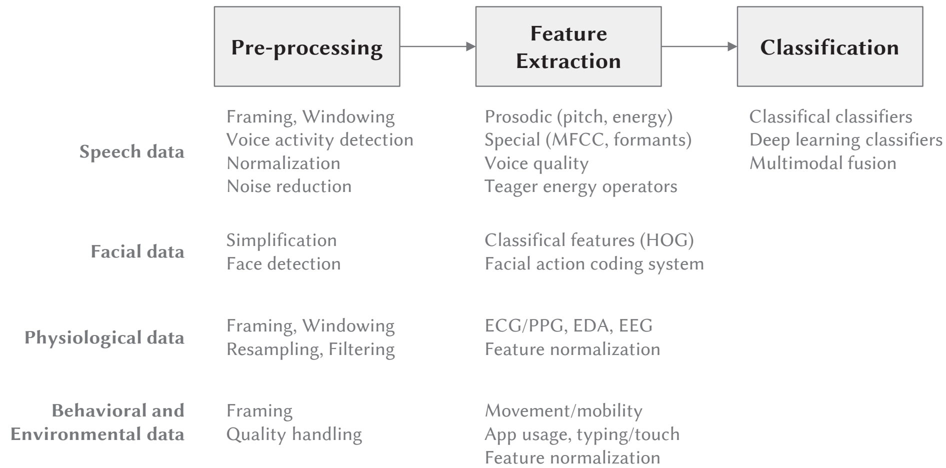


Figure 5: Overall process of mapping for emotion recognition.

time frames (e.g., 20-30 milliseconds). The framed voice data may contain abrupt signal changes at the beginning and the end due to segmentation. Such abrupt changes are then smoothed by applying a window function such as the Hamming window to the framed voiced data. The smoothed signals are tested to check whether there are any voice activities by automatically filtering out such unvoiced speech or silence frames. A common approach to detect voice activity is to capture unique characteristics of voice signals, such as high zero crossing rates (frequency of signal changes across the zero point) or repeating patterns (time-delayed signal similarity). The signals are normalized, and noise reduction techniques are applied to remove noise. Readers can find a detailed introduction about speech emotion recognition in this book (Schuller & Batliner, 2013).

Feature extraction can then commence. Speech emotion recognition typically uses prosodic, spectral, voice quality, and Teager energy operator (TEO) based features (Schuller & Batliner, 2013). Prosodic features convey emotional content through aspects like fundamental frequency (pitch), energy, and duration. These features correlate with emotional states; for example, high-arousal emotions increase fundamental frequency and vocal intensity. Spectral features derived from the vocal tract's shape include Mel frequency cepstral coefficients (MFCC) and linear prediction cepstral coefficients (LPCC), which provide short-term power spectrum representations of speech. Voice quality features reflect the vocal tract's physical properties, including jitter, shimmer, and harmonics-to-noise ratio, which indicate voice quality changes associated with emotions. TEO-based features focus on stress and anger detection through the non-linear interaction in vocal production, with specific TEO features outperforming traditional pitch and MFCC features under stress conditions (Zhao et al., 2019). A recent review (Akçay & Oğuz, 2020) shows the effectiveness of these features individually and in combination, with improvements in emotion recognition accuracy when integrating prosodic, spectral, and voice quality features.

Speech emotion recognition classifies emotions in speech using either traditional or deep learning classifiers. Traditional classifiers, such as support vector machines (SVM), k-nearest neighbor (KNN), and decision trees. Unlike traditional classifiers, deep learning classifiers, such as convolutional neural networks (CNN) or long short-term memory (LSTM) networks, automatically select features, typically outperforming traditional classifiers (Akçay & Oğuz, 2020; Zhao et al., 2019). In addition, transcribed text data can be further used for emotion recognition (Poria et al., 2017); e.g., by leveraging "a bag of words" with an emotion lexicon or by applying end-to-end deep learning models with word embedding.

3.2.2 Facial emotion recognition

The overall process of facial emotion recognition using image data is very similar to speech emotion recognition, as illustrated in a recent review (Canal et al., 2022). The preprocessing stage involves image simplification and face detection, which are the key steps in recognizing facial expressions. Image simplification involves grayscale conversation, which aims to remove possible confusion originating from color information in face detection. Face detection focuses on isolating the face within images despite challenges like pose and illumination variations. Techniques include the Viola-Jones algorithm, known for its low computational cost and precision using Haar-like features, and the Haar cascade classifier, which utilizes pixel intensity differences for object detection. Deep learning approaches, such as convolutional neural networks, have significantly advanced face detection with superior performance (Canal et al., 2022).

Classical feature extraction methods, such as local binary patterns and histograms of oriented gradients, segment images into cells to create histograms based on pixels or gradients. Alternatively, deep learning models such as CNNs have also been employed for facial feature extraction. As a human-understandable feature extraction, the facial action coding system (FACS), established by Friesen and Ekman (1978), codes facial movements related to emotions through action units, enriching the emotional recognition process with a muscle-movement-focused analysis based on action units.

In relation to classification, traditional machine learning models, such as SVM and decision trees, are used for facial image processing. Deep learning models integrate feature extraction and classification into a seamless process, using convolution operations to analyze images and classify emotions effectively. Both classic and deep learning approaches contribute significantly to the evolving field of facial emotion recognition, offering varied methodologies to enhance accuracy and efficiency in classification tasks.

3.2.3 Physiological responses for emotion recognition

In the data collection and pre-processing phase, physiological data are first segmented into specific time frames as in speech data processing (e.g., 10 to 60 seconds). Signals are smoothed by applying a window function as in speech signal processing. Different sensors (e.g., ECG, EEG, EDA) may have different sampling rates (or the number of samples per second), and thus data are resampled to adjust sampling rates per source. Basic signal processing involves filtering low- or high-bandwidth noise signals, e.g., using a Butterworth filter.

When it comes to feature extraction, physiological features depend on the sensor types: ECG/PPG, EDA, and EEG features. ECG/PPG data mostly focused on heart rate variability metrics obtained from peak-to-peak interval data with lower variability generally indicating higher stress and emotional arousal. For EDA feature extraction, raw signals are separated into tonic (baseline conductivity) and phasic (response to stimuli) components. Likewise, EEG feature extraction involves spectrum separation into five frequency bands (theta, alpha_low, alpha_high, beta, gamma). From these separate signals, key features such as mean, standard deviation, and peak counts are extracted. All features are normalized (e.g., using z-normalization) for each user.

As in speech and facial emotion recognition, both classical and deep learning models are used for physiology-based emotion recognition. A classical feature-based approach necessitates expert knowledge for each data source, as stated above. In contrast, deep learning as an end-to-end approach bypasses feature extraction by directly inputting raw signals into deep learning models, allowing the models to autonomously identify pertinent information.

