Theoretical/Methodological/Review Article

ASSOCIATION FOR PSYCHOLOGICAL SCIENCE

Clinical Psychological Science
2022, Vol. 10(1) 3–26

DOI: 10.1177/21677026211011982
www.psychologicalscience.org/CPS
SAGE

Digital Technologies for Emotion-Regulation Assessment and Intervention: A Conceptual Review

Alexandra H. Bettis[1], Taylor A. Burke[2,3], Jacqueline Nesi[2,3], and Richard T. Liu[4,5]

[1]Department of Psychiatry & Behavioral Sciences, Vanderbilt University Medical Center; [2]Department of Psychiatry & Human Behavior, Brown Medical School; [3]Rhode Island Hospital, Providence, Rhode Island; [4]Department of Psychiatry, Harvard Medical School; and [5]Massachusetts General Hospital, Boston, Massachusetts

Abstract

The ability to regulate emotions in response to stress is central to healthy development. Whereas early research in emotion regulation predominantly employed static, self-report measurement, the past decade has seen a shift in focus toward understanding the dynamic nature of regulation processes. This is reflected in recent refinements in the definition of emotion regulation that emphasize the importance of the ability to flexibly adapt regulation efforts across contexts. The latest proliferation of digital technologies employed in mental health research offers the opportunity to capture the state- and context-sensitive nature of emotion regulation. In this conceptual review, we examine the use of digital technologies (ecological momentary assessment; wearable and smartphone technology, physical activity, acoustic data, visual data, and geo-location; smart-home technology; virtual reality; social media) in the assessment of emotion regulation and describe their application to interventions. We also discuss challenges and ethical considerations and outline areas for future research.

Keywords

assessment and intervention, conceptual review, digital technology, emotion regulation

Received 12/8/20; Revision accepted 3/26/21

The ways in which individuals regulate emotions are fundamental to health and well-being across the life span. Digital technologies are a central feature of daily life for many children, adolescents, and adults, and these technologies afford researchers the opportunity to examine a wide range of emotion-regulation processes as they unfold in real time. Despite recent advancements in digital tools for assessment and intervention and their potential to provide new insights into emotion-regulation processes, no prior reviews have synthesized existing research on this topic.

Defining Emotion Regulation

Definitions of emotion regulation highlight its multifaceted, dynamic nature. *Emotion regulation* refers to the processes by which an individual monitors, evaluates, and changes emotional responses, with an emphasis on doing so to achieve a specific goal (Gross, 2015; Gross & Thompson, 2007). Theories of emotion regulation emphasize the fluctuating nature of this process and underscore that regulating emotions in response to the environment is not a static, singular action but rather an adaptive and ongoing series of behaviors, cognitions, and physiological responses. Furthermore, the process of regulating emotions may occur both explicitly and implicitly, and both automatic and controlled processes contribute to the process of changing or altering an emotional experience (Braunstein et al., 2017). Different motivations for regulating emotions, including both hedonic and instrumental motivation,

Corresponding Author:
Alexandra H. Bettis, Department of Psychiatry & Behavioral Sciences, Vanderbilt University Medical Center
E-mail: alexandra.h.bettis.1@vumc.org

may further influence how and when an individual engages in regulation efforts (Tamir et al., 2016).

The dynamic nature of emotion regulation is reflected in its evolving definitions, highlighted both in the extended process model (Gross, 2015) and the regulatory flexibility framework (Aldao, 2013; Aldao et al., 2015; Bonanno & Burton, 2013). Both models involve the identification of a situation under which an individual is regulating emotional responses (e.g., sensitivity to context), the selection of regulatory strategies (e.g., an individual's repertoire of emotion-regulation strategies), and the implementation of the selected strategies. These factors constitute an ongoing cycle, which may be modified in response to feedback over the course of an emotional experience or stressful event (Bonanno & Burton, 2013; Gross, 2015). The role of flexibility is essential to these theoretical models, and greater regulatory flexibility is presumed to be positively associated with optimal psychological outcomes and well-being.

Limits of Emotion-Regulation Measurement

Gaps in the understanding of emotion-regulation processes are due, in part, to limitations inherent in using static, self-report, or laboratory task-based designs to capture a state-sensitive process. Systematic narrative and meta-analytic reviews conducted to date regarding associations between emotion regulation and psychological outcomes provide insight into how emotion-regulation processes have been measured in prior work (Aldao et al., 2010; Compas et al., 2017; Zimmer-Gembeck & Skinner, 2011). Note that studies included in these reviews employed primarily cross-sectional designs, used self-report measures, and emphasized measurement at the level of strategy selection (i.e., what type and how often specific strategies or domains of strategies are used). Self-report measures are typically bound to a single context (e.g., how one copes with a specific stressor; Connor-Smith et al., 2000) or capture no context at all (e.g., how one generally responds to emotions; Carver et al., 1989; Perez et al., 2012). How individuals implement these strategies flexibly across contexts, including the role of variability in strategy selection, effectiveness of implementation, and ability to read cues in the environment and modify one's approach accordingly, is not well captured by solely self-report questionnaire measures.

Many studies have also incorporated task-based measurement to better understand neural responses during emotionally evocative tasks. For example, a common task-based emotion-regulation paradigm prompts individuals to employ a specific strategy (e.g., cognitive reappraisal, Ochsner et al., 2002; distraction or reappraisal, Bettis et al., 2018; McRae et al., 2012), choose from a set of strategies (e.g., Sheppes et al., 2011, 2014; Sheppes & Gross, 2013), or select and switch strategies midtask (Birk & Bonanno, 2016) and subsequently rate their negative affect. Although they provide an index of strategy selection, implementation effectiveness, and/or modification, task-based designs are constrained to a small and finite range of strategies (e.g., cognitive reappraisal vs. distraction; Bettis et al., 2018; McRae et al., 2012) that may not represent an individual's full repertoire of available skills. These tasks are further constrained by context because they rely on predetermined images or film clips meant to evoke negative or positive emotions. In summary, these methods have provided a foundation on which researchers now understand how strategies may be effective or ineffective at the group level; however, incorporating novel methods in emotion-regulation research is needed to better understand the full process of regulation, from understanding and evaluating context to the implementation and modification of strategies.

Current Review

Digital-technology tools are uniquely suited to address the major limitations that have plagued emotion-regulation research. These tools present an opportunity to extend the understanding of the state-sensitive processes by which individuals effectively or ineffectively employ emotion-regulation strategies in their daily lives. The use of smartphones, wearables, online social-networking platforms, and Internet-connected home devices has increased substantially over the past decade (Pew Research Center, 2019a, 2019b, 2019c). A growing number of digital tools such as these, with both active and passive assessment capabilities, may aid in refining measurement of the specific emotion-regulation processes defined in the extended process model (Gross, 2015) and the regulatory flexibility framework (Aldao, 2013; Aldao et al., 2015; Bonanno & Burton, 2013). Specifically, digital technologies permit the fine-grained assessment of the contexts under which individuals are employing regulation strategies, the ways in which they employ or modify these strategies, and the effectiveness of these strategies across situations and time. Compared with traditional self-report or experimental approaches, these tools may also better capture both explicit and implicit regulation efforts as they unfold in daily life. Moreover, leveraging advances in technology to capture regulation processes will directly inform the development of digitally delivered interventions for a broad range of mental health problems and may augment treatment as usual or serve as stand-alone treatments.

In the current review, we aim to provide an overview of the application of digital technologies to assess emotion regulation and how these methodologies may be applied to interventions. We begin by discussing the applications of ecological momentary assessment (EMA) and passive-sensing technologies to the study of these processes. In our discussion of passive sensing, we outline particularly promising technologies for emotion-regulation assessment, including wearable, portable (i.e., smartphones, virtual reality), and home devices that assess a wide range of state-sensitive data (e.g., geo-location, acoustic, visual, social media). We then discuss the potential for modifying emotion-regulation processes through ecological momentary interventions, just-in-time adaptive interventions, virtual-reality programs, and the integration of passive-sensing tools into intervention work. Finally, we highlight challenges and future directions for this work.

Throughout this review, we emphasize how these tools may best capture efforts to down-regulate negative emotional experiences and the ability for these methods to enhance the understanding of stressful or arousing contexts in which an individual may want or need to reduce negative emotions because reducing negative affect is often a focus of interventions targeting mental health. Although emotion-regulation research in the context of mental health has largely focused on reducing negative affect, individuals may choose to up-regulate or down-regulate both negative and positive emotional states, depending on their motivations and the context. Therefore, we also briefly discuss applications to positive emotions in future directions for this work. In this review, we also discuss limitations to currently available digital tools on their own for assessing emotion-regulation processes, including difficulties parsing the motivation behind a given behavior assessed via passive sensing and challenges differentiating between various stages of the emotion-regulation process. We focus our review on the *potential* offered by new digital tools, but we caution that much of this work is preliminary, and there are limited data on the validity and reliability of these tools for detecting emotion regulation. Note that we discuss how maximally leveraging the potential of these emerging technologies for assessing emotion-regulation processes would require future work in this area to integrate multiple technologies to allow each to contextualize the data derived from the other (e.g., EMA in combination with biological indices of emotion regulation and acoustic and language data).

Digital Technology for Emotion-Regulation Assessment

Ecological momentary assessment

EMA, also referred to as experience sampling, involves real-time, repeated sampling of an individual's experiences, including behavior, affect, and cognition. EMA allows for frequent assessment of constructs of interest in an individual's real-world environment, enhancing ecological validity and reducing recall bias (Shiffman et al., 2008). EMA is typically conducted via repeated surveys administered using smartphone apps. Sampling may occur at random or specific intervals throughout the day (e.g., every 2 hr), may be contingent on an event occurring (e.g., every time an individual engages in self-harm), may occur at a single point in the day (e.g., every morning or evening), or may include a combination of these approaches (for a review on methodological considerations for EMA in psychological research, see Trull & Ebner-Priemer, 2020). Experience-sampling approaches offer the opportunity to capture each stage of the regulation process. Repeated sampling of these processes over a period of several days, weeks, or months provides intensive longitudinal data, which can be used to explore both between- and within-persons variation in indices of regulation. Indeed, EMA is ideally suited to capture state- and context-sensitive explicit emotion-regulation processes. Furthermore, given the ubiquity of smartphone use across the life span, the feasibility and acceptability of using these approaches is high and offers a promising avenue for translation to real-world, clinical applications.

Identification of context. EMA methods provide opportunities to capture multiple stages of the emotion-regulation process. First, EMA designs allow for the measurement of the context under which individuals experience and regulate emotions. Within an EMA survey, participants may be prompted to report on various indices of context, including their current affective state, whether a life event or stressor has occurred in a specific time frame, whom they are with, where they are located, and/or what activities they are engaging in at the moment. Ratings across these features of the environment can provide a rich source of information regarding how and when individuals are using specific regulatory strategies and may inform when to deliver in-the-moment interventions. Several studies have used EMA to assess regulation in the context of stress (e.g., Connolly & Alloy, 2017; Goldschmidt et al., 2014). Researchers may restrict assessment to the context of a recent stressor (e.g., discrimination experiences, Livingston et al., 2017) or ask about regulation without a specific stressor context (Daniel et al., 2019). Research using EMA has also highlighted the importance of the social context—or how engaging in regulation with another person, including caregivers or peers, may influence psychological outcomes (Silk, 2019; Waller et al., 2014). For example, to directly test the influence of social context, Aldrich and colleagues (2019) conducted an EMA study in a sample of adolescents and measured corumination, or how often youths engage in excessive discussions of problems with others. Results showed that engaging in corumination predicted later rumination without others present, which suggests that the social context in which individuals engage in regulatory strategies may influence later strategy selection (Aldrich et al., 2019).

Strategy selection. Experience-sampling designs also permit the study of what strategies individuals select to manage distress in their daily lives. To date, studies have primarily assessed strategy use by asking individuals to report what emotion-regulation strategies they have employed over the course of a specified time period (e.g., right now, in the past hour) or in response to a specified event from a predetermined list of strategies (e.g., Burr et al., 2020; Short et al., 2018; Stone et al., 2019; Tan et al., 2012). Repeated assessment of emotion-regulation strategy selection allows for the exploration of both variability in the use of a single strategy and variability in the selection of different emotion-regulation strategies over time (Blanke et al., 2020; Dixon-Gordon et al., 2015), which directly tests the theory that a greater repertoire of strategies and/or higher variability in strategy use are optimal for health and well-being. In support of theories purporting the importance of regulatory flexibility, a 21-day EMA study examined emotion-regulation repertoire by prompting participants to rate the frequency with which they used 10 emotion-regulation strategies several times throughout the day. Note that individuals with more diverse emotion-regulation profiles who engaged primarily in active regulation strategies reported lower negative affect (Grommisch et al., 2020).