3.2.4 Behavioral and environmental data for emotion recognition

Behavioral data (e.g., physical activity and digital device usage) and environmental data (e.g., visited places and temperature) can be captured with various sensors including mobile and wearable devices. The range of everyday situations may include commuting/driving and work contexts. Research in emotion detection through body movement and activity examines gestures, posture, body motions like gait patterns, and physical activities using sensors from mobile devices, such as accelerometer, gyroscope, and compass, which minimally disrupt users (U. Lee et al., 2019). Global positioning system (GPS) and Wi-Fi data can be used for tracking where the users are visiting (GPS for outdoor movements and Wi-Fi for indoor movements), and environmental conditions, such as temperature and humidity, can be collected from IoT sensors or external weather databases. Additionally, data on digital devices, such as smartphone usage, offer insights into emotional states (Kang et al., 2023). This includes analysis of social interactions, content within communications, and application usage patterns. Emotions have also been inferred from typing interactions or keystroke dynamics, e.g., slower keystroke movements in sadness (Epp et al., 2011; Maalej

& Kallel, 2020).

In typing and touch behavior studies, feature extraction encompasses a variety of parameters such as touch frequency, pressure, contact area, typing speed, and the frequency of backspace or special character usage. For body movement and activity, accelerometer and gyroscope data are crucial. Time and frequency domain features are extracted to represent body movements (e.g., calculating acceleration magnitudes to determine activity levels), offering a comprehensive view of physical behavior and its potential for emotional state inference. As in physiological signals, all features are normalized for each user.

In line with other signals, both traditional machine learning techniques (such as SVM and decision trees) and deep learning models (like CNN and LSTM) are employed for model building. Research has further advanced into *multimodal fusion*, integrating diverse data sources to enhance inference accuracy; i.e., feature-level fusion combines features extracted from various sources before inputting them into a model, while decision-level fusion aggregates the outputs of multiple models to make a final decision.

3.3 Implications to Emotion Regulation Intervention Design

Existing emotion recognition methods provide several concrete directions for emotion regulation at work. Take, for example, situation selection and modification as strategies that can be used to manage one's own feelings. To support such strategies, context-sensing features can track a user's everyday life situations (e.g., major locations where they need to perform emotion regulations) and situational cues that are useful for individuals to conduct emotion regulations (e.g., changes in physical activity patterns, variations in social interactions, or shifts in environmental conditions like temperature or noise levels) can be automatically captured using mobile, wearable, and IoT devices. As another example, prior studies showed that there are notable physiological and behavioral differences when a person uses the strategies of reappraisal and suppression to manage their feelings in stressful situations (Gross, 2002). We can extend existing emotion recognition methods to automatically detect a user's current emotion regulation status, by using various data sources, such as speech, physiological, and behavioral data, to detect whether individuals are currently suppressing their emotions.

Prior emotion recognition methods typically offer real-time classification; for example, speech emotion recognition produces recognition results every 20 milliseconds, and physiology-based emotion recognition every 10 to 30 seconds. Likewise, existing emotion recognition methods help people track their emotion and stress levels in real-time. Mapping for emotion regulation can also leverage real-time classifications of situational sensing/mapping and emotion regulation strategies. Training such models requires fine-grained labels; e.g., a call center agent may need to retrospectively label the level of emotion suppression as part of preparing for the training data (Gabriel & Diefendorff, 2015).

4 AI for Emotion Regulation: Acting for Intrapersonal and Interpersonal Interventions

The final phase of the AI-assisted emotion regulation framework, acting, plays a crucial role in both intrapersonal and interpersonal emotion regulation. Intrapersonal interventions can include methods such as awareness and reflection support, psycho-educational assistance, and experiential biofeedback, like breathing exercises, as classified by Slovak et al. (2023). For interpersonal emotion regulation, acting extends to various forms of social interaction, from one-on-one engagements to larger group dynamics. The development of these interventions requires careful consideration of design elements, including the level of proactiveness, the channels through which interventions are delivered, the methods of physical actuation, and the mechanisms for sharing emotions and offering social support.

4.1 Intrapersonal Interventions

The first type of interpersonal intervention focuses on awareness and reflection support. This aims to encourage users to reflect on their present feelings or to examine a record of their past emotional experiences. Users can self-report their emotional experiences via ecological momentary assessment, or automated tracking can be alternatively used for data collection. EmotiCal (Hollis et al., 2017) offers a mood-monitoring interface where users can rate their mood, energy, and contextual factors, like time and location. It enables the selection of mood triggers and visualizes mood trajectories alongside these triggers, also providing emotional forecasting to help predict and improve future moods through suggested actions. MindScope (T. Kim et al., 2022) assists in managing college students' stress by looking into the specifics of sensing, mapping, and action. MindScope collects data from smartphones to predict users' stress levels and provides intervention content to address stress. For personalized stress detection, smartphone sensor and log data are collected, and users periodically self-report their current emotional states. It helps users to overview their emotional states and further offers micro-tasks that can relieve stress when stress is detected.

Psycho-educational support is another approach that strives to gain insights into emotion regulation skills by providing comprehensive explanations of the process. PopTherapy (P. Paredes et al., 2014) explores the integration of positive psychology, cognitive behavioral, meta-cognitive, and somatic exercises into mobile applications to enhance emotional regulation and stress-coping mechanisms. Techniques such as practicing gratitude, envisioning a best future self, cognitive reframing, mindfulness, and physical activities like exercise and relaxation are highlighted for their benefits in improving well-being and managing stress. Additionally, specific strategies for assisting children with autism spectrum disorder (Fage et al., 2019) include emotion identification through simplified emoticon selection and tailored coping strategies involving personal multimedia content.

There are also various methods for providing experiential feedback to assist in emotion regulation and stress management, such as audio, screen, tactile feedback, and ambient environmental adjustments. Audio feedback (Bergstrom et al., 2014) includes melody-based breathing cues and sonification of heart rate, aiming to synchronize breathing with music or heart rate changes. Screen feedback (Moraveji et al., 2011) involves animations and visual cues, such as a moving bar or brightness adjustments on screens, to guide breathing. Tactile feedback, through haptic vibrations, offers a more physical form of guidance for breathing exercises, found to be effective and less distracting than audio cues (P. E. Paredes et al., 2018). BoostMeUp (Costa et al., 2019) delivers personalized haptic feedback on desired heartbeats via a smartwatch, which can unobtrusively help reduce anxiety and stress.

Finally, the concept of digital emotion regulation has garnered significant attention in the research community, especially in recent years (Smith et al., 2022; Wadley et al., 2020). Defined as the use of digital technologies, such as smartphones and social media, to regulate or modify one's emotional state in daily life, this phenomenon represents a modern twist on traditional methods of emotion management. A series of studies have shed light on how individuals leverage digital platforms for emotion regulation, revealing the intricacies and outcomes of such practices. For instance, Verma et al. (2023) investigated the role of social media in emotion regulation, highlighting how activities like messaging friends, browsing Instagram, or watching YouTube shorts serve hedonic purposes by alleviating unpleasant feelings. Furthermore, Shi et al. (2023) and Tuck et al. (2023) examined the effects of digital emotion regulation activities. Shi et al. (2023) found that smartphones are often used as tools for immediate emotional relief, albeit with effects that are short-lived.

4.2 Interpersonal Interventions

Intrapersonal interventions can also be extended to interpersonal scenarios. One such extension involves awareness and reflection support of targets. AI demonstrates significant potential in enhancing emotional regulation both individually and within groups. In customer call centers, AI analyzes emotions from customer voices, providing real-time feedback to service agents through emotion data visualization, thus improving interpersonal emotion regulation (Henkel et al., 2020). This suggests AI's role could be to augment human capabilities in service interactions. EduSense (Ahuja et al., 2019), in educational settings, uses audio and video to monitor classroom dynamics, employing computer vision to assess engagement and emotions based on indicators like attention and smiles. Both examples illustrate AI's ability to support emotional awareness and reflection, showing its application in personal and interpersonal contexts for better understanding and management of emotions.