Implementation effectiveness and modification. Finally, strategy implementation effectiveness can also be explored via EMA methods. Perceived effectiveness may be examined by directly asking participants whether a given strategy helped or changed how they felt (e.g., Daniel et al., 2019) or may be deduced from negative affect ratings following emotion-regulation efforts (e.g., King et al., 2018). Alternatively, identifying strategy effectiveness may be tied to specific events or outcomes also measured via EMA, such as physical health symptoms (e.g., Massey et al., 2009) or alcohol/substance use (e.g., Roos et al., 2020). Furthermore, given the ability to ask a range of questions within one set of momentary surveys, multiple components of the emotion-regulation process may be examined simultaneously using this method; indeed, several studies have included inquiries about both strategy use and effectiveness (e.g., Daniel et al., 2019; Lennarz et al., 2019) or context and strategy use (e.g., Stone et al., 2019).

Limitations of ecological momentary assessment. Several limitations to the assessment of emotion regulation using EMA highlight the need for passive assessment methodologies to complement the resultant data. First, EMA relies on self-report of an individual's experience. Significant limitations of self-report measurement apply to EMA research, including that participants may have limited insight into their own emotion-regulation processes (Nisbett & Wilson, 1977), even when measured in the moment. Second, several practical limitations exist. Intensive longitudinal data collection may be time-consuming and burdensome for participants, reducing the ability to sample over long periods (e.g., several weeks to months) of time. This limitation in feasibility makes it challenging to capture emotion regulation in response to severe stressors, which naturally occur relatively infrequently but are also precisely the types of stressors that have been found to be most relevant to risk for mental health outcomes (Hammen, 2005; Paykel et al., 1975). Even with repeated sampling throughout the day, researchers are still limited in the maximum number of times it may be appropriate to assess these processes while minimizing burden and increasing the likelihood that participants will complete surveys and continue in the study. Furthermore, limitations in the number of questions that can be included in daily repeated assessments restrict the range of strategies, responses to strategies, or contextual factors that can be assessed. Finally, during school or work hours, the accessibility of smartphones to complete EMA surveys may be limited. Below, we discuss additional digital technologies that directly address some of these limitations and allow for continuous, objective assessment with limited effort required from research participants, particularly for implicit emotion-regulation process.

Passive sensing technologies

Wearable devices and smartphones. An exciting development in recent years is a class of devices, often called *wearables*, that has potential to advance assessment and intervention strategies for emotion regulation in real-world settings. These small, portable devices are designed to be unobtrusively worn by individuals continuously over an extended period. Individuals wear the device in naturalistic settings as they go about their day-to-day activities, and the device passively collects data over that time period. In addition, smartphone technology has rapidly evolved such that most smartphones now include technology to track data often collected by wearables, including geo-location, heart rate, and physical activity. High rates of smartphone ownership across all age groups support the potential value in using smartphone technology for real-time, continuous assessment of emotion-regulation processes. In addition, these tools may provide insight into both explicit and implicit emotion-regulation processes. Below, we outline several applications of both wearables and smartphone devices to the assessment of emotion regulation.

Biological indices of regulation. Particularly relevant to the study of emotion regulation are mobile sensors designed to detect autonomic nervous system (ANS) activity. Aberrant ANS activity in response to stress (e.g., dysregulation of electrodermal activity [EDA] and respiratory sinus arrhythmia or heart rate variability [HRV]), as characterized by blunted parasympathetic and sympathetic nervous system responses, has been identified as an index of emotion-regulation capacity and has been implicated in several negative mental health outcomes (Beauchaine, 2001; Beauchaine & Thayer, 2015; Crowell et al., 2005; El-Sheikh et al., 2010; Sarchiapone et al., 2018; Wilson et al., 2016). Moreover, ANS activity has a very low temporal latency (about 2 s poststimulus in the case of EDA; Benedek & Kaernbach, 2010), which makes it ideal for studying the temporal dynamics of emotion-regulation responses.

Several mobile devices have been designed to assess indices of ANS activity, EDA, and heart rate, in particular. In recent years, a number of valid and practical devices have become available (Enewoldsen et al., 2016; Fletcher et al., 2010; Kutt et al., 2018). Regarding mobile electrocardiographic (ECG) devices for assessing HRV, options are currently available for use across a range of time scales, from minutes to months (for a discussion of several of these devices, see Fung et al., 2015). Wireless mobile devices, including bracelets, smart watches, and patches, the latter being part of the emerging field of epidermal electronics (D. H. Kim et al., 2011; Y. Zhang & Tao, 2019),[1] have also been developed to measure heart rate unobtrusively, potentially allowing for longer continuous ECG monitoring. Promising wireless adhesive devices for real-time ECG monitoring include the NUVANT Mobile Cardiac Telemetry Monitor (Engel et al., 2012) and the Zio patch (Steinhubl et al., 2018); all of these have been approved by the U.S. Food and Drug Administration.

These devices have the potential to inform both when an individual would most benefit from engaging in regulation strategies (i.e., assessing responses to a given context) and whether regulation efforts are successful (i.e., implementation effectiveness). In addition to ECG, blood pressure may serve as a useful physiological index of emotion-regulation strategy selection. Specifically, emotion suppression appears to result in increased blood pressure (Dan-Glauser & Gross, 2011). A recently developed ultrasound patch for real-time monitoring of blood pressure (Wang et al., 2018) thus may provide an index of efforts to suppress emotions. This small and lightweight patch is designed to be worn unobtrusively on the neck and is uniquely advantageous in that—unlike "gold standard" measures of central blood pressure that require inserting a catheter in blood vessels guided to the aorta—it is not invasive. Its accuracy and reliability as an index of blood pressure, however, have yet to be fully evaluated, and likewise, whether this may also be a reliable index of suppression (or other regulation efforts) outside of a controlled laboratory environment remains to be determined.

Physical activity. Accelerometers, which are used to assess physical activity, have drawn considerable empirical interest. Accelerometers are often built into wearable devices (e.g., FitBits, Apple watches) and are found in most smartphones. The potential of accelerometers to inform emotion-regulation research is due, in part, to their near ubiquity and the convenience of collecting data unobtrusively for extended periods of time. There are already data providing general support for the validity of this technology for measuring physical activity, including through both wearables and smartphones (Case et al., 2015; Pannicke et al., 2020).

Physical activity data may provide, at the simplest level, an index of whether individuals are using exercise as a regulation strategy (i.e., strategy selection). Delineating exercise as a regulation strategy may or may not also involve EMA approaches asking about whether physical activity was used explicitly to regulate emotions. Furthermore, exercise may function as an implicit regulation strategy—that is, individuals who are engaging in physical activity may do so for other explicit reasons (e.g., physical health) but may also gain an added benefit of improving their day-to-day emotion regulation. Accelerometer data may also be useful as an index of moment-to-moment effectiveness of emotion-regulation strategies broadly (i.e., implementation effectiveness). A necessary first consideration, then, is whether physical activity itself may serve to index moment-to-moment changes in affect. Suggestive of this possibility, especially as relates to clinical phenomena, is the observation that depression has long been associated with behavioral withdrawal and self-isolative tendencies (Joiner, 2000; Kumar et al., 2017) and a sizeable body of research linking physical exercise to improvements in mood (Carter et al., 2016; Kvam et al., 2016). Furthermore, one intriguing study in which EMA was used found that among both depressed and nondepressed individuals, self-reported physical activity was positively associated with positive affect at the subsequent prompt (Mata et al., 2012). Moreover, in another study, momentary affect was positively correlated with both subjective and objective physical activity; negative affect decreased and positive affect increased with greater physical activity (Pannicke et al., 2020). Given these data, in-the-moment physical activity data may provide a window into whether individuals are effectively or ineffectively regulating their emotions on a day-to-day basis.

Global positioning systems. Global positioning systems (GPS) technology, a core feature of the passive smartphone sensing suite and measured by many wearable devices (e.g., Apple watches), allows for the accurate and real-time tracking and storage of location information. GPS technology is embedded in the vast majority of smartphone devices, increasing its potential utility in emotion-regulation research. Its ubiquity is demonstrated in its broad use in the burgeoning area of research using smartphones to quantify health-related outcomes. In a recent systematic review of passive sensing using smartphones, GPS was used in more than 40% of the 118 identified studies (Trifan et al., 2019).

As with accelerometers, the feasibility of collecting continuous GPS data has been bolstered by dramatic increases in the percentage of the population who carry their smartphone with them the majority of time. This has led to a proliferation of research aimed at computationally analyzing GPS data and the integration of this technology into numerous mental health applications. Such advances have already been used to elucidate emotion-regulation processes and have significant promise in accelerating related assessment and intervention research. For example, GPS technology can be used to help individuals improve or supplement their skills in identifying situations in which engaging in regulation skills would be beneficial. Previous studies have used GPS to identify contexts that are associated with specific emotional responses (e.g., Besoain et al., 2020; Epstein et al., 2014; Kwan et al., 2019; Pramana et al., 2018). By identifying contexts associated with risk, individuals can be alerted to preemptively engage in emotion-regulation strategies to ameliorate aversive emotional responses.

GPS can also be used to assess strategy selection and implementation for a range of emotion-regulation strategies. For example, GPS can quantify physical mobility, which may serve as a proxy for engagement in behavioral activation as an emotion-regulation strategy (Rohani et al., 2017). GPS can be used to identify whether an individual has visited a specific location associated with a specific emotion-regulation strategy (e.g., a museum, a movie theater, gym) as well as to assess the duration of emotion-regulation strategy employment. Finally, GPS can be used to alert individuals that strategy use is indicated and to determine the effectiveness of emotion-regulation strategies through quantifying mood before and/or after strategy use. Indeed, GPS-derived features such as circadian movement, overall mobility, location entropy, and time spent at home have shown promise in modeling mood (Chow et al., 2017; Saeb et al., 2015, 2016).

Acoustic and language data. Advances in software and computational approaches to collect and assess acoustic input may also be of high relevance to the assessment of emotion-regulation processes. A burgeoning body of evidence has demonstrated the ability of algorithms to increasingly accurately detect emotion through acoustic and linguistic analysis of spoken language (Schuller & Schuller, 2021).

Whereas early versions of this technology as applied to the passive assessment of emotion have required participants to carry hardware specifically developed for recording purposes (e.g., Mehl & Robbins, 2012), recent developments have permitted this technology to be used through apps that can access a smartphone's microphone (Kaplan et al., 2020) or, most recently, through wearables, such as the Amazon Halo. Such software can be used to passively assess individuals' emotions continuously and in real time with little associated burden (e.g., Spyrou et al., 2019). In addition, it can permit the assessment of social context through analyzing vocalizations from people within an individual's environment (e.g., Lu et al., 2012). Therefore, this passive technology could aid individuals in identifying changes in one's emotion that may signal that the use of an emotion-regulation strategy could be helpful and can also help to identify contexts in which employing emotion-regulation strategies would be helpful (e.g., detecting high stress in one's environment). Relatedly, acoustic and language analysis may be helpful in quantifying strategy implementation effectiveness. Indeed, it may be used to passively assess emotion on the basis of acoustic features of voice before and after the implementation of a specific strategy or set of strategies.

Acoustic analysis can also aid, alongside the use of active data collection (e.g., EMA), in detecting explicit strategy selection, identification, and modification. For example, recent evidence suggests that acoustic analysis can identify diaphragmatic breathing patterns (Shih et al., 2016), thereby demonstrating its potential to identify whether, when, and for how long an individual employs deep breathing as an emotion-regulation strategy. Acoustic analysis may also be able to detect other commonly employed regulation strategies amenable to acoustic detection (e.g., exercise, playing, or listening to music). Finally, this technology has promise in detecting emotion-regulation strategy modification, such as changing breathing patterns in response to an initial regulation approach being ineffective.

Visual data. Computational approaches to visual analysis offer additional exciting possibilities for passively and automatically assessing processes of emotion regulation. Advances in computer vision allow detection of emotion from images or videos of individuals' faces and body pose/movements (e.g., Ko, 2018). Smartphones (e.g., Kosch et al., 2020; Sarsenbayeva et al., 2020) and wearable cameras (e.g., Kwon et al., 2016; Rincon et al., 2018) have shown early promise in capturing images/video and, in turn, detecting an individual's emotion. Furthermore, such devices may be used to passively assess the emotions of other people in an individual's environment, highlighting when an individual may consider employing an emotion-regulation strategy to buffer against contextual stress. Like acoustic analysis, the visual analysis of faces and body pose/movement may aid in emotion identification.

Advances in computer vision, and specifically in human activity recognition (e.g., Wu et al., 2017; H.-B. Zhang et al., 2019), may aid in detecting the full range of the emotion-regulation process. With such advances, researchers might train an algorithm to identify whether an individual is engaging in a specific emotion-regulation strategy (e.g., exercise, deep breathing, social engagement) as well as whether the selected strategy is modified over time. Like many of the technologies reviewed, computer vision algorithms trained to assess emotion over time via facial and pose analysis may also play a role in evaluating the effectiveness of regulation efforts. To validate emotion-regulation processes, active data collection of regulatory intentions alongside activity recognition will be needed.

Relatedly, eye tracking has been widely used in vision research, primarily relying on specialty equipment requiring large-scale desktop displays. Smartphone-based eye-tracking devices, which capture eye movement on an individual's phone display, show considerable promise for use in research compared with both desktop devices and glasses designed for eye-tracking purposes because of their accuracy and lower cost (Valliappan et al., 2020). Pupillary response, as assessed via eye-tracking devices, is considered an index of emotional arousal by measuring attention allocation in the context of emotional stimuli (Bardeen & Daniel, 2017), although reported effect sizes were small (rs = .18–.25). Mobile eye-tracking devices have been employed to examine emotion-regulation-relevant attention deployment in younger and older adults by using participant-selected stimuli to assess pupillary response and associations with mood (Isaacowitz et al., 2015). This technology permits the study of individuals' engagement with emotional cues in their digital environment and may be particularly informative when paired with active data collection as well as other passive data tools, such as social-media trace data.

Social media. One of the most notable digital technological innovations in recent years is the advent of social media, or platforms that allow users to interact, self-present, and create and consume content (Carr & Hayes, 2015). This may include social-networking sites, such as Facebook, Twitter, and Instagram; messaging tools, such as text messaging or messaging apps; and even online forums or support groups. Social-media use is prevalent among U.S. adults; 72% used at least one social-media site in 2019, up from just 5% in 2005 (Anderson & Jiang, 2018). Social-media use may be even higher for adolescents, among whom 95% have access to a smartphone and 89% report going online several times per day or more (Anderson & Jiang, 2018).

Given the widespread and frequent use of social media, social-media data have increasingly been recognized as possible tools for assessment and intervention purposes. Studies have begun to incorporate social-media trace data, representing the collection of "digital traces" that users may leave as they interact with social-media platforms (Settanni et al., 2018). Trace data may consist of both user-generated social-media content (e.g., messages sent, photos posted) as well as metadata reflecting a user's activity (e.g., timing of posts, number of friends or followers). Researchers have analyzed social-media trace data on both large and small scales. In the context of big data (Conway & O'Connor, 2016), investigators mine massive data sets of publicly accessible social-media posts, whereas in the context of smaller scale studies, users typically opt in to provide their social-media data (e.g., Reece & Danforth, 2017). The analysis of these social-media digital traces has rarely been applied to the study of emotion regulation specifically. However, given the potential for this type of data to provide detailed information on individuals' social contexts and emotional sentiments, it represents a promising tool to assess emotion-regulation processes.

One growing area of relevant research emphasizes the detection of signals of distress or negative affect within social-media data, and there is an increasing number of studies in which features of users' social-media data are analyzed to predict the presence of mental health disorders (for a review, see Chancellor & De Choudhury, 2020). Such studies typically employ machine-learning techniques (Shatte et al., 2019) to identify patterns across a range of features: the topics and style of language used in individuals' social-media posts; the frequency, volume, and timing of user interaction with the site (i.e., posts) and with other users (i.e., messages, comments); the brightness, content, and color patterns of posted images; and the valence, sentiment, and intensity of emotions expressed in posts, photo captions, and messages. Such features have significant promise for identifying emotion-regulation processes, including assessing the context in which an individual is employing a strategy, strategy selection, strategy implementation, and even strategy effectiveness.

In conjunction with other tools, such as EMA, social-media data can provide a real-time, objective snapshot of individuals' social and emotional lives as well as a portrait of how these factors change dynamically over time. In terms of situational context, social-media data can offer a window into individuals' social environments, showcasing the topics and emotional valence of users' communications with others (Ehrenreich et al., 2020). As a proxy for social engagement, the frequency and intensity of these communications can be assessed (Ehrenreich et al., 2020), as can the size and density of a user's social network (Stephens & Poorthuis, 2015). Social-media data sets are one of the few sources from which researchers can also gather objective information on the behavior of other people that make up the target individual's social context. Furthermore, social media may also be considered its own, unique social context (Nesi et al., 2018a, 2018b) in which individuals are embedded, and trace data provide information on the ways in which users navigate this often emotionally charged space.

Social-media data can provide key insights into users' emotional states through the analysis of text, photo, and even video content. Most commonly, natural-language-processing techniques are used to analyze the topics, word patterns, and structure of text elements in a user's data (Kern et al., 2016). Although one-time assessments of the emotional sentiment of users' data have been conducted in a number of studies, only recently have researchers begun to consider the dynamic processes that may underlie emotional expression on social media. This may be especially relevant for future applications to emotion regulation because the ability to detect changes in users' emotional experiences—either over time or in response to the use of specific regulation strategies—is a critical aspect of measuring regulatory flexibility and effectiveness. For example, in a recent study of Twitter and Facebook users, Seabrook et al. (2018) examined emotional instability over time by analyzing the use of positive and negative emotion words within status updates. Instability in the use of negative emotion words on Facebook was associated with greater depression severity on Facebook with medium effect sizes (r = .44), whereas the opposite pattern emerged for Twitter (r = .34). Work in the area of suicide detection via social-media data also has begun to consider dynamic changes in users' content over time, finding that shifts in language use and emotional expression may signal risk for suicide both in Twitter and Reddit data (Coppersmith et al., 2016; De Choudhury & Kiciman, 2017) and in text-message content (Glenn et al., 2020).

The ability to track users' social and emotional contexts over time via social media may offer key insights into users' implementation of regulatory strategies and the effectiveness of these strategies, particularly when combined with other assessment methods (e.g., EMA). For example, researchers might track changes in the valence or intensity of users' emotional expression on social media following self-reported use of various regulatory strategies. Furthermore, social-media data may allow for an examination of when and how users implement regulation strategies that may be specific to social media, or *digital emotion regulation* (Wadley et al., 2020). Preliminary work has aimed to examine broader coping styles on social media (Golbeck, 2016) and has reviewed the potential utility of social-media tools for emotion-regulation and coping purposes (Wadley et al., 2020; Wolfers & Schneider, 2021). Examining the content of users' requests for social support, for example, as well as the feedback that they receive on these posts or messages (Niven et al., 2015) may provide insight into the effectiveness of these strategies. Despite its promise, however, the application of objective social-media data to the assessment of state-specific changes in emotion-regulation processes remains understudied.

Smart-home technologies. Not surprisingly, multimodal analysis, combining and syncing multiple types of passive data, demonstrates even greater promise in accurately detecting emotion, strategy selection and implementation, modification, and effectiveness compared with unimodal analysis. One avenue for effective multimodal assessment is through smart-home technology. Smart-home devices enable the collection of information from multiple data streams through a single device. For example, visual data may be collected via cameras, audio data via microphones and smart speakers, and physical activity and sleep data via motion sensors. Smart-home technologies can also provide data on additional elements of the home environment, including lighting, temperature, and even websites visited. In a recent review, Nelson and Allen (2018) outlined the benefits of smart-home technology in comparison with other assessment methods. They noted that these technologies provide continuous, passive collection of ecologically valid, multimodal data, providing a third-person perspective in observing individuals' environments and behavior. Furthermore, these technologies can provide data on more than one individual (e.g., an entire family) simultaneously, expanding opportunities for assessment of the social and familial contexts (Fernández-Caballero et al., 2016). Although such technologies have traditionally been implemented in the home environment, one could also envision their implementation for assessment and intervention within health care facilities, schools, and other public areas; recent literature indicates that such technology may be extended to cars to assess emotion, promote regulation, and thus foster driver safety (Braun et al., 2020).

In the context of emotion-regulation research, smart-home devices have the potential to detect individuals' emotional state, regulation strategies implemented, and the effectiveness of such strategies. To date, only a small number of studies have incorporated smart-home technology to examine behavior change and cognitive health (for a review, see Nelson & Allen, 2018). Research on the use of smart-home technology explicitly for the assessment of emotion dynamics remains limited. However, given recent advances in the collection and analysis of lab-based and ambulatory visual, auditory, and physical activity data, the use of smart-home technologies, which extend and integrate these methods, will likely become a more common feature of emotion-regulation research.

Virtual reality. Virtual-reality technology simulates multisensory, interactive environments and can be used for assessment and intervention research across a range of physical (e.g., chronic pain; Mallari et al., 2019) and mental health problems (e.g., Breuninger et al., 2017). Computer graphics are integrated with sensory experiences to create an environment that mirrors the real world and allows individuals to interact and engage in real-world scenarios (Rizzo et al., 2013; Rus-Calafell et al., 2018). Low-cost, consumer-available, virtual-reality devices have been developed for mobile use outside of the lab, which extends the promise of the technology.

There are clear extensions of virtual-reality research to the study of emotion regulation. The use of virtual reality allows for the direct control and modulation of an emotional environment and thus is ideally suited when paired with other assessment tools to capture the complete regulation process. These tools have been used to directly assess an individual's behavior, physiological reactivity, or neurological responses to a given, predetermined emotional context (e.g., Breuninger et al., 2017; Lorenzetti et al., 2018). Tracking responses to varied virtual environments with a range of stressor or emotion intensities may provide insight into an individual's sensitivity to the environment and ability to detect emotional cues. In addition, presenting an individual with stressful or emotional scenarios via virtual-reality simulations may allow for direct assessment of emotion-regulation strategy selection across widely varied contexts. Although virtual-reality tools are constrained to predetermined contexts, they also allow researchers and clinicians to simulate contexts that may be rare or hard to replicate in daily life.

Other devices. Novel devices are continuing to be developed that may be well suited to capture the full spectrum of emotion-regulation processes. For example, as the field of epidermal electronics continues to develop, new possibilities for real-time assessment of stress and emotion regulation are emerging. There has been recent work in the development of wearable devices capable of microfluidic sampling (Bandodkar & Wang, 2014; Bariya et al., 2018; J. Kim et al., 2019). Indeed, ambulatory measurement of proinflammatory cytokines via skin patches has been found to be associated with depression (Cizza et al., 2008), which is notable insofar as inflammatory cytokine reactivity, in turn, has been linked with emotional stress (Shields et al., 2016). Other novel wearable devices, which may contain sensors to obtain physiological data or may be wirelessly enabled to sync with other digital devices, are also being rapidly developed. Such tools may include e-textiles (e.g., smart garments, including shirts and foot and hand wear), smart jewelry, smart eyewear (e.g., glasses and contact lenses), and even e-tattoos (Seneviratne et al., 2017). These devices are in their early stages, and thus additional research is needed both to improve these technologies and to realize their potential in the study of emotion regulation.

Digital Health Interventions for Emotion Regulation

Evidence-based psychosocial interventions for mental health problems emphasize, to varying degrees, learning emotion-regulation skills to manage distress and improve mood, daily functioning, and overall health. There is a proliferation of research on digital health interventions that shows significant promise for enhancing accessibility of mental health services and the ability to deliver support in real time. As individuals enter into contexts that may provoke negative emotions or increase the likelihood of risky behaviors, the aforementioned digital technologies offer an opportunity for personalized, timely intervention.

Ecological momentary interventions

Ecological momentary interventions (EMIs) are mobile-phone-delivered interventions that may serve as stand-alone or adjunctive treatments for a range of psychiatric and physical health problems. Formats may include preprogrammed text messages delivered at specific intervals (e.g., Ranney et al., 2014) or app-based content delivered at predetermined times or available over a window of time (e.g., Dahne et al., 2017; Stoll et al., 2017). These tools may be used both for monitoring (i.e., EMA) and for direct intervention by prompting users to engage in a specific skill, by offering a range of skills to choose from, or by providing psychoeducation and support. In addition, apps have been developed as an adjunct to traditional or Internet-delivered therapy. For example, in studies in which Internet-based treatment for social anxiety was examined, researchers added a smartphone app component to support exposures between sessions and found that using both the Internet-based intervention and adjunctive app resulted in significant reductions in social anxiety (Boettcher et al., 2018; Silk et al., 2020).

EMI tools have been employed across numerous populations and for the treatment or management of a wide range of problems (e.g., anxiety, Pramana et al., 2014; depression, Ranney et al., 2017, 2019; alcohol use, Stevenson et al., 2020; and many others). In addition to research-based digital interventions, free and low-cost smartphone apps are now widely available for general use for a range of disorders and problems, including apps for mood monitoring, relaxation and mindfulness, general well-being, and treating specific disorders (Bry et al., 2018; Wasil et al., 2019; Wisniewski et al., 2019). The efficacy and effectiveness of digital health tools compared with traditional in-person therapeutic approaches remain understudied. Feasibility and acceptability of digital health interventions is generally high; however, preliminary evidence suggests they are most effective when paired with other treatment modalities (Grist et al., 2017; Weisel et al., 2019).

Just-in-time adaptive interventions

Just-in-time adaptive interventions (JITAIs; El-Toukhy & Nahum-Shani, 2014; Nahum-Shani et al., 2015; Spruijt-Metz & Nilsen, 2014) are particularly relevant to intervening in the emotion-regulation process. JITAIs are interventions delivered in the moment in response to contextual cues indicating the need for regulation or support. The just-in-time aspect of these interventions means that individuals receive tailored intervention responses, both in terms of content delivered and time of delivery, based on cues assessed via ambulatory measures. The goals of the JITAI design are to identify when an individual needs to be delivered a skill or prompt and to do so adaptively according to the momentary needs and contexts of the individual (Nahum-Shani et al., 2015). Thus, these interventions may rely on both active and passive-sensing technologies, including sensors in smartphones or wearables, to detect the optimal window for delivering the optimal intervention component.