Another such approach involves emotional cue filtering. AI technologies offer promising strategies for mediating communications to support emotional well-being in professional settings. One approach involves voice modulation in call centers, where the sound of customer voices is altered in real-time to reduce stress and improve emotional regulation among workers (D. Lee et al., 2024). By modulating the pitch of a customer's voice, a study found significant reductions in perceived stress, suggesting that such technology could greatly improve workplace environments and customer interactions. Another strategy uses AI, specifically ChatGPT, to rephrase inappropriate text in customer service interactions (Ko et al., 2023). AI can proactively moderate the tone of customer inquiries and responses, aiming to maintain the original intent while preventing verbal abuse. Both examples demonstrate AI's potential to proactively mediate communications, offering tools to filter emotional cues such as abusive voice tones or text, thus fostering healthier interpersonal interactions. However, there is also a possibility that by filtering these cues, employees may fail to fully understand the customer's feelings, potentially making them less responsive to customer needs, which could negatively impact the customer's experience.

Finally, interactive systems facilitate emotional sharing across different social scales, from personal circles to broader communities, enhancing awareness and support. Studies show that in friend networks, individuals share a wider range of emotions, eliciting more supportive and emotional responses, especially for posts conveying self-worth feelings (Burke & Develin, 2016). In the workplace, Mood Squeezer (Gallacher et al., 2015) encourages employees to express their moods by squeezing colored balls, with these moods then visually aggregated and displayed, fostering a collective emotional awareness. Meanwhile, Emotion Map (Huang et al., 2015), a location-based mobile app, allows users to log and share their emotions with details like time and place, either publicly or anonymously. This app enhances emotional regulation and awareness by mapping emotions to specific contexts, providing insights into emotional patterns across different settings and activities on a university campus. StressTrendmeter (R. Choi et al., 2022) facilitates anonymous stress sharing among college students through hashtags and trending topics, enhancing community awareness and support.

4.3 Implications to Emotion Regulation Intervention Design

As illustrated earlier, intervention design can leverage both intrapersonal and interpersonal intervention strategies. Interactive technologies with AI can greatly expand design options for acting in terms of proactiveness and delivery channels (including physical actuation). When it comes to the social sharing of emotion, the level of details and social support mechanisms should be carefully considered.

4.3.1 Proactiveness

AI systems are increasingly being designed to offer proactive interventions based on user context, including specific locations, activities, or during stressful situations. Such intervention contexts can be set by either users or experts for proactive intervention delivery. Since interventions are automatically delivered in specific contexts, this approach is also known as just-in-time intervention.

In relation to location, individuals can be encouraged to use emotion-regulation strategies, whenever they arrive in geofenced areas identified as stressful or anxiety-provoking. For instance, Pramana et al. (2018) illustrated how a mobile application could facilitate anxiety management within geofenced regions by facilitating behavioral activation, such as encouraging users to engage in a calming breathing exercise when they arrive at a location associated with stress.

For routine activities such as driving, innovations like haptic feedback and emotionally aware in-vehicle assistants (e.g., Buzz Car) aim to transform these experiences into opportunities for mindfulness and stress reduction. By adjusting the driver's breathing rate through haptic and voice guidance, these technologies promote a calming experience without compromising safety (P. E. Paredes et al., 2018). In public spaces, social robots, such as HelloBot (Cha et al., 2018), can detect individuals who routinely walk by and proactively give greetings to them that solicit smiling to induce a positive feeling.

Interventions for emotion regulation could also be delivered when users are experiencing negative well-being or stress. Interventions can be differentiated by the method of evaluating the user's states through self-reporting or automatic tracking mechanisms. For self-reported well-being states, for example, individuals could receive tailored reminders to practice stress management techniques upon self-reporting high stress or negative emotions (Smyth & Heron, 2016). Tools like StressShoe offer a DIY toolkit for people working in sedentary professions (e.g., office workers) to automatically track stress in real-time and receive just-in-time personalized stress interventions (Elvitigala et al., 2021). The system uses a motion sensor mounted on a shoe to infer stress levels based on food movements, enabling interventions tailored to the moment's needs. Similarly, research on digital workplace stress-reduction systems (Howe et al., 2022) has explored the efficacy of just-in-time interventions triggered by automated stress level detection, finding that while just-in-time interventions saw higher completion rates, stress reduction outcomes were similar between just-in-time and pre-scheduled interventions.

4.3.2 Delivery channels and physical actuations

Delivery channels refer to the mediums through which interventions are conveyed, which can vary from single-device applications to multi-device ecosystems. An example of the latter is ParentGuardians (Pina et al., 2014), a system that integrates both a mobile phone application, supporting text and image, and a glanceable display for images only. This setup is designed to help parents remember and apply strategies learned in therapeutic sessions, facilitating the application of these strategies in daily life without needing further guidance.

Physical actuations extend the concept of interventions into the physical environment, leveraging more than just digital devices to facilitate emotion regulation. Notably, as summarized in a recent review (Braun et al., 2021), the automotive industry has embraced this approach with initiatives such as Mercedes-Benz's 10-minute coaching program, which uses a combination of climate control, ambient lighting, and music to help increase driver alertness during long drives (Mercedes-Benz, 2020). Automotive examples underscore the potential of physical actuations to create immersive environments that actively support emotional regulation and well-being.

4.3.3 Emotion sharing and social support

Designing interventions for emotion sharing and social support necessitates a thoughtful approach to how users express emotions, with whom they share these emotions, and how others can engage to provide support. Seeking social support is, in fact, a form of interpersonal emotion regulation, where the individual recruits others to help manage their emotional states. These considerations are crucial in creating a supportive ecosystem that promotes emotional well-being and community care. We will illustrate the key design dimensions based on the following examples.

Mood Squeezer (Gallacher et al., 2015) exemplifies an intervention where emotions are expressed through the use of color balls, representing different feelings. This method allows for a simplified yet effective conveyance of emotional states to a specific audience, in this case, co-workers. The engagement from others comes through a shared display that aggregates these color-coded emotions, providing a collective emotional snapshot of the company at any given time. This approach fosters a sense of community and shared experience, encouraging mutual understanding and support.

StressTrendmeter (R. Choi et al., 2022) targets stress as a specific emotional domain, particularly within campus environments. Users share their stressors using hashtags, making the expression both concise and easily relatable. The platform is designed for public sharing within a community (e.g., a university campus), encouraging broad engagement. Features like an empathy button and hashtag chats empower users to not only share their stressors but also to find and offer support efficiently. This system highlights the role of the community in addressing common stressors, providing a space for collective empathy and support.

These examples illustrate the diverse approaches to designing emotional sharing and support interventions, emphasizing the importance of considering the level of detail in emotion expression, the audience for sharing, and the mechanisms for engagement. Each approach offers unique benefits, whether it is fostering a sense of community, providing context for emotions, facilitating targeted support, or showcasing the potential of technology to enhance social support and emotional well-being.

5 Ethics for AI-assisted Emotion Regulation at Work

In deploying emotion AI in the workplace, the balance between mental well-being enhancement and privacy infringement is precarious. While intended to foster a supportive environment by identifying stressors and promoting mental health, the overarching risks cannot be ignored. The technology's capacity to exacerbate biases, amplify stigmas against marginalized groups, and erode emotional privacy raises significant ethical concerns (Corvite et al., 2023). Such erosion compromises workers' agency and autonomy, creating a workplace atmosphere fraught with distrust and anxiety. Moreover, when used for surveillance (Roemmich et al., 2023), emotion AI risks coercing employees into conforming to emotional labor expectations, altering their emotional expressions to align with job requirements, such as emotional display rules. This coerced emotional regulation not only impinges on emotional privacy but also imposes an undue psychological burden, potentially leading to emotional dissonance and burnout (Ajunwa, 2018). The ethical deployment of emotion AI necessitates stringent safeguards to protect emotional privacy and worker rights (Roemmich et al., 2023). In this section, we review existing research on the ethics of emotion recognition technologies and the new regulation of the EU AI Act and suggest practical ethical and legal considerations for building and deploying AI-assisted emotion regulation at work.

5.1 Enhancing Data Privacy in Emotion AI

In the context of data collection for emotion AI, using proxy data requires gathering information from multiple individuals and then applying machine learning for aggregate modeling. A significant ethical consideration in this process is obtaining informed consent, where participants must be fully aware of the potential risks and benefits. However, current practices face challenges in allowing users to control their data effectively, especially with one-off consent processes that do not accommodate personal contextual preferences, such as preventing data collection in sensitive locations. The MyData movement (Alorwu et al., 2021), which emphasizes empowering users by granting them direct access to and control over their personal data, offers a promising approach. This concept is in line with the European Union's General Data Protection Regulation (GDPR), aiming to enhance user control over personal data. There is a recognized need for further research to develop user-friendly tools, similar to the Platform for Privacy Preferences (P3P) (Cranor et al., 2006), to enable direct data access and control within emotion AI systems. Additionally, future developments in emotion AI should focus on creating mechanisms for "dynamic consent," allowing (H. Lee & Lee, 2022) users to adjust their consent in response to changing contexts and situations, thereby enhancing privacy and user autonomy in emotional artificial intelligence applications (H. Lee et al., 2024).

5.2 The Impact of AI on Emotional Diversity

The classification of emotions by AI not only describes emotional states but also prescribes them, influencing how individuals perceive and express their own emotions (Stark, 2018; Stark & Hoey, 2021). This prescriptive nature, through data aggregation and the simplification of complex emotional experiences into categories, can lead individuals to adjust their behaviors to align with these "objective" measures due to emotional display rules or norms, potentially narrowing the human emotional experience to what can be quantified and algorithmically categorized and enforced (Stark & Hoey, 2021). This issue is particularly pronounced in settings like call centers, where aggregate modeling ignores the nuanced ways in which individuals modulate their emotions over time to meet the expectations set by their employers. For example, a call center agent might suppress frustration or anger during a challenging call and instead project calmness and empathy to adhere to company policies on customer service, or deliberately use positive emotional displays, such as cheerfulness and enthusiasm, even when they do not feel that way internally. Overall, the reliance on AI for emotion classification can lead to a reductive view of human emotions, constraining them within the limits of predefined categories and ignoring the rich variability of human emotional life. The takeaway for designers and implementers of emotion recognition technologies is the importance of acknowledging the prescriptive power these technologies hold. There is a critical need for a value-based design approach that prioritizes mental well-being and respects individual agency and autonomy (Andalibi & Buss, 2020). Furthermore, the use of AI for surveillance and enforcing compliance should be critically examined for its potential to undermine personal agency and autonomy, suggesting a cautious approach to the deployment of these technologies in sensitive contexts (Roemmich et al., 2023).

5.3 Towards Transparency and Understanding

Addressing errors and biases in emotion recognition technology is crucial for ensuring its reliability and fairness. Existing research acknowledges that while some emotion recognition outcomes align with expectations, a significant portion does not, highlighting the technology's inability to account for individual differences. This limitation becomes particularly problematic when the technology could be inaccurate or biased (Cooney et al., 2018), failing to accurately read the emotions of certain individuals, such as those whose physiological responses diverge significantly from the majority or those with autism spectrum disorder, making it challenging to capture their emotional states with standard data models. One of the key issues is that the failures of emotion recognition technology are often not apparent to users, which can lead to misguided reliance on inaccurate or biased AI assessments. To address these concerns, prior work (Boyd & Andalibi, 2023) suggests enhancing transparency (e.g., data and modeling), which could help to highlight the technology's limitations and improve its application. This highlights the need for an interactive tool that allows for the examination of classification results, incorporating explainable AI features. Such a tool would enable users to gain a better understanding of how classification results are derived, thus fostering a more nuanced approach to interpreting emotion AI outputs. This approach not only aims to mitigate biases but also promotes a deeper understanding of the technology's capabilities and limitations, ultimately contributing to more ethical and effective use of emotion recognition and regulation systems.

5.4 Ethical AI Use According to the EU AI Act

The EU AI Act addresses critical legal issues related to the deployment of artificial intelligence systems, particularly emphasizing the prohibition of certain AI practices (Häuselmann et al., 2023). Recital 44 (European Union, 2024) outlines the prohibitions due to significant shortcomings in AI technologies, including emotion recognition. These shortcomings encompass the limited reliability of emotion categories, the lack of specificity in physical or physiological expressions matching emotion categories, and the limited generalizability considering the effects of context and culture. The Act particularly highlights the risks of deploying such technologies in sensitive areas like workplaces and educational institutions due to reliability issues and the potential for abuse.

The permissible usage of AI under the AI Act in workplace settings emphasizes the importance of applications that bolster personal well-being and productivity without extending into organizational performance monitoring or surveillance. Although there is ambiguity around the voluntary use of AI tools for personal work assistance, the potential misuse of data for surveillance and evaluation calls for cautious consideration. The guidelines advocate for AI-assisted emotional recognition to prioritize personal well-being and productivity over organizational surveillance, highlighting the delicate balance between beneficial use and privacy concerns in the context of the EU AI Act.

6 Practical Considerations for AI-assisted Emotion Regulation at Work

6.1 Datasets and Ground Truths

In the realm of emotion recognition research, there is a prevalent use of datasets that categorize emotions into discrete labels such as “angry” or “happy,” or dimensional labels that describe emotions on scales like arousal and valence. The majority of studies have traditionally used datasets generated in controlled laboratory settings, where participants are exposed to specific stimuli to elicit targeted emotional responses, such as stress. While this controlled approach facilitates the creation of machine learning models, it faces challenges when applied to real-world scenarios, where emotions are more fluid and context-dependent. Recognizing these limitations, there is a growing shift towards using datasets gathered in naturalistic settings (Mattingly et al., 2019; C. Y. Park et al., 2020). These datasets, collected through mobile devices where participants self-report their emotions in everyday contexts, offer enhanced ecological validity. However, they also introduce new challenges, such as the reduced accuracy of models due to the variability and unreliability of self-reported data, influenced by factors like interruptions and contextual noise (Kang et al., 2022). Additionally, the dynamic nature of emotions complicates the collection of a sufficient number of samples to accurately represent an individual’s emotional state. These challenges highlight the need for further research into developing machine learning models that are both realistic and applicable in natural settings. Advancing the field requires creating large-scale, longitudinal datasets that capture the complexity of real-world emotional experiences, thereby leading to more accurate and nuanced emotion recognition and regulation.