The use of JITAIs in psychological research is in its nascent stages, and the majority of studies to date have focused on health behavior change. JITAIs have been developed to intervene in mental health (e.g., schizophrenia, e.g., Firth & Torous, 2015; smoking cessation, e.g., Cerrada et al., 2017; Huh et al., 2021; McClernon & Roy Choudhury, 2013; sleep, e.g., Pulantara et al., 2018; and alcohol use, e.g., Gustafson et al., 2014). There are direct applications of JITAIs to emotion-regulation-focused interventions. The JITAI framework aligns well with the aforementioned models of emotion regulation, extending beyond the reach of session-based, skills-focused interventions to providing real-time, tailored support in the appropriate context and at the ideal time. A combination of both active (i.e., EMA) and passive data collection via digital technology opens the door for JITAIs to comprehensively assess an individual's emotional state and trigger interventions to regulate emotions across different contexts. Pairing passive-sensing data with in-the-moment interventions may assist in the treatment of psychiatric disorders. For example, Pramana and colleagues (2018) developed a mobile health treatment that prompts youths to engage in emotion-regulation skill use when they enter a geo-fenced area prespecified as anxiety provoking. Beyond using GPS to assess participant-endorsed contextual triggers, prior studies have also used GPS to assess hypothesized contextual triggers for risky behaviors (e.g., locations where sexual contact is likely, locations where there is greater access to drugs; Besoain et al., 2020) as well as a wide variety of established contextual stressors related to mental health (e.g., location-based assessments of community social economic status, crime rates, drug activity rates; Epstein et al., 2014; Kwan et al., 2019). Pairing geo-location with in-the-moment skill prompts offers an avenue for assessing and intervening in real time for a variety of psychological problems, including practicing exposures to anxiety-provoking settings, prompting behavioral activation, or reducing the likelihood of risk behaviors.

Ongoing tracking of an individual's emotional state and regulatory efforts may allow for JITAIs to continuously intervene, if needed, in the emotion-regulation process as it unfolds—determining when a strategy is effective and prompting other strategies if one approach is ineffective. JITAIs may also provide answers to critical questions regarding how and when to intervene with regard to emotion regulation: (a) Are tailored emotion-regulation interventions more effective than predetermined, skills-focused interventions? (b) If so, for whom and for what outcomes are they most effective? (c) If a broader emotion-regulation repertoire is more adaptive, can direct, tailored interventions expand individuals' emotion-regulation repertoire? (d) If so, what is the necessary and sufficient dosage of intervention to achieve the optimal repertoire? (e) Likewise, what combination of passive data collection is optimal to adequately determine the necessity and type of intervention needed? There is much promise in the future of JITAIs to both enhance the understanding of the emotion-regulation process and support individuals in improving their ability to effectively engage in regulation across contexts.

Promising research highlights the potential benefits of using passive assessments to inform the delivery of JITAIs. When considering the use of wearable devices to detect distress, complementary apps are needed to identify indications of distress in ambulatory psychophysiological data. Apps currently in development hint at the potential for advancement in this area. There is, for example, some preliminary work on app development involving individual-level HRV in which the app is calibrated to the individual's stress levels during a learning phase to determine thresholds for stress alerts and accompanying biofeedback (Maier et al., 2014; Reimer et al., 2020). Another recent study reflects the early potential of mobile EDA devices for monitoring and teaching emotion-regulation strategies in real-world environments. This pilot study evaluated an EDA sensor band worn over 3 months and paired with a smartphone app that provided a JITAI designed to reinforce the use of elements of cognitive behavior therapy and mindfulness taught during in-person sessions (Leonard et al., 2018). Specifically, whenever the sensor band detected EDA levels exceeding the individually predetermined threshold, it triggered an alert on the accompanying smartphone app to remind the user to engage in a coping skill. Although preliminary, this study found support for the acceptability and feasibility of the combination of EDA sensor band and smartphone app over a 3-month intervention period. Furthermore, Miri and colleagues (2018) developed the ER-in-the-Wild system, a framework for applying wearable technologies, emotion-regulation theory, haptics, and biofeedback to intervene in real time. They applied this framework to an intervention using a personalized breathing pacer to reduce anxiety; preliminary results implementing this technology in a controlled laboratory setting are promising (Miri et al., 2020).

Other intervention applications

Advancements in technology also have permitted the delivery of interventions without direct participant engagement. Systems that are capable of passively monitoring affective cues through visual, auditory, and physical activity data can also potentially provide direct intervention by adjusting the environment for an individual without actually prompting an individual to select and enact strategies themselves. Through changes in lighting and music, for example, smart-home technology may provide an opportunity to intervene in users' emotional state. Fernández-Caballero and colleagues (2016) outlined a framework for a "smart health environment" that detects and intervenes in regulating individuals' emotions. Specifically, they outlined integrated data streams (e.g., cameras to assess facial expressions and track behavior, body sensors to track physiological indices of arousal) that may serve as assessment tools for determining and then intervening with the valence, intensity, and duration of an individual's emotional state (Fernández-Caballero et al., 2016). Relatedly, in a recent study, a pilot test was conducted on a smart-toy intervention that delivered in-the-moment emotion-regulation support to preadolescents, and initial results supported the feasibility and acceptability of this device for emotion regulation (Theofanopoulou et al., 2019).

As discussed above, studies also support the use of virtual reality in the treatment of disorders marked by emotion dysregulation, including psychosis (e.g., Rus-Calafell et al., 2018), posttraumatic stress disorder (Deng et al., 2019; Gonçalves et al., 2012), and anxiety disorders (Benbow & Anderson, 2019; Chesham et al., 2018). With an emphasis on exposure-based treatment, virtual-reality interventions provide individuals with opportunities to practice regulation strategies in a wide range of contexts that may be difficult to simulate in the real world. Furthermore, there may even be opportunities for therapy to be automated in certain contexts and for certain populations using virtual-reality technology (e.g., Miloff et al., 2019), allowing for broader testing and dissemination of effective treatments.

In addition, there has been some debate over the possibility of incorporating patient-generated data (e.g., physiological monitoring via Apple watches or phones) into electronic medical records (Comstock, 2014). If indices of emotion dysregulation are identified over a period of time, which may indicate risk for or the onset of psychological distress, such data could allow for clinicians and physicians to track patients remotely and could signal a provider to initiate an appointment or check-in (Adams et al., 2017).

The future of digital health interventions is promising and presents an opportunity to deliver effective and timely interventions that may directly influence how people regulate emotions in response to their natural environments. Rigorous research is needed to demonstrate the efficacy and effectiveness of digital health interventions integrating passive-sensing tools and active intervention components to target emotion-regulation processes directly. It is also important to consider how emotion-regulation-focused JITAIs may contend with scenarios in which high negative emotions may be adaptive or preferred. Furthermore, because individuals' emotions and responses to those emotions may change depending on context, so may their motives for regulating emotional states (for a review, see Tamir, 2016). Many of the JITAIs described above offer some level of choice for participants once the intervention is cued—thus, participants could, in theory, ignore the alert from their smartphone or wristband if it were inappropriate to the situation. However, other interventions described above may be automatically triggered via smart-home devices, toys, or other passive tools. Whether these tools will be able to evolve such that they can differentiate between desired or necessary negative emotional states and undesirable or maladaptive emotional responses is an outstanding question. As this technology evolves, the ability to accurately assess context will be central to resolving these questions.

Limitations and Special Considerations

With the rise of active and passive data collection and intervention tools at researchers' and consumers' disposal comes important practical considerations as well as ethical and scientific challenges.

The first considerations that arise in relation to digital assessment and intervention tools are those of reliability and validity. When examining the potential of passive-sensing technologies, the questions of whether and how one can reliably detect the full range of emotion-regulation processes become critically important. Research on the use of wearable and smartphone sensing devices to assess emotion regulation has to contend with the complexity of the regulation process as it unfolds within an individual and the real-world context the individual is encountering. Given the noise present in continuous streams of passive data in an uncontrolled context, studies using both passive and active data collection will be important to move this field forward. Passive sensing of physiological arousal, for example, may pose particular challenges. Research using this technology will benefit from initially pairing it with active assessment tools as a step toward evaluating its reliability and validity. EMA reports of what individuals have been doing, what stressors they have encountered, how they are feeling, and what regulation strategies they have intentionally employed will help to inform the utility of these data. Another possibility is embedding some active assessment tools within passive-sensing tools. For example, some wristbands used for passive physiological data collection come equipped with buttons to indicate the occurrence of an event; thus, participants could be instructed to mark when they feel distressed or when they engage in regulation using the event button. Such integration may streamline the collection of important contextual data, permit the measurement of explicit emotion regulation, and ultimately improve the accuracy of these tools over time. Furthermore, consistent reporting of the strength of the association between these different assessment tools will be important to guide the understanding of their validity in the assessment of regulation efforts.

In addition, a single assessment tool may provide indications of multiple components of the emotion-regulation process. As digital methods become increasingly sophisticated, the interpretation of these massive quantities of data requires careful thought and consideration. For some tools, extracting separate indices of context, strategy selection, and implementation effectiveness may be relatively straightforward. For example, social-media data can provide contextual information about who a person is interacting with, but in addition, the quality or valence of what is shared on social media may provide information about the strategy selected. However, for other tools, this may be less clear. That is, the utility of detecting emotion regulation relies also on the ability to detect an emotional state, and whether some tools can do this effectively remains a source of considerable debate. For example, recent work from Barrett and colleagues (2019) highlights the challenges of detecting emotions from facial expressions alone given that efforts to use computer vision or artificial intelligence technology to decode emotions may miss the nuances of intraindividual, situational, and cultural variability in emotional expression.

To give another example, GPS alone cannot measure explicit emotion-regulation strategy selection, implementation, or effectiveness without concurrently assessing regulatory intentions through active data collection methods. Likewise, analysis of deep breathing patterns highlights the challenges of differentiating between aspects of the emotion-regulation process with a single source of passively collected digital data—given that the detection of changing breathing patterns could be a possible indication of strategy selection, identification, and/or modification. With regard to social media, detecting digital trace data that reflect an individual's emotional state or social context does not, on its own, constitute measurement of emotion regulation; rather, it may provide only one piece of a larger puzzle requiring multiple assessment tools and data streams. Collectively, these considerations point to the importance and unique potential for the use of multiple technologies in concert to provide greater clarity regarding emotion regulation in the real world than is possible with any single technology alone.

Another set of critical considerations is of practicality and feasibility. For wearable, smartphone, and other technological devices to yield value in real-world settings, several important questions need to be considered. Assuming that reliability and validity have been demonstrated, questions related to length of usage become relevant to a device's practicability. These include the following: (a) How long can the device feasibly be used before it or one of its components needs to be replaced? (b) How long does a full battery charge typically last? (c) If the device is rechargeable, how long does it take to return it to full charge? (d) Do the data stay stored on a chip in the device until manually downloaded, or are they regularly uploaded to the cloud? If the former, how long can data be stored before the memory on the device becomes full? If the latter, how often does this occur, and how large is the temporal lag between data collection and data upload? (e) At what temporal resolution are the data collected and/or presented, and does this align with the temporal dynamics of emotion-regulation processes? (f) Is the device resistant to water and other potential damage? (g) Finally, how physically appealing or unappealing is the device? This last consideration is not a trivial one because no matter how impressive the operational features of a device may be, if it is bulky, uncomfortable, or otherwise physically unappealing, adherence to device usage by the end user (i.e., patient or research participant) becomes a concern, especially in the case of adolescent and young adult populations.

Other questions concern the technology itself and the extent to which technologies are evolving over time. New wearable devices and smartphone apps emerge continually, and the popularity of specific devices and platforms can shift over time. Within a single device or platform, the data structure and elements that may be extracted may also shift over time because they are not under the control of researchers using them. This creates new challenges in attempts to collect, manage, and ultimately analyze these complex data sets.

Another challenge that arises in the use of digital tools is that of security, privacy, and confidentiality. In many cases, digital tools allow for the collection of big data, or massive, complex data sets that require the use of new computational tools for analysis. The availability of big data invites the question of how researchers or providers will ensure that these data are secure. Mechanisms have been developed to protect big data through the process of data collection, storage, and processing (Jain et al., 2016), and recommendations have been put forth by researchers to ensure the safety of participants' social-media data, including staying up to date on each platform's terms and conditions regarding data privacy (e.g., Arigo et al., 2018). Relatedly, some technologies may inadvertently collect data on other individuals in the environment who have not given consent for such data to be collected and analyzed. For example, when considering collecting acoustic data in a real-world setting, concerns may arise regarding consent because several states require two-party consent to have conversations recorded. An added challenge in this domain is often researchers' lack of expertise or technical knowledge. In addition, protecting individuals' confidentiality remains complex in the collection of digital data. For example, even when data collected from these sources are deidentified, certain types of data may be easy to reidentify (e.g., photos, IP addresses, geo-location). An additional concern is the fact that many digital devices (e.g., wearables, smartphones) are commercial products. These products may be subject to data breaches and security issues outside of the control of the researcher or provider.