6.2 Data Availability and Data Quality

In the domain of emotion recognition and regulation, the diversity and accessibility of data play a pivotal role. However, the availability of such data can significantly vary across different contexts due to a myriad of sensing challenges and privacy concerns. For instance, mobility issues can affect the reliability of face capturing, while environmental noise can impede the accuracy of speech emotion recognition in public settings such as noisy restaurants. These practical challenges highlight the complexities involved in collecting high-quality data essential for training robust machine learning models. Moreover, the tracking of sensitive personal data, including voice recordings, images, and behavioral data like locations visited or app usage patterns, raises significant privacy concerns (H. Lee et al., 2022). These concerns not only affect the willingness of individuals to participate in data collection efforts but also impose legal and ethical constraints on the types of data that can be collected and analyzed.

The issue of data quality cannot be overstated in the context of sensor-driven research. Common challenges include missing or low-quality data, often resulting from the unpredictable nature of free-living conditions under which the data is collected. Users might forget to wear their devices, fail to charge them, or operate in environments with excessive noise, all of which contribute to compromised data integrity (Jeong et al., 2017). Historically, the impact of data quality on the research process has been underestimated, but there is an increasing awareness of the "data cascade" phenomenon (Sambasivan et al., 2021), where poor data quality adversely affects all stages of model development, evaluation, and deployment. There is, therefore, a need for meticulous examination of the variations in data quality arising from individual and contextual differences, as these factors significantly influence the performance and generalizability of emotion recognition models.

6.3 Accuracy and Trust

The performance of emotion recognition models significantly varies depending on the source and quality of the datasets used for training. Models developed from clean, laboratory-based datasets generally achieve impressive accuracy levels. For instance, stress detection models that utilize physiological signals can reach accuracy rates exceeding 90% (Dzieżyc et al., 2020). The use of multimodal data, incorporating vocal and facial expressions alongside physiological and behavioral information, further enhances model accuracy.

Contrastingly, models trained on datasets collected in uncontrolled, real-world environments ("in the wild") exhibit notably low accuracy, typically ranging between 60–70% (Kang et al., 2023; Meegahapola et al., 2023). This discrepancy poses a significant challenge for applying emotion recognition technologies in everyday contexts where ecological validity is crucial. Models trained in the laboratory, despite their high accuracy under controlled conditions, often fail to generalize effectively to the complexities and nuances of real-world emotional experiences. Conversely, models trained on real-world data, while more relevant to daily life, suffer from poor performance due to the messy and unstructured nature of the data collected.

The challenge of achieving high accuracy in emotion recognition models has critical implications for the development and deployment of effective intervention systems. Research indicates a strong correlation between the accuracy of these models and their perceived usefulness and potential for adoption by end users. This underscores the importance of not only developing technically accurate models but also ensuring that these models are practically useful in real-life emotion regulation contexts. One promising avenue for enhancing the accuracy and applicability of emotion recognition models is through personalization (T. Kim et al., 2022). By tailoring models to leverage an individual user's data through techniques such as fine-tuning or few-shot adaptation, the relevance and effectiveness of the models can be significantly improved.

6.4 Model and Intervention Validation

The field of emotion recognition has seen numerous studies focused on model building and evaluation using datasets collected in controlled environments. However, there is a noticeable gap in the literature concerning field evaluations of these systems when deployed in real-world settings. This scarcity is often attributed to the practical challenges associated with system development and the high costs of deployment. As a result, the majority of existing field studies involve a relatively small number of participants, typically ranging from 20 to 30 individuals. This limitation restricts their applicability and generalizability to diverse populations.

Large-scale controlled experiments that could provide more robust evidence of effectiveness are rare due to the logistical challenges and resources required to engage a large and diverse group of participants. Moreover, engagement heterogeneity—a variance in how different users interact with and respond to digital interventions—is a common occurrence in digital mental health applications. This variability further complicates the process of evaluating intervention effectiveness and underscores the need for more inclusive and extensive research designs.

The validation of AI-assisted emotion regulation systems necessitates a comprehensive approach that extends beyond initial small-scale studies to include large-scale, long-term evaluations. Such studies should aim to capture the diversity of user populations and the complexity of real-world environments where these interventions are deployed. Continuous evaluation of these interventions, even after they have been commercially deployed, is crucial for monitoring and ensuring their effectiveness throughout their lifecycle. Given the high costs and logistical complexities associated with conducting randomized control trials, alternative methodologies should be considered. One promising approach is the utilization of observational sensor data for causal analysis (U. Lee et al., 2023) which refers to the process of identifying and understanding cause-and-effect relationships within real-world sensor data, as opposed to controlled experimental settings. By addressing these validation challenges through innovative research designs and methodologies, the field can move closer to developing effective, evidence-based emotion recognition and regulation interventions that are scalable, inclusive, and responsive to the needs of diverse user populations.

6.5 Implementation and Deployment Considerations

The accessibility of devices capable of capturing the necessary sensor data for emotion recognition presents a significant hurdle. While mobile, wearable, and IoT devices abound, the reality is that only a select few allow developers access to the diverse sensor data needed for comprehensive emotion analysis. Commercial devices like Garmin wearable trackers and the Samsung Watch stand out, but these are exceptions rather than the norm. Research-oriented devices, such as OpenBCI EmotiBit, offer open and affordable options, yet they are few and far between. Furthermore, validated wearables like the Empatica Embrace, which provide reliable data, come at a higher cost compared to mainstream wearables like the Samsung Watch and Apple Watch. Recent efforts have aimed to bridge this gap by utilizing off-the-shelf wearable devices for real-time sensing, indicating a growing trend towards making sensor data more accessible for research (Han et al., 2023; Nishiyama & Sezaki, 2023).

Another critical challenge is the scalability of the data architecture required to support emotion recognition systems. The collection of heterogeneous data from a wide array of sources—including wearable, desktop, and IoT devices—poses significant difficulties. System and data heterogeneity can impede interoperability, complicating the integration of diverse data formats into cohesive models. Additionally, the need for real-time data collection to ensure timely analysis and response further stresses the importance of scalable system architecture. Considerations for scalable service architecture are often overlooked in small-scale deployments. In practice, the bandwidth requirements for streaming data from a large user base can be considerable, necessitating architectures capable of handling such demands, such as Apache Kafka.

7 Concluding Remarks

This chapter underscores the transformative potential of AI in enhancing workplace health, well-being, and productivity through advanced emotion regulation capabilities. By integrating a comprehensive review of affective computing and emotion regulation literature with practical applications and ethical considerations, we highlight the multifaceted role AI plays in augmenting human intelligence and managing emotions in work contexts. The exploration of multimodal sensing via the sensing, mapping, and acting framework showcases how AI can navigate the complexities of human emotions to offer tailored interventions in a timely fashion. These interventions, ranging from intrapersonal support (e.g., self-reflection and biofeedback) to interpersonal support (e.g., social awareness and support), underscore the importance of designing AI with a deep understanding of both intrapersonal and interpersonal emotion regulation dynamics. Furthermore, ethical considerations, such as data privacy, emotional diversity, and the handling of biases, are paramount to fostering trust and ensuring the responsible deployment of emotion AI in the workplace. As we navigate the challenges and opportunities presented by AI-assisted emotion regulation interventions, this chapter calls for ongoing research, robust model development, and ethical guidelines that align with global standards such as the EU AI Act. The journey towards creating empathetic, intelligent, and ethically sound AI systems for workplace emotion regulation is just beginning. This chapter lays a foundation for future explorations, encouraging a holistic approach that combines technological innovation with an unwavering commitment to ethical responsibility and human-centric design. Through such endeavors, we can aspire to create work environments where technology not only enhances productivity but also fosters an atmosphere of psychological safety, well-being, and emotional resilience.

References

Ahuja, K., Kim, D., Xhakaj, F., Varga, V., Xie, A., Zhang, S., Townsend, J. E., Harrison, C., Ogan, A., & Agarwal, Y. (2019). Edusense: Practical classroom sensing at scale. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *3*(3), 1–26.

Ajunwa, I. (2018). Algorithms at work: Productivity monitoring applications and wearable technology as the new data-centric research agenda for employment and labor law. . *Louis ULJ*, *63*, 21.

Akçay, M. B., & Oğuz, K. (2020). Speech emotion recognition: Emotional models, databases, features, preprocessing methods, supporting modalities, and classifiers. *Speech Communication*, *116*, 56–76.

Alorwu, A., Kheirinejad, S., Van Berkel, N., Kinnula, M., Ferreira, D., Visuri, A., & Hosio, S. (2021). Assessing mydata scenarios: Ethics, concerns, and the promise. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–11.

Andalibi, N., & Buss, J. (2020). The human in emotion recognition on social media: Attitudes, outcomes, risks. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16.

Anderson, D. J., & Adolphs, R. (2014). A framework for studying emotions across species. *Cell*, *157*(1), 187–200.

Barrett, L. F. (2009). The future of psychology: Connecting mind to brain. *Perspectives on psychological science*, *4*(4), 326–339.

Barrett, L. F., & Westlin, C. (2021). Navigating the science of emotion. In *Emotion measurement* (pp. 39–84). Elsevier.

Bergstrom, I., Seinfeld, S., Arroyo-Palacios, J., Slater, M., & Sanchez-Vives, M. V. (2014). Using music as a signal for biofeedback. *International Journal of Psychophysiology*, *93*(1), 140–149.

Boyd, K. L., & Andalibi, N. (2023). Automated emotion recognition in the workplace: How proposed technologies reveal potential futures of work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1–37.

Braun, M., Weber, F., & Alt, F. (2021). Affective automotive user interfaces–reviewing the state of driver affect research and emotion regulation in the car. *ACM Computing Surveys (CSUR)*, *54*(7), 1–26.

Burke, M., & Develin, M. (2016). Once more with feeling: Supportive responses to social sharing on facebook. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 1462–1474.

Canal, F. Z., Müller, T. R., Matias, J. C., Scotton, G. G., de Sa Junior, A. R., Pozzebon, E., & Sobieranski, A. C. (2022). A survey on facial emotion recognition techniques: A state-of-the-art literature review. *Information Sciences*, *582*, 593–617.

Cha, N., Kim, I., Park, M., Kim, A., & Lee, U. (2018). Hellobot: Facilitating social inclusion with an interactive greeting robot. *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*, 21–24.

Choi, R., Yun, C., Cho, H., Hong, H., Lee, U., & Lee, S.-J. (2022). You are not alone: How trending stress topics brought #awareness and #resonance on campus. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2), 1–30.

Choi, W., Park, S., Kim, D., Lim, Y.-k., & Lee, U. (2019). Multi-stage receptivity model for mobile just-in-time health intervention. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, *3*(2), 1–26.

Cooney, M., Pashami, S., Sant'Anna, A., Fan, Y., & Nowaczyk, S. (2018). Pitfalls of affective computing: How can the automatic visual communication of emotions lead to harm, and what can be done to mitigate such risks. *Companion Proceedings of the The Web Conference 2018*, 1563–1566.

Corvite, S., Roemmich, K., Rosenberg, T. I., & Andalibi, N. (2023). Data subjects' perspectives on emotion artificial intelligence use in the workplace: A relational ethics lens. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1–38.

Costa, J., Guimbretière, F., Jung, M. F., & Choudhury, T. (2019). Boostmeup: Improving cognitive performance in the moment by unobtrusively regulating emotions with a smartwatch. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *3*(2), 1–23.

Cranor, L. F., Guduru, P., & Arjula, M. (2006). User interfaces for privacy agents. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *13*(2), 135–178.

Davidson, R. J. (1998). Affective style and affective disorders: Perspectives from affective neuroscience. *Cognition & emotion*, *12*(3), 307–330.

Dzieżyc, M., Gjoreski, M., Kazienko, P., Saganowski, S., & Gams, M. (2020). Can we ditch feature engineering? end-to-end deep learning for affect recognition from physiological sensor data. *Sensors*, *20*(22), 6535.

Edelman, G. M. (1989). *The remembered present: A biological theory of consciousness.* Basic Books.

Ekman, P. (1971). Universals and cultural differences in facial expressions of emotion. *Nebraska symposium on motivation*.

Elvitigala, D. S., Scholl, P. M., Suriyaarachchi, H., Dissanayake, V., & Nanayakkara, S. (2021). Stressshoe: A diy toolkit for just-in-time personalised stress interventions for office workers performing sedentary tasks. *Proceedings of the 23rd International Conference on Mobile Human-Computer Interaction*, 1–14.

Epp, C., Lippold, M., & Mandryk, R. L. (2011). Identifying emotional states using keystroke dynamics. *Proceedings of the sigchi conference on human factors in computing systems*, 715–724.

European Union. (2024). Regulation (eu) 2024/1689 [Recital 44]. *Official Journal of the European Union*, *L 255*, 1. https://eur-lex.europa.eu/

Fage, C., Consel, C., Etchegoyhen, K., Amestoy, A., Bouvard, M., Mazon, C., & Sauzéon, H. (2019). An emotion regulation app for school inclusion of children with asd: Design principles and evaluation. *Computers & Education*, *131*, 1–21.

Friesen, E., & Ekman, P. (1978). Facial action coding system: A technique for the measurement of facial movement. *Palo Alto*, *3*(2), 5.

Fritz, T., & Müller, S. C. (2016). Leveraging biometric data to boost software developer productivity. *2016 IEEE 23rd international conference on software analysis, evolution, and reengineering (SANER)*, *5*, 66–77.

Gabriel, A. S., & Diefendorff, J. M. (2015). Emotional labor dynamics: A momentary approach. *Academy of management Journal*, *58*(6), 1804–1825.

Gallacher, S., O'Connor, J., Bird, J., Rogers, Y., Capra, L., Harrison, D., & Marshall, P. (2015). Mood squeezer: Lightening up the workplace through playful and lightweight interactions. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 891–902.