Perhaps some of the most complex considerations in the use of digital technology are ethical ones. First, there is the issue of consent (Moreno et al., 2013). The collection and analysis of digital data can often be done without first obtaining consent because data sets are often publicly available. For example, publicly posted content on social-media sites (e.g., Twitter, YouTube, Reddit) can often be downloaded directly through the use of the sites' application programing interface. Questions have arisen around the ethics of using such data. Should users need to consent to the use of their publicly available data? Does this research classify as human subjects research and thus necessitate approval from an institutional review board? Furthermore, the extent to which users of social-media apps and pages understand what they are consenting to when they create a user profile with regard to data safety and privacy is highly variable (Bart et al., 2014). This may be especially true for minors, who may legally sign up for many social-media sites as early as age 13 and may not fully appreciate the availability of their data to the public. Social-media and digital-device companies may often sell aspects of users' data for financial gain. What are the implications of researchers accessing such data? And does the same standard of consent apply to these data as in traditional clinical research?

Significant ethical concerns also exist regarding the risk of racial bias in how these technologies are developed and implemented. There is emerging research that suggests that facial-recognition systems demonstrate bias toward the misidentification of Black individuals, which poses a real threat as these technologies are adopted in real-world settings (Garvie & Frankle, 2016). This may further put Black people and other people of color at risk in the context of research and clinical studies that use facial-recognition technology for deidentification of visual data. Similar racial biases have been identified in other health care related technologies, such as using algorithms to detect medical risk using electronic health record information (e.g., Parikh et al., 2019). The advent of advanced technological and statistical approaches to use large streams of passive data collection comes with a responsibility for researchers to actively seek to use inclusive samples from which to develop and apply these algorithms; furthermore, it highlights the importance of including racially and ethnically diverse scientists in the development of these methods.

Finally, advancements in the accuracy of passive-sensing technologies raise questions regarding researchers' and clinicians' responsibility if the resultant data reveal that a participant might be at elevated risk. At what point is an intervention necessary, and in some cases, at what point is breaking confidentiality necessary? These ethical questions become more complex when considering how responsibility may shift depending on the sources of the data (i.e., publicly available data vs. data from participants enrolled in a study or patients using digital health interventions). We recommend that researchers and clinicians alike consider these questions carefully before using these technologies for emotion-regulation research. We direct readers to the Connected and Open Research Ethics (Torous & Nebeker, 2017), a resource for researchers and stakeholders to share and discuss ethical practices related to the use of passive-sensing technologies.

Summary and Future Directions

For decades, researchers have asked the question of how we can help individuals most effectively regulate emotions. At the core of emotion-regulation research is the idea that if we can improve individuals' emotional responses in their daily lives, we can promote psychological health and reduce negative psychological outcomes. The deployment of the digital tools outlined in this review will undoubtedly improve the conceptual understanding of how emotion regulation is learned and how it unfolds across development. This, in turn, will inform how we develop, refine, and implement interventions that target the various components of the emotion-regulation process beyond traditional psychotherapy approaches employed to date.

At the broadest level, research shows that difficulties in emotion regulation are associated with a multitude of psychological outcomes. To move the field toward understanding how the process unfolds, rigorously designed, theory-driven studies are needed. The digital tools outlined in this review may be one answer to unpacking how individuals regulate emotions in their daily lives. The potential utility of these data for assessing these processes is considerable: Passive sensing tools may allow for scalable and accessible assessment tools that may be effectively translated into real-time interventions for users. Furthermore, they allow for time-sensitive, passive data collection that can provide objective measurement of complex processes. However, although many of these technologies are both novel and exciting, it is equally important that we be critical of what can be drawn from them. Indeed, there is much work to be done to best understand how to employ these tools to validly capture the emotion-regulation process. Some of the tools described above may provide a wealth of information to inform how we assess and teach skills to manage emotions across the life span, whereas others may prove to be less valuable. Multimethod studies, perhaps incorporating qualitative and quantitative approaches, may provide insight into the specific indicators drawn from these large data streams that are most relevant for understanding emotion-regulation processes. Furthermore, incorporation of both passive assessment approaches with more active approaches, as described above, will allow for both subjective and objective assessment of an individual's emotion-regulation experience. Such studies may provide needed context for interpreting passively collected data and have the potential to help to move clinical translational work in this area forward.

The large amount of data that can be drawn from both active and passive technologies described in this review also highlights the necessity of using a team science approach in emotion-regulation research.

Beyond the technology itself, the application of digital technology to emotion-regulation research extends beyond the individual level. These devices may be particularly useful for advancing the understanding of regulation in various social contexts and across development. When considering the development of emotion regulation in children and adolescents, the family context becomes especially relevant. When worn or used by multiple members in a family at the same time, particularly caregiver–child dyads, data from wearable and smartphone devices may shed light on coregulation processes. Furthermore, these technologies are ideally suited to the study of emotion-regulation socialization, or the process by which a child learns how to regulate emotions on the basis of interactions with their caregivers (Hajal et al., 2020). For example, in a recent study, mother-child dyads' physical activity and emotional state were monitored over a 7-day window, and results demonstrated associations not only between an individual's physical activity and the individual's own affective state but also between an individual's physical activity and the affective states of others (Yang et al., 2020). For children in particular, this finding points to an important consideration regarding how influences outside the individual (e.g., parental) may influence one's affective state and how novel methods outlined in this review may inform the knowledge of this developmental process. Recent work developing a device worn by both caregivers and their very young children, the TotTag, highlights the potential for identifying how emotion-regulation capacity develops from infancy through adulthood by measuring proximity to caregivers (Salo et al., 2020). Enhancing the knowledge of emotion regulation in the family system, as well as across other key social contexts (e.g., peer and romantic relationships), is an exciting area for future research using the tools described in this review.

In this review, we largely focus on how these tools may be applied in the context of experiencing stressful or arousing situations and thus how they may aid in down-regulating negative emotional experiences. Indeed, with regard to research on mental health and emotion regulation, much attention has been paid to how to reduce negative affect to improve psychological outcomes. Yet individuals experience a range of both positive and negative emotions on a daily basis both in and outside the context of a stressful event. In some instances, the up-regulation of positive emotional experiences may be equally or more important than the down-regulation of negative emotions. The digital tools discussed in this review also have the potential to inform the understanding of regulation in the context of positive experiences and emotions. Several EMA studies have taken this approach, studying both positive and negative affect regulation in daily life (e.g., Bosley et al., 2020; Troy et al., 2019), whereas passive-sensing approaches have primarily targeted the assessment of negative emotional states. The potential value of capturing the context and regulation of positive affective states for in-the-moment intervention delivery is clear—understanding not only when individuals are struggling but also when they are doing well can inform what type of intervention may be most useful to deliver. It is also important to consider that strategies to reduce negative affect may differ from those that are effective at enhancing positive affect. The methods described above can help to answer these critical questions and provide important insight into the full range of emotion regulation in individuals' daily lives.

Finally, there is immense opportunity to enhance the quality of emotion-regulation interventions and expand their reach to populations with limited access to mental health care resources through digital intervention delivery tools.

First, advancements in emotion-regulation assessment offer the potential for refining and developing novel intervention approaches to improve individuals' emotion-regulation responses. Because emotion-regulation processes underlie many psychological symptoms and disorders, the ability to more accurately target this mechanism could greatly improve both prevention programs and treatments for psychological problems. An exciting area of future research is in personalized treatment approaches targeting these processes. As these digital assessment tools and the understanding of the data they collect become more sophisticated, so will the ability to provide truly individualized treatments and to prescribe the appropriate intervention given a presentation of emotion-regulation deficits or difficulties. Indeed, emotion-regulation interventions may be further improved by taking an idiographic approach, a burgeoning area of interest in both mental health assessment and intervention.

Second, new models of mental health treatment are needed that move beyond traditional weekly psychotherapy (Schleider et al., 2020). The ethical and practical challenges outlined above notwithstanding, these digital tools could radically change the mental health service landscape. Mental health service utilization in the United States is low (e.g., Merikangas et al., 2011; Mojtabai et al., 2011), and there are many well-documented barriers to accessing care, including cost/insurance coverage, transportation, attitudes toward mental health, and availability of providers. Digital health has the ability to address many of these barriers directly. These tools may be especially important to consider in the context of mental health prevention because large numbers of individuals may be reached via digital health tools before the onset of mental illness. Considering a stepped-care approach, digital tools that directly target emotion regulation, such as stand-alone skills-based apps or single-session online interventions, may be one feasible and accessible frontline approach for patients with low levels of difficulties or symptoms. Rigorous and collaborative research is needed to determine both the utility of these digital technologies for altering emotion-regulation processes and the ways in which these methods may be implemented in health care systems and communities effectively.

Conclusion

Exciting developments in digital technology offer exciting new avenues for the study of emotion-regulation processes. Guided by theory in emotion regulation, we find that data drawn from these tools, including EMA, wearable and smartphone devices, smart-home devices, virtual reality, and social media, have great potential to inform the understanding of how people regulate emotions in their daily life. Although there are numerous ethical and practical challenges that require thoughtful consideration before embarking on this type of research, there is also opportunity for enormous growth in the field of emotion regulation through the use of these methods.

Transparency

Action Editor: Aidan G. C. Wright
Editor: Kenneth J. Sher
Author Contributions
A. H. Bettis formulated the idea for the conceptual review manuscript and contributed to writing, editing, and revising the manuscript. T. A. Burke, J. Nesi, and R. T. Liu contributed to refining the conceptual review idea and writing, editing, and revising the manuscript. All of the authors approved the final manuscript for submission.
Declaration of Conflicting Interests
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.
Funding
A. H. Bettis is supported by the American Psychological Foundation John & Polly Sparks Early Career Grant, a Klingenstein Foundation Access to Care Fellowship grant, and National Institute of Mental Health (NIMH) Grant K23-MH122737. T. A. Burke is supported by NIMH Grant T32-MH019927. J. Nesi is supported by the NIMH Grant K23-MH122669 and by American Foundation for Suicide Prevention Grant PDF-010517. R. T. Liu is supported by NIMH Grants RF1-MH120830, R01-MH101138, and R01-MH115905. The granting agencies had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; or decision to submit the manuscript for publication. The content is solely the responsibility of the authors.

ORCID iDs

Alexandra H. Bettis https://orcid.org/0000-0002-4442-4951
Taylor A. Burke https://orcid.org/0000-0001-8816-1463
Jacqueline Nesi https://orcid.org/0000-0001-5869-6360

Note

1. More long-term options are also available, including implantable devices with the ability to monitor ECG data for up to 2 or 3 years (e.g., implantable loop recorders, pacemakers, and Reveal LINQ Insertable Cardiac Monitors). Given the invasive nature of these devices and substantially greater associated costs (Fung et al., 2015), however, they may be more warranted in medical contexts in which close monitoring of severe heart conditions is the focus of concern. Therefore, we have chosen to focus on the applicability of noninvasive devices to emotion-regulation assessment and intervention.

References

Adams, Z., McClure, E. A., Gray, K. M., Danielson, C. K., Treiber, F. A., & Ruggiero, K. J. (2017). Mobile devices for the remote acquisition of physiological and behavioral biomarkers in psychiatric clinical research. *Journal of Psychiatric Research*, *85*, 1–14.

Aldao, A. (2013). The future of emotion regulation research: Capturing context. *Perspectives on Psychological Science*, *8*, 155–172. https://doi.org/10.1177/1745691612459518

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*, 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Aldao, A., Sheppes, G., & Gross, J. J. (2015). Emotion regulation flexibility. *Cognitive Therapy and Research*, *39*, 263–278. https://doi.org/10.1007/s10608-014-9662-4

Aldrich, J. T., Lisitsa, E., Chun, S. K., & Mezulis, A. H. (2019). Examining the relationship between daily co-rumination and rumination in response to negative events among adolescents using ecological momentary assessment. *Journal of Social and Clinical Psychology*, *38*, 704–719. https://doi.org/10.1521/jscp.2019.38.7.704

Anderson, M., & Jiang, J. (2018). *Teens, social media, & technology*. Pew Research Center. https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/

Arigo, D., Pagoto, S., Carter-Harris, L., Lillie, S. E., & Nebeker, C. (2018). Using social media for health research: Methodological and ethical considerations for recruitment and intervention delivery. *Digital Health*, *4*. https://doi.org/10.1177/2055207618771757

Bandodkar, A. J., & Wang, J. (2014). Non-invasive wearable electrochemical sensors: A review. *Trends in Biotechnology*, *32*, 363–371. https://doi.org/10.1016/j.tibtech.2014.04.005

Bardeen, J. R., & Daniel, T. A. (2017). An eye-tracking examination of emotion regulation, attentional bias, and pupillary response to threat stimuli. *Cognitive Therapy and Research*, *41*, 853–866. https://doi.org/10.1007/s10608-017-9860-y

Bariya, M., Nyein, H. Y. Y., & Javey, A. (2018). Wearable sweat sensors. *Nature Electronics*, *1*, 160–171. https://doi.org/10.1038/s41928-018-0043-y

Barrett, L. F., Adolphs, R., Martinez, A., Marsella, S., & Pollak, S. (2019). Emotional expressions reconsidered:

Challenges to inferring emotion in human facial movements. *Psychological Science in the Public Interest*, *20*(1), 1–68. https://doi.org/10.1177/1529100619832930

Bart, C., Simone, V., der, H., & Bart, S. (2014). Privacy expectations of social media users: The role of informed consent in privacy policies. *Policy and Internet*, *6*(3), 268–295. https://doi.org/10.1002/1944-2866.POI366

Beauchaine, T. (2001). Vagal tone, development, and Gray' s motivational theory: Toward an integrated model of autonomic nervous system functioning in psychopathology. *Development and Psychopathology*, *13*, 183–214.

Beauchaine, T. P., & Thayer, J. F. (2015). Heart rate variability as a transdiagnostic biomarker of psychopathology. *International Journal of Psychophysiology*, *98*, 338–350. https://doi.org/10.1016/j.ijpsycho.2015.08.004

Benbow, A. A., & Anderson, P. L. (2019). A meta-analytic examination of attrition in virtual reality exposure therapy for anxiety disorders. *Journal of Anxiety Disorders*, *61*, 18–26. https://doi.org/10.1016/j.janxdis.2018.06.006

Benedek, M., & Kaernbach, C. (2010). A continuous measure of phasic electrodermal activity. *Journal of Neuroscience Methods*, *190*, 80–91. https://doi.org/10.1016/j.jneumeth.2010.04.028

Besoain, F., Perez-Navarro, A., Aviño, C. J., Caylà, J. A., Barriga, M. A., & Garcia de Olalla, P. (2020). Prevention of HIV and other sexually transmitted infections by geofencing and contextualized messages with a Gamified App, UBESAFE: Design and creation study. *JMIR MHealth and UHealth*, *8*(3), Article e14568. https://doi.org/10.2196/14568.

Bettis, A. H., Henry, L., Prussien, K. V., Vreeland, A., Smith, M., Adery, L. H., & Compas, B. E. (2019). Laboratory and self-report methods to assess reappraisal and distraction in youth. *Journal of Clinical Child and Adolescent Psychology*, *48*(6), 855–865. https://doi.org/10.1080/15374416.2018.1466306

Birk, J. L., & Bonanno, G. A. (2016). When to throw the switch: The adaptiveness of modifying emotion regulation strategies based on affective and physiological feedback. *Emotion*, *16*, 657–670. https://doi.org/10.1037/emo0000157

Blanke, E. S., Brose, A., Kalokerinos, E. K., Erbas, Y., Riediger, M., & Kuppens, P. (2020). Mix it to fix it: Emotion regulation variability in daily life. *Emotion*, *20*(3), 473–485. https://doi.org/10.1037/emo0000566

Boettcher, J., Magnusson, K., Marklund, A., Berglund, E., Blomdahl, R., Braun, U., Delin, L., Lundén, C., Sjöblom, K., Sommer, D., von Weber, K., Andersson, G., & Carlbring, P. (2018). Adding a smartphone app to internet-based self-help for social anxiety: A randomized controlled trial. *Computers in Human Behavior*, *87*, 98–108. https://doi.org/10.1016/j.chb.2018.04.052

Bonanno, G. A., & Burton, C. L. (2013). Regulatory flexibility: An individual differences perspective on coping and emotion regulation. *Perspectives on Psychological Science*, *8*, 591–612. https://doi.org/10.1177/1745691613504116

Braun, M., Weber, F., & Alt, F. (2020). *Affective automotive user interfaces – Reviewing the state of emotion regulation in the car*. ArXiv. https://arxiv.org/abs/2003.13731

Bosley, H. G., Sandel, D. B., & Fisher, A. J. (2020). Idiographic dynamics of positive affect in GAD: Modeling emotion regulation at the person level. *European Journal of Psychological Assessment*, *36*(3), 500–509. https://doi.org/10.1027/1015-5759/a000580

Braunstein, L. M., Gross, J. J., & Ochsner, K. N. (2017). Explicit and implicit emotion regulation: A multi-level framework. *Social Cognitive and Affective Neuroscience*, *12*, 1545–1557.

Breuninger, C., Sláma, D. M., Krämer, M., Schmitz, J., & Tuschen-Caffier, B. (2017). Psychophysiological reactivity, interoception and emotion regulation in patients with agoraphobia during virtual reality anxiety induction. *Cognitive Therapy and Research*, *41*, 193–205. https://doi.org/10.1007/s10608-016-9814-9

Bry, L. J., Chou, T., Miguel, E., & Comer, J. S. (2018). Consumer smartphone apps marketed for child and adolescent anxiety: A systematic review and content analysis. *Behavior Therapy*, *49*, 249–261.

Burr, D. A., Castrellon, J. J., Zald, D. H., & Samanez-Larkin, G. R. (2021). Emotion dynamics across adulthood in everyday life: Older adults are more emotionally stable and better at regulating desires. *Emotion*, *21*(3), 453–464. https://doi.org/10.1037/emo0000734

Carr, C. T., & Hayes, R. A. (2015). Social media: Defining, developing, and divining. *Atlantic Journal of Communication*, *23*, 46–65.

Carter, T., Morres, I. D., Meade, O., & Callaghan, P. (2016). The effect of exercise on depressive symptoms in adolescents: A systematic review and meta-analysis. *Journal of the American Academy of Child and Adolescent Psychiatry*, *55*, 580–590. https://doi.org/10.1016/j.jaac.2016.04.016

Carver, C. S., Scheier, M. F., & Weintraub, J. K. (1989). Assessing coping strategies: A theoretically based approach. *Journal of Personality and Social Psychology*, *56*, 267–283.

Case, M. A., Burwick, H. A., Volpp, K. G., & Patel, M. S. (2015). Accuracy of smartphone applications and wearable devices for tracking physical activity data. *JAMA*, *313*, 625–626. https://doi.org/10.1001/jama.2014.17841

Cerrada, C. J., Dzubur, E., Blackman, K. C. A., Mays, V., Shoptaw, S., & Huh, J. (2017). Development of a just-in-time adaptive intervention for smoking cessation among Korean American emerging adults. *International Journal of Behavioral Medicine*, *24*, 665–672.

Chancellor, S., & De Choudhury, M. (2020). Methods in predictive techniques for mental health status on social media: A critical review. *NPJ Digital Medicine*, *3*, Article 43. https://doi.org/10.1038/s41746-020-0233-7

Chesham, R. K., Malouff, J. M., & Schutte, N. S. (2018). Meta-analysis of the efficacy of virtual reality exposure therapy for social anxiety. *Behaviour Change*, *35*, 152–166. https://doi.org/10.1017/bec.2018.15

Chow, P. I., Fua, K., Huang, Y., Bonelli, W., Xiong, H., Barnes, L. E., & Teachman, B. A. (2017). Using mobile sensing to test clinical models of depression, social anxiety, state affect, and social isolation among college students. *Journal of Medical Internet Research*, *19*(3), Article e62. https://doi.org/10.2196/jmir.6820

Cizza, G., Marques, A. H., Eskandari, F., Christie, I. C., Torvik, S., Silverman, M. N., Phillips, T. M., & Sternberg, E. M. (2008). Elevated neuroimmune biomarkers in sweat patches and plasma of premenopausal women with major depressive disorder in remission: The POWER Study. *Biological Psychiatry*, *64*, 907–911. https://doi.org/10.1016/j.biopsych.2008.05.035

Compas, B. E., Jaser, S. S., Bettis, A. H., Watson, K. H., Gruhn, M. A., Dunbar, J. P., Williams, E., & Thigpen, J. C. (2017). Coping, emotion regulation, and psychopathology in childhood and adolescence: A meta-analysis and narrative review. *Psychological Bulletin*, *143*, 939–991. https://doi.org/10.1037/bul0000110

Comstock, J. (2014, October 15). Will patient-generated data from HealthKit reshape the EMR. *MobiHealth News*. https://www.mobihealthnews.com/37417/will-patient-generated-data-from-healthkit-reshape-the-emr

Connolly, S. L., & Alloy, L. B. (2017). Rumination interacts with life stress to predict depressive symptoms: An ecological momentary assessment study. *Behaviour Research and Therapy*, *97*, 86–95.

Connor-Smith, J., Compas, B. E., Wadsworth, M. E., Thomsen, A. H., & Saltzman, H. (2000). Responses to stress in adolescence: Measurement of coping and involuntary stress responses. *Journal of Consulting and Clinical Psychology*, *68*, 976–992.

Conway, M., & O'Connor, D. (2016). Social media, big data, and mental health: Current advances and ethical implications. *Current Opinion in Psychology*, *9*, 77–82.

Coppersmith, G., Ngo, K., Leary, R., & Wood, A. (2016). Exploratory analysis of social media prior to a suicide attempt. In K. Hollingshead & L. Ungar (Eds.), *Proceedings of the Third Workshop on Computational Linguistics and Clinical Psychology* (pp. 106–117). Association for Computational Linguistics. https://doi.org/10.18653/v1/W16-0311

Crowell, S. E., Beauchaine, T. P., Cauley, E. M., Smith, C. J., Stevens, A. L., & Sylvers, P. (2005). Psychological, autonomic, and serotonergic correlates of parasuicide among adolescent girls. *Development and Psychopathology*, *17*(4), 1105–1127. https://doi.org/10.1017/s0954579405050522

Dahne, J., Lejuez, C. W., Kustanowitz, J., Felton, J. W., Diaz, V. A., Player, M. S., & Carpenter, M. J. (2017). Moodivate: A self-help behavioral activation mobile app for utilization in primary care—Development and clinical considerations. *International Journal of Psychiatry in Medicine*, *52*, 160–175. https://doi.org/10.1177/0091217417720899.Moodivate

Dan-Glauser, E. S., & Gross, J. J. (2011). The temporal dynamics of two response-focused forms of emotion regulation: Experiential, expressive, and autonomic consequences. *Psychophysiology*, *48*, 1309–1322. https://doi.org/10.1111/j.1469-8986.2011.01191.x

Daniel, K. E., Baee, S., Boukhechba, M., Barnes, L. E., & Teachman, B. A. (2019). Do I really feel better? Effectiveness of emotion regulation strategies depends on the measure and social anxiety. *Depression and Anxiety*, *36*, 1182–1190. https://doi.org/10.1002/da.22970

De Choudhury, M., & Kiciman, E. (2017). The language of social support in social media and its effect on suicidal ideation risk. *Proceedings of the International AAAI Conference on Weblogs and Social Media*, *2017*, 32–41

Deng, W., Hu, D., Xu, S., Liu, X., Zhao, J., Chen, Q., Liu, J., Zhang, Z., Jiang, W., Ma, L., Hong, X., Cheng, S., Liu, B., & Li, X. (2019). The efficacy of virtual reality exposure therapy for PTSD symptoms: A systematic review and meta-analysis. *Journal of Affective Disorders*, *257*, 698–709. https://doi.org/10.1016/j.jad.2019.07.086

Dixon-Gordon, K. L., Aldao, A., & De Los Reyes, A. (2015). Emotion regulation in context: Examining the spontaneous use of strategies across emotional intensity and type of emotion. *Personality and Individual Differences*, *86*, 271–276. https://doi.org/10.1016/j.paid.2015.06.011

Ehrenreich, S. E., Beron, K. J., Burnell, K., Meter, D. J., & Underwood, M. K. (2020). How adolescents use text messaging through their high school years. *Journal of Research on Adolescence*, *30*, 521–540.

El-Sheikh, M., Kouros, C. D., Erath, S., Cummings, E. M., Keller, P., & Staton, L. (2010). Marital conflict and children's externalizing behavior: Pathways involving interactions between parasympathetic and sympathetic nervous system activity. *Monographs of the Society for Research in Child Development*, *74*, 1–66. https://doi.org/10.1111/j.1540-5834.2009.00501.x.Marital

El-Toukhy, S., & Nahum-Shani, I. (2014). The JITAI Code: A primer on just-in-time-adaptive interventions. *Wiley StatsRef: Statistics Reference Online*. https://doi.org/10.1002/9781118445112.stat08192

Enewoldsen, N. M., Noordzij, M. L., Pieterse, M. E., & van Lier, H. G. (2016). *Analysis of the quality of electrodermal activity and heart rate data recorded in daily life over a period of one week with an E4 wristband* [Unpublished bachelor's thesis], University of Twente.