Goldin, P. R., McRae, K., Ramel, W., & Gross, J. J. (2008). The neural bases of emotion regulation: Reappraisal and suppression of negative emotion. *Biological psychiatry*, *63*(6), 577–586.

Grandey, A. A. (2000). Emotional regulation in the workplace: A new way to conceptualize emotional labor. *Journal of occupational health psychology*, *5*(1), 95.

Gross, J. J. (1998a). Antecedent-and response-focused emotion regulation: Divergent consequences for experience, expression, and physiology. *Journal of personality and social psychology*, *74*(1), 224.

Gross, J. J. (1998b). The emerging field of emotion regulation: An integrative review. *Review of general psychology*, *2*(3), 271–299.

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*(3), 281–291.

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological inquiry*, *26*(1), 1–26.

Gross, J. J., & Levenson, R. W. (1997). Hiding feelings: The acute effects of inhibiting negative and positive emotion. *Journal of abnormal psychology*, *106*(1), 95.

Han, Y., Toshnazarov, K. E., Kim, B. H., Noh, Y., & Lee, U. (2023). Watchppg: An open-source toolkit for ppg-based stress detection using off-the-shelf smartwatches. *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing*, 208–209.

Häuselmann, A., Sears, A. M., Zard, L., & Fosch-Villaronga, E. (2023). Eu law and emotion data. *2023 11th International Conference on Affective Computing and Intelligent Interaction (ACII)*, 1–8.

Henkel, A. P., Bromuri, S., Iren, D., & Urovi, V. (2020). Half human, half machine–augmenting service employees with ai for interpersonal emotion regulation. *Journal of Service Management*, *31*(2), 247–265.

Hollis, V., Konrad, A., Springer, A., Antoun, M., Antoun, C., Martin, R., & Whittaker, S. (2017). What does all this data mean for my future mood? actionable analytics and targeted reflection for emotional well-being. *Human–Computer Interaction*, *32*(5-6), 208–267.

Howe, E., Suh, J., Bin Morshed, M., McDuff, D., Rowan, K., Hernandez, J., Abdin, M. I., Ramos, G., Tran, T., & Czerwinski, M. P. (2022). Design of digital workplace stress-reduction intervention systems: Effects of intervention type and timing. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–16.

Huang, Y., Tang, Y., & Wang, Y. (2015). Emotion map: A location-based mobile social system for improving emotion awareness and regulation. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 130–142.

Hwang, I., Yoo, C., Hwang, C., Yim, D., Lee, Y., Min, C., Kim, J., & Song, J. (2014). Talkbetter: Family-driven mobile intervention care for children with language delay. *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, 1283–1296.

Jeong, H., Kim, H., Kim, R., Lee, U., & Jeong, Y. (2017). Smartwatch wearing behavior analysis: A longitudinal study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(3), 1–31.

Kang, S., Choi, W., Park, C. Y., Cha, N., Kim, A., Khandoker, A. H., Hadjileontiadis, L., Kim, H., Jeong, Y., & Lee, U. (2023). K-emophone: A mobile and wearable dataset with in-situ emotion, stress, and attention labels. *Scientific data*, *10*(1), 351–351.

Kang, S., Park, C. Y., Kim, A., Cha, N., & Lee, U. (2022). Understanding emotion changes in mobile experience sampling. *Proceedings of the 2022 Chi conference on human factors in computing systems*, 1–14.

Kim, S. H., & Hamann, S. (2012). The effect of cognitive reappraisal on physiological reactivity and emotional memory. *International Journal of Psychophysiology*, *83*(3), 348–356.

Kim, T., Kim, H., Lee, H. Y., Goh, H., Abdigapporov, S., Jeong, M., Cho, H., Han, K., Noh, Y., Lee, S.-J., & Hong, H. (2022). Prediction for retrospection: Integrating algorithmic stress prediction into personal informatics systems for college students' mental health. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3491102.3517701

Ko, H.-K., Son, K., Jin, H., Choi, Y., & Chen, X. 'A. (2023). Moderating customer inquiries and responses to alleviate stress and reduce emotional dissonance of customer service representatives. *ACM CHI Workshop on Combating Toxicity, Harassment, and Abuse in Online Social Spaces*.

Lam, S., Dickerson, S. S., Zoccola, P. M., & Zaldivar, F. (2009). Emotion regulation and cortisol reactivity to a social-evaluative speech task. *Psychoneuroendocrinology*, *34*(9), 1355–1362.

Lee, D., Nam, K., & Lee, U. (2024). Supporting interpersonal emotion regulation of call center workers via customer voice modulation. *Extended Abstracts of the Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*.

Lee, H., Jung, Y., Law, H. Y., Bae, S., & Lee, U. (2024). Priviaware: Exploring data visualization and dynamic privacy control support for data collection in mobile sensing research. *The Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*.

Lee, H., Kang, S., & Lee, U. (2022). Understanding privacy risks and perceived benefits in open dataset collection for mobile affective computing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *6*(2), 1–26.

Lee, H., & Lee, U. (2022). Toward dynamic consent for privacy-aware pervasive health and well-being: A scoping review and research directions. *IEEE Pervasive Computing*, *21*(4), 25–32.

Lee, U., Han, K., Cho, H., Chung, K.-M., Hong, H., Lee, S.-J., Noh, Y., Park, S., & Carroll, J. M. (2019). Intelligent positive computing with mobile, wearable, and iot devices: Literature review and research directions. *Ad Hoc Networks*, *83*, 8–24.

Lee, U., Jung, G., Ma, E.-Y., San Kim, J., Kim, H., Alikhanov, J., Noh, Y., & Kim, H. (2023). Toward data-driven digital therapeutics analytics: Literature review and research directions. *IEEE/CAA Journal of Automatica Sinica*, *10*(1), 42–66.

Maalej, A., & Kallel, I. (2020). Does keystroke dynamics tell us about emotions? a systematic literature review and dataset construction. *2020 16th International Conference on Intelligent Environments (IE)*, 60–67.

Mattingly, S. M., Gregg, J. M., Audia, P., Bayraktaroglu, A. E., Campbell, A. T., Chawla, N. V., Das Swain, V., De Choudhury, M., D'Mello, S. K., Dey, A. K., Gao, G., Jagannath, K., Jiang, K., Lin, S., Liu, Q., Mark, G., Martinez, G. J., Masaba, K., Mirjafari, S., . . . Striegel, A. (2019). The tesserae project: Large-scale, longitudinal, in situ, multimodal sensing of information workers. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–8. https://doi.org/10.1145/3290607.3299041

Meegahapola, L., Droz, W., Kun, P., de Götzen, A., Nutakki, C., Diwakar, S., Correa, S. R., Song, D., Xu, H., Bidoglia, M., Gaskell, G., Chagnaa, A., Ganbold, A., Zundui, T., Caprini, C., Miorandi, D., Hume, A., Zarza, J. L., Cernuzzi, L., . . . Gatica-Perez, D. (2023). Generalization and personalization of mobile sensing-based mood inference models: An analysis of college students in eight countries. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, *6*(4). https://doi.org/10.1145/3569483

Mercedes-Benz. (2020). *CLA 250* [Retrieved: January 10, 2020]. https://www.mercedes-benz.com/en/exhibitions/ces/vehicles/cla-250/

Moors, A., Ellsworth, P. C., Scherer, K. R., & Frijda, N. H. (2013). Appraisal theories of emotion: State of the art and future development. *Emotion review*, *5*(2), 119–124.