Engel, J. M., Mehta, V., Fogoros, R., & Chavan, A. (2012). Study of arrhythmia prevalence in NUVANT mobile cardiac telemetry system patients. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (pp. 2440–2443). https://doi.org/10.1109/EMBC.2012.6346457

Epstein, D. H., Tyburski, M., Craig, I. M., Phillips, K. A., Jobes, M. L., Vahabzadeh, M., Mezghanni, M., Lin, J. L., Furr-Holden, C. D. M., & Preston, K. L. (2014). Real-time tracking of neighborhood surroundings and mood in urban drug misusers: Application of a new method to study behavior in its geographical context. *Drug and Alcohol Dependence*, *134*, 22–29. https://doi.org/10.1016/j.drugalcdep.2013.09.007

Fernández-Caballero, A., Martínez-Rodrigo, A., Pastor, J. M., Castillo, J. C., Lozano-Monasor, E., López, M. T., Zangróniz, R., Latorre, J. M., & Fernández-Sotos, A. (2016). Smart environment architecture for emotion detection and regulation. *Journal of Biomedical Informatics*, *64*, 55–73.

Firth, J., & Torous, J. (2015). Smartphone apps for schizophrenia: A systematic review. *JMIR MHealth and UHealth*, *3*(4), Article e102. https://doi.org/10.2196/mhealth.4930

Fletcher, R. R., Dobson, K., Goodwin, M. S., Eydgahi, H., Wilder-Smith, O., Fernholz, D., Kuboyama, Y., Hedman,

E. B., Poh, M. Z., & Picard, R. W. (2010). ICalm: Wearable sensor and network architecture for wirelessly communicating and logging autonomic activity. *IEEE Transactions on Information Technology in Biomedicine*, *14*, 215–223. https://doi.org/10.1109/TITB.2009.2038692

Fung, E., Järvelin, M. R., Doshi, R. N., Shinbane, J. S., Carlson, S. K., Grazette, L. P., Chang, P. M., Sangha, R. S., Huikuri, H. V., & Peters, N. S. (2015). Electrocardiographic patch devices and contemporary wireless cardiac monitoring. *Frontiers in Physiology*, *6*, Article 149. https://doi.org/10.3389/fphys.2015.00149

Garvie, C., & Frankle, J. (2016, April 7). Facial-recognition software might have a racial bias problem. *The Atlantic*. https://www.theatlantic.com/technology/archive/2016/04/the-underlying-bias-of-facial-recognition-systems/476991/

Glenn, J. J., Nobles, A. L., Barnes, L. E., & Teachman, B. A. (2020). Can text messages identify suicide risk in real time? A within-subjects pilot examination of temporally sensitive markers of suicide risk. *Clinical Psychological Science*, *8*, 704–722.

Golbeck, J. (2016). Detecting coping style from Twitter. In E. Spiro & Y.-Y. Ahn (Eds.), *Social Informatics: 8th International Conference, SocInfo 2016* (pp. 454–467). Springer. https://doi.org/10.1007/978-3-319-47880-7_28

Goldschmidt, A. B., Wonderlich, S. A., Crosby, R. D., Engel, S. G., Lavender, J. M., Peterson, C. B., Crow, S. J., Cao, L., & Mitchell, J. E. (2014). Ecological momentary assessment of stressful events and negative affect in bulimia nervosa. *Journal of Consulting and Clinical Psychology*, *82*, 30–39. https://doi.org/10.1037/a0034974

Gonçalves, R., Pedrozo, A. L., Coutinho, E. S. F., Figueira, I., & Ventura, P. (2012). Efficacy of virtual reality exposure therapy in the treatment of PTSD: A systematic review. *PLOS ONE*, *7*(12), Article e48469. https://doi.org/10.1371/journal.pone.0048469

Grist, R., Porter, J., & Stallard, P. (2017). Mental health mobile apps for preadolescents and adolescents: A systematic review. *Journal of Medical Internet Research*, *19*, Article e176. https://doi.org/10.2196/jmir.7332

Grommisch, G., Koval, P., Hinton, J. D. X., Gleeson, J., Hollenstein, T., Kuppens, P., & Lischetzke, T. (2020). Modeling individual differences in emotion regulation repertoire in daily life with multilevel latent profile analysis. *Emotion*, *20*(8), 1462–1474. https://doi.org/10.1037/emo0000669

Gross, J. J. (2015). Emotion regulation: Current status and future prospects. *Psychological Inquiry*, *26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781

Gross, J. J., & Thompson, R. A. (2007). Emotion regulation: Conceptual foundations. In J. J. Gross (Ed.), *Handbook of emotion regulation* (p. 3–24). The Guilford Press.

Gustafson, D. H., McTavish, F. M., Chih, M. Y., Atwood, A. K., Johnson, R. A., Boyle, M. G., Levy, M. S., Driscoll, H., Chisholm, S. M., Dillenburg, L., Isham, A., & Shah, D. (2014). A smartphone application to support recovery from alcoholism: A randomized clinical trial. *JAMA Psychiatry*, *71*(5), 566–572.

Hajal, N. J., & Paley, B. (2020). Parental emotion and emotion regulation: A critical target of study for research and intervention to promote child emotion socialization. *Developmental Psychology*, *56*(3), 403–417. https://doi.org/10.1037/dev0000864

Hammen, C. (2005). Stress and depression. *Annual Review of Clinical Psychology*, *1*, 293–319.

Huh, J., Cerrada, C. J., Dzubur, E., Dunton, G. F., Spruijt-Metz, D., & Leventhal, A. M. (2021). Effect of a mobile just-in-time implementation intention intervention on momentary smoking lapses in smoking cessation attempts among Asian American young adults. *Translational Behavioral Medicine*, *11*(1), 216–225. https://doi.org/10.1093/tbm/ibz183

Isaacowitz, D. M., Livingstone, K. M., Harris, J. A., & Marcotte, S. L. (2015). Mobile eye tracking reveals little evidence for age differences in attentional selection for mood regulation. *Emotion*, *15*, 151–161. https://doi.org/10.1037/emo0000037

Jain, P., Gyanchandani, M., & Khare, N. (2016). Big data privacy: A technological perspective and review. *Journal of Big Data*, *3*, Article 25. https://doi.org/10.1186/s40537-016-0059-y

Joiner, T. E. (2000). Depression's vicious scree: Self-propagating and erosive processes in depression chronicity. *Clinical Psychology: Science and Practice*, *7*, 203–218. https://doi.org/10.1093/clipsy/7.2.203

Kaplan, D. M., Rentscher, K. E., Lim, M., Reyes, R., Keating, D., Romero, J., Shah, A., Smith, A. D., York, K. A., & Milek, A. (2020). Best practices for Electronically Activated Recorder (EAR) research: A practical guide to coding and processing EAR data. *Behavior Research Methods*, *52*(4), 1538–1551. https://doi.org/10.3758/s13428-019-01333-y

Kern, M. L., Park, G., Eichstaedt, J. C., Schwartz, H. A., Sap, M., Smith, L. K., & Ungar, L. H. (2016). Gaining insights from social media language: Methodologies and challenges. *Psychological Methods*, *21*, 507–525. https://doi.org/10.1037/met0000091

Kim, D. H., Lu, N., Ma, R., Kim, Y. S., Kim, R. H., Wang, S., Wu, J., Won, S. M., Tao, H., Islam, A., Yu, K. J., Kim, T., Chowdhury, R., Ying, M., Xu, L., Li, M., Chung, H. J., Keum, H., McCormick, M., . . . Rogers, J. A. (2011). Epidermal electronics. *Science*, *333*, 838–843. https://doi.org/10.1126/science.1206157

Kim, J., Campbell, A. S., de Ávila, B. E. F., & Wang, J. (2019). Wearable biosensors for healthcare monitoring. *Nature Biotechnology*, *37*(4), 389–406. https://doi.org/10.1038/s41587-019-0045-y

King, K. M., Feil, M. C., & Halvorson, M. (2018). Negative urgency is correlated with the use of reflexive and disengagement emotion regulation strategies. *Clinical Psychological Science*, *6*, 822–834.

Ko, B. C. (2018). A brief review of facial emotion recognition based on visual information. *Sensors*, *18*(2), Article 401. https://doi.org/10.3390/s18020401

Kosch, T., Hassib, M., Reutter, R., & Alt, F. (2020). Emotions on the go: Mobile emotion assessment in real-time using facial expressions. In G. Tortora, G. Vitiello, & M. Winckler (Eds.), *AVI '20: Proceedings of the International Conference on Advanced Visual Interfaces*. Association for Computing Machinery. https://doi.org/10.1145/3399715.3399928

Kumar, P., Waiter, G. D., Dubois, M., Milders, M., Reid, I., & Steele, J. D. (2017). Increased neural response to social rejection in major depression. *Depression and Anxiety*, *34*, 1049–1056. https://doi.org/10.1002/da.22665

Kutt, K., Binek, W., Misiak, P., Nalepa, G. J., & Bobek, S. (2018). Towards the development of sensor platform for processing physiological data from wearable sensors. In L. Rutkowski, R. Scherer, M. Korytkowski, W. Pedrycz, R. Tadeusiewicz, & J. Zurada (Eds), *Artificial Intelligence and Soft Computing. ICAISC 2018. Lecture Notes in Computer Science* (Vol 10842). Springer. https://doi.org/10.1007/978-3-319-91262-2_16

Kvam, S., Kleppe, C. L., Nordhus, I. H., & Hovland, A. (2016). Exercise as a treatment for depression: A meta-analysis. *Journal of Affective Disorders*, *202*, 67–86. https://doi.org/10.1016/j.jad.2016.03.063

Kwan, M. P., Wang, J., Tyburski, M., Epstein, D. H., Kowalczyk, W. J., & Preston, K. L. (2019). Uncertainties in the geographic context of health behaviors: A study of substance users' exposure to psychosocial stress using GPS data. *International Journal of Geographical Information Science*, *33*, 1176–1195. https://doi.org/10.1080/13658816.2018.1503276

Kwon, J., Kim, D.-H., Park, W., & Kim, L. (2016). A wearable device for emotional recognition using facial expression and physiological response. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, *2016*, 5765–5768. https://doi.org/10.1109/EMBC.2016.7592037

Lennarz, H. K., Hollenstein, T., Lichtwarck-Aschoff, A., Kuntsche, E., & Granic, I. (2019). Emotion regulation in action: Use, selection, and success of emotion regulation in adolescents' daily lives. *International Journal of Behavioral Development*, *43*(1), 1–11. https://doi.org/10.1177/0165025418755540

Leonard, N. R., Casarjian, B., Fletcher, R. R., Prata, C., Sherpa, D., Kelemen, A., Rajan, S., Salaam, R., Cleland, C. M., & Gwadz, M. V. (2018). Theoretically-based emotion regulation strategies using a mobile app and wearable sensor among homeless adolescent mothers: Acceptability and feasibility study. *Journal of Medical Internet Research*, *1*(1), Article e1. https://doi.org/10.2196/pediatrics.9037

Livingston, N. A., Flentje, A., Heck, N. C., Szalda-Petree, A., & Cochran, B. N. (2017). Ecological momentary assessment of daily discrimination experiences and nicotine, alcohol, and drug use among sexual and gender minority individuals. *Journal of Consulting and Clinical Psychology*, *85*, 1131–1143. https://doi.org/10.1037/ccp0000252

Lorenzetti, V., Melo, B., Basílio, R., Suo, C., Yücel, M., Tierra-Criollo, C. J., & Moll, J. (2018). Emotion regulation using virtual environments and real-time fMRI neurofeedback. *Frontiers in Neurology*, *9*, Article 390. https://doi.org/10.3389/fneur.2018.00390

Lu, H., Frauendorfer, D., Rabbi, M., Mast, M. S., Chittaranjan, G. T., Campbell, A. T., Gatica-Perez, D., & Choudhury, T. (2012). Stresssense: Detecting stress in unconstrained acoustic environments using smartphones. In *UbiComp '12: Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 351–360). Association for Computing Machinery. https://doi.org/10.1145/2370216.2370270

Maier, E., Reimer, U., Laurenzi, E., Ridinger, M., & Ulmer, T. (2014). Smart coping: A mobile solution for stress recognition and prevention. *Proceedings of the International Conference on Health Informatics - HEALTHINF, (BIOSTEC 2014*, 428–433. https://doi.org/10.5220/0004903704280433

Mallari, B., Spaeth, E. K., Goh, H., & Boyd, B. S. (2019). Virtual reality as an analgesic for acute and chronic pain in adults: A systematic review and meta-analysis. *Journal of Pain Research*, *12*, 2053–2085. https://doi.org/10.2147/JPR.S200498

Massey, E. K., Garnefski, N., Gebhardt, W. A., & Van Der Leeden, R. (2009). Daily frustration, cognitive coping and coping efficacy in adolescent headache: A daily diary study. *Headache: The Journal of Head and Face Pain*, *49*(8), 1198–1205.

Mata, J., Thompson, R. J., Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Gotlib, I. H. (2012). Walk on the bright side: Physical activity and affect in major depressive disorder. *Journal of Abnormal Psychology*, *121*, 297–308. https://doi.org/10.1037/a0023533

McClernon, F. J., & Roy Choudhury, R. (2013). I am your smartphone, and I know you are about to smoke: The application of mobile sensing and computing approaches to smoking research and treatment. *Nicotine & Tobacco Research*, *15*, 1651–1654.