Moraveji, N., Olson, B., Nguyen, T., Saadat, M., Khalighi, Y., Pea, R., & Heer, J. (2011). Peripheral paced respiration: Influencing user physiology during information work. *Proceedings of the 24th annual ACM symposium on User interface software and technology*, 423–428.

Müller, S. C., & Fritz, T. (2015). Stuck and frustrated or in flow and happy: Sensing developers' emotions and progress. *2015 IEEE/ACM 37th IEEE International Conference on Software Engineering*, *1*, 688–699.

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2018). Just-in-time adaptive interventions (jitais) in mobile health: Key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine*, 1–17.

Nepal, S., Martinez, G. J., Pillai, A., Saha, K., Mirjafari, S., Swain, V. D., Xu, X., Audia, P. G., Choudhury, M. D., Dey, A. K., Striegel, A., & Campbell, A. T. (2024). A survey of passive sensing in the workplace. https://arxiv.org/abs/2201.03074

Nilsson, N. J. (1998). *Artificial intelligence: A new synthesis*. Morgan Kaufmann.

Nishiyama, Y., & Sezaki, K. (2023). Smartwatch-based sensing framework for continuous data collection: Design and implementation. *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing*, 620–625.

Ochsner, K. N., Bunge, S. A., Gross, J. J., & Gabrieli, J. D. (2002). Rethinking feelings: An fmri study of the cognitive regulation of emotion. *Journal of cognitive neuroscience*, *14*(8), 1215–1229.

Paredes, P., Gilad-Bachrach, R., Czerwinski, M., Roseway, A., Rowan, K., & Hernandez, J. (2014). Poptherapy: Coping with stress through pop-culture. *Proceedings of the 8th international conference on pervasive computing technologies for healthcare*, 109–117.

Paredes, P. E., Zhou, Y., Hamdan, N. A.-H., Balters, S., Murnane, E., Ju, W., & Landay, J. A. (2018). Just breathe: In-car interventions for guided slow breathing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *2*(1), 1–23.

Park, C. Y., Cha, N., Kang, S., Kim, A., Khandoker, A. H., Hadjileontiadis, L., Oh, A., Jeong, Y., & Lee, U. (2020). K-emocon, a multimodal sensor dataset for continuous emotion recognition in naturalistic conversations. *Scientific Data*, *7*(1), 293.

Park, E., Lee, D., Han, Y., Diefendorff, J., & Lee, U. (2024). Hide-and-seek: Detecting workers' emotional workload in emotional labor contexts using multimodal sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *8*(3).

Pina, L., Rowan, K., Roseway, A., Johns, P., Hayes, G. R., & Czerwinski, M. (2014). In situ cues for adhd parenting strategies using mobile technology. *Proceedings of the 8th international conference on pervasive computing technologies for healthcare*, 17–24.

Poria, S., Cambria, E., Bajpai, R., & Hussain, A. (2017). A review of affective computing: From unimodal analysis to multimodal fusion. *Information fusion*, *37*, 98–125.

Pramana, G., Parmanto, B., Lomas, J., Lindhiem, O., Kendall, P. C., & Silk, J. (2018). Using mobile health gamification to facilitate cognitive behavioral therapy skills practice in child anxiety treatment: Open clinical trial. *JMIR Serious Games*, *6*(2), e9. https://doi.org/10.2196/games.8902

Roemmich, K., Schaub, F., & Andalibi, N. (2023). Emotion ai at work: Implications for workplace surveillance, emotional labor, and emotional privacy. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–20.

Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach*. Pearson.

Sambasivan, N., Kapania, S., Highfill, H., Akrong, D., Paritosh, P., & Aroyo, L. M. (2021). "everyone wants to do the model work, not the data work": Data cascades in high-stakes ai. *proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–15.

Schilit, B., Adams, N., & Want, R. (1994). Context-aware computing applications. *1994 first workshop on mobile computing systems and applications*, 85–90.

Schuller, B., & Batliner, A. (2013). *Computational paralinguistics: Emotion, affect and personality in speech and language processing*. John Wiley & Sons.

Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. *Frontiers in public health*, *5*, 258.

Sharma, K., Castellini, C., van den Broek, E. L., Albu-Schaeffer, A., & Schwenker, F. (2019). A dataset of continuous affect annotations and physiological signals for emotion analysis. *Scientific data*, *6*(1), 196–13.

Shi, Y., Koval, P., Kostakos, V., Goncalves, J., & Wadley, G. (2023). "instant happiness": Smartphones as tools for everyday emotion regulation. *International Journal of Human-Computer Studies*, *170*, 102958.

Slovak, P., Antle, A., Theofanopoulou, N., Daudén Roquet, C., Gross, J., & Isbister, K. (2023). Designing for emotion regulation interventions: An agenda for hci theory and research. *ACM Transactions on Computer-Human Interaction*, *30*(1), 1–51.

Smith, W., Wadley, G., Webber, S., Tag, B., Kostakos, V., Koval, P., & Gross, J. J. (2022). Digital emotion regulation in everyday life. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–15.

Smyth, J. M., & Heron, K. E. (2016). Is providing mobile interventions" just-in-time" helpful? an experimental proof of concept study of just-in-time intervention for stress management. *2016 IEEE Wireless Health (WH)*, 1–7.

Snyder, J., Matthews, M., Chien, J., Chang, P. F., Sun, E., Abdullah, S., & Gay, G. (2015). Moodlight: Exploring personal and social implications of ambient display of biosensor data. *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*, 143–153.

Stark, L. (2018). Algorithmic psychometrics and the scalable subject. *Social Studies of Science*, *48*(2), 204–231.

Stark, L., & Hoey, J. (2021). The ethics of emotion in artificial intelligence systems. *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 782–793.

Tian, L., Oviatt, S., Muszynski, M., Chamberlain, B., Healey, J., & Sano, A. (2022). Applied affective computing.

Tuck, A. B., Long, K. A., & Thompson, R. J. (2023). Social media's influence on momentary emotion based on people's initial mood: An experimental design. *Cognition and Emotion*, *37*(5), 1049–1056.

Verma, A., Islam, S., Moghaddam, V., & Anwar, A. (2023). Digital emotion regulation on social media. *arXiv preprint arXiv:2307.13187*.

Wadley, G., Smith, W., Koval, P., & Gross, J. J. (2020). Digital emotion regulation. *Current Directions in Psychological Science*, *29*(4), 412–418.

Webb, T. L., Miles, E., & Sheeran, P. (2012). Dealing with feeling: A meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. *Psychological bulletin*, *138*(4), 775.

Zaki, J., & Williams, W. C. (2013). Interpersonal emotion regulation. *Emotion*, *13*(5), 803.

Zhao, J., Mao, X., & Chen, L. (2019). Speech emotion recognition using deep 1d & 2d cnn lstm networks. *Biomedical signal processing and control*, *47*, 312–323.

Zirar, A., Ali, S. I., & Islam, N. (2023). Worker and workplace artificial intelligence (ai) coexistence: Emerging themes and research agenda. *Technovation*, *124*, 102747.