McRae, K., Gross, J. J., Weber, J., Robertson, E. R., Sokol-Hessner, P., Ray, R. D., Gabrieli, J. D. E., & Ochsner, K. N. (2012). The development of emotion regulation: An fMRI study of cognitive reappraisal in children, adolescents and young adults. *Social Cognitive and Affective Neuroscience*, *7*, 11–22. https://doi.org/10.1093/scan/nsr093

Mehl, M. R., & Robbins, M. L. (2012). Naturalistic observation sampling: The Electronically Activated Recorder (EAR). In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (p. 176–192). The Guilford Press.

Merikangas, K. R., He, J. P., Burstein, M., Swendsen, J., Avenevoli, S., Case, B., Georgiades, K., Heaton, L., Swanson, S., & Olfson, M. (2011). Service utilization for lifetime mental disorders in U.S. adolescents: Results of the national comorbidity survey—adolescent supplement (NCS-A). *Journal of the American Academy of Child and Adolescent Psychiatry*, *50*, 32–45. https://doi.org/10.1016/j.jaac.2010.10.006

Miloff, A., Lindner, P., Dafgård, P., Deak, S., Garke, M., Hamilton, W., Heinsoo, J., Kristoffersson, G., Rafi, J., & Sindemark, K. (2019). Automated virtual reality exposure therapy for spider phobia vs. in-vivo one-session treatment: A randomized non-inferiority trial. *Behaviour Research and Therapy*, *118*, 130–140.

Miri, P., Jusuf, E., Uusberg, A., Margarit, H., Flory, R., Isbister, K., Marzullo, K., & Gross, J. J. (2020). Evaluating a Personalizable, Inconspicuous Vibrotactile (PIV) breathing pacer for in-the-moment affect regulation. In *CHI '20: Proceedings of the 2020 CHI Conference on Human*

Factors in Computing Systems. Association for Computing Machinery. https://doi.org/10.1145/3313831.3376757

Miri, P., Uusberg, A., Culbertson, H., Flory, R., Uusberg, H., Gross, J. J., Marzullo, K., & Isbister, K. (2018). Emotion regulation in the wild: Introducing WEHAB system architecture. In *CHI EA '18: Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery. https://doi.org/10.1145/3170427.3188495

Mojtabai, R., Olfson, M., Sampson, N. A., Jin, R., Druss, B., Wang, P. S., Wells, K. B., Pincus, H. A., & Kessler, R. C. (2011). Barriers to mental health treatment: Results from the National Comorbidity Survey Replication (NCS-R). *Psychological Medicine*, *41*(8), 1751–1761. https://doi.org/10.1017/S0033291710002291

Moreno, M. A., Goniu, N., Moreno, P. S., & Diekema, D. (2013). Ethics of social media research: Common concerns and practical considerations. *Cyberpsychology, Behavior, and Social Networking*, *16*, 708–713.

Nahum-Shani, I., Hekler, E. B., & Spruijt-Metz, D. (2015). Building health behavior models to guide the development of just-in-time adaptive interventions: A pragmatic framework. *Health Psychology*, *34*, 1209–1219. https://doi.org/10.1037/hea0000306

Nelson, B. W., & Allen, N. B. (2018). Extending the passive-sensing toolbox: Using smart-home technology in psychological science. *Perspectives on Psychological Science*, *13*, 718–733.

Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018a). Transformation of adolescent peer relations in the social media context: Part 1—A theoretical framework and application to dyadic peer relationships. *Clinical Child and Family Psychology Review*, *21*(3), 267–294. https://doi.org/10.1007/s10567-018-0261-x

Nesi, J., Choukas-Bradley, S., & Prinstein, M. J. (2018b). Transformation of adolescent peer relations in the social media context: Part 2—Application to peer group processes and future directions for research. *Clinical Child and Family Psychology Review*, *21*(3), 295–319. https://doi.org/10.1007/s10567-018-0262-9

Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review*, *84*, 231–259.

Niven, K., Garcia, D., Van der Löwe, I., Holman, D., & Mansell, W. (2015). Becoming popular: Interpersonal emotion regulation predicts relationship formation in real life social networks. *Frontiers in Psychology*, *6*, Article 1452. https://doi.org/10.3389/fpsyg.2015.01452

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.

Pannicke, B., Reichenberger, J., Schultchen, D., Pollatos, O., & Blechert, J. (2020). Affect improvements and measurement concordance between a subjective and an accelerometric estimate of physical activity. *European Journal of Health Psychology*, *27*, 66–75. https://doi.org/10.1027/2512-8442/a000050

Parikh, R. B., Teeple, S., & Navathe, A. S. (2019). Addressing bias in artificial intelligence in health care. *JAMA*, *322*, 2377–2378.

Paykel, E. S., Prusoff, B. A., & Myers, J. K. (1975). Suicide attempts and recent life events: A controlled comparison. *Archives of General Psychiatry*, *32*, 327–333.

Perez, J., Venta, A., Garnaat, S., & Sharp, C. (2012). The difficulties in emotion regulation scale: Factor structure and association with nonsuicidal self-injury in adolescent inpatients. *Journal of Psychopathology and Behavioral Assessment*, *34*, 393–404. https://doi.org/10.1007/s10862-012-9292-7

Pew Research Center. (2019a). *Internet/broadband fact sheet*. https://www.pewresearch.org/internet/fact-sheet/internet-broadband/

Pew Research Center. (2019b). *Mobile fact sheet*. https://www.pewresearch.org/internet/fact-sheet/mobile/

Pew Research Center. (2019c). *Social media fact sheet*. https://www.pewresearch.org/internet/fact-sheet/social-media/

Pramana, G., Parmanto, B., Kendall, P. C., & Silk, J. S. (2014). The SmartCAT: An m-health platform for ecological momentary intervention in child anxiety treatment. *Telemedicine and E-Health*, *20*, 419–427. https://doi.org/10.1089/tmj.2013.0214

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) Article e9. https://doi.org/10.2196/games.8902

Pulantara, I. W., Parmanto, B., & Germain, A. (2018). Clinical feasibility of a just-in-time adaptive intervention app (iREST) as a behavioral sleep treatment in a military population: Feasibility comparative effectiveness study. *Journal of Medical Internet Research*, *20*(12), Article e10124. https://doi.org/10.2196/10124

Ranney, M. L., Choo, E. K., Cunningham, R. M., Spirito, A., Thorsen, M., Mello, M. J., & Morrow, K. M. (2014). Acceptability, language, and structure of text message-based behavioral interventions for high-risk adolescent females: A qualitative study. *Journal of Adolescent Health*, *55*, 33–40. https://doi.org/10.1016/j.jadohealth.2013.12.017

Ranney, M. L., Golstick, J., Eisman, A., Carter, P. M., Walton, M., & Cunningham, R. M. (2017). Effects of a brief ED-based alcohol and violence intervention on depressive symptoms. *General Hospital Psychiatry*, *46*, 44–48.

Ranney, M. L., Patena, J. V., Dunsiger, S., Spirito, A., Cunningham, R. M., Boyer, E., & Nugent, N. R. (2019). A technology-augmented intervention to prevent peer violence and depressive symptoms among at-risk emergency department adolescents: Protocol for a randomized control trial. *Contemporary Clinical Trials*, *82*, 106–114. https://doi.org/10.1016/j.cct.2019.05.009

Reece, A. G., & Danforth, C. M. (2017). Instagram photos reveal predictive markers of depression. *EPJ Data Science*, *6*, Article 15. https://doi.org/10.1140/epjds/s13688-017-0110-z

Reimer, U., Maier, E., & Ulmer, T. (2020). SmartCoping: A mobile solution for recognizing stress and coping with it. In N. Wickramasinghe & F. Bodendorf (Eds.), *Delivering superior health and wellness management with IoT and analytics* (pp. 119–143). Springer. https://doi.org/10.1007/978-3-030-17347-0_6

Rincon, J. A., Costa, A., Novais, P., Julian, V., & Carrascosa, C. (2018). Intelligent wristbands for the automatic detection of emotional states for the elderly. In H. Yin, D. Camacho, P. Novais, & A. J. Tallón-Ballesteros (Eds.), *Intelligent Data Engineering and Automated Learning – IDEAL 2018. IDEAL 2018. Lecture Notes in Computer Science* (*Vol. 11314*). Springer. https://doi.org/10.1007/978-3-030-03493-1_54

Rizzo, A. S., Galen Buckwalter, J., Forbell, E., Reist, C., Difede, J. A., Rothbaum, B. O., Lange, B., Koenig, S., & Talbot, T. (2013). Virtual reality applications to address the wounds of war. *Psychiatric Annals*, *43*, 123–138. https://doi.org/10.3928/00485713-20130306-08

Rohani, D. A., Tuxen, N., Kessing, L. V., & Bardram, J. E. (2017). Designing for hourly activity sampling in behavioral activation. In *PervasiveHealth '17: Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare* (pp. 431–435). Association for Computing Machinery. https://doi.org/10.1145/3154862.3154919

Roos, C. R., Kober, H., Trull, T. J., MacLean, R. R., & Mun, C. J. (2020). Intensive longitudinal methods for studying the role of self-regulation strategies in substance use behavior change. *Current Addiction Reports*, *7*, 301–316. https://doi.org/10.1007/s40429-020-00329-5

Rus-Calafell, M., Garety, P., Sason, E., Craig, T. J. K., & Valmaggia, L. R. (2018). Virtual reality in the assessment and treatment of psychosis: A systematic review of its utility, acceptability and effectiveness. *Psychological Medicine*, *48*, 362–391. https://doi.org/10.1017/S0033291717001945

Saeb, S., Lattie, E. G., Schueller, S. M., Kording, K. P., & Mohr, D. C. (2016). The relationship between mobile phone location sensor data and depressive symptom severity. *PeerJ*, *4*, Article e2537. https://doi.org/10.7717/peerj.2537

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: An exploratory study. *Journal of Medical Internet Research*, *17*, Article e175. https://doi.org/10.2196/jmir.4273

Salo, V. C., Pannuto, P., Hedgecock, W., Biri, A., & Russo, D. A. (2020). *Measuring naturalistic proximity as a window into caregiver–child interaction patterns*. PsyArXiv. https://doi.org/10.31234/osf.io/h2fy6

Sarchiapone, M., Gramaglia, C., Iosue, M., Carli, V., Mandelli, L., Serretti, A., Marangon, D., & Zeppegno, P. (2018). The association between electrodermal activity (EDA), depression and suicidal behaviour: A systematic review and narrative synthesis. *BMC Psychiatry*, *18*, Article 22. https://doi.org/10.1186/s12888-017-1551-4

Sarsenbayeva, Z., Marini, G., van Berkel, N., Luo, C., Jiang, W., Yang, K., Wadley, G., Dingler, T., Kostakos, V., & Goncalves, J. (2020). Does smartphone use drive our emotions or vice versa? A causal analysis. In *CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery. https://doi.org/10.1145/3313831.3376163

Schleider, J. L., Dobias, M. L., Sung, J. Y., & Mullarkey, M. C. (2020). Future directions in single-session youth mental health interventions. *Journal of Clinical Child & Adolescent Psychology*, *49*(2), 264–278.

Schuller, D. M., & Schuller, B. W. (2021). A review on five recent and near-future developments in computational processing of emotion in the human voice. *Emotion Review*, *13*(1), 44–50. https://doi.org/10.1177/1754073919898526

Seabrook, E. M., Kern, M. L., Fulcher, B. D., & Rickard, N. S. (2018). Predicting depression from language-based emotion dynamics: Longitudinal analysis of Facebook and Twitter status updates. *Journal of Medical Internet Research*, *20*(5), Article e168. https://doi.org/10.2196/jmir.9267

Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., & Seneviratne, A. (2017). A survey of wearable devices and challenges. *IEEE Communications Surveys & Tutorials*, *19*, 2573–2620.

Settanni, M., Azucar, D., & Marengo, D. (2018). Predicting individual characteristics from digital traces on social media: A meta-analysis. *Cyberpsychology, Behavior, and Social Networking*, *21*, 217–228.

Shatte, A. B. R., Hutchinson, D. M., & Teague, S. J. (2019). Machine learning in mental health: A scoping review of methods and applications. *Psychological Medicine*, *49*, 1426–1448.

Sheppes, G., & Gross, J. J. (2013). Emotion regulation effectiveness: What works when. In H. Tennen, J. Suls, & I. B. Weiner (Eds.), *Handbook of psychology: Personality and social psychology* (p. 391–405). John Wiley & Sons, Inc.

Sheppes, G., Scheibe, S., Suri, G., & Gross, J. J. (2011). Emotion-regulation choice. *Psychological Science*, *22*, 1391–1396.

Sheppes, G., Scheibe, S., Suri, G., Radu, P., Blechert, J., & Gross, J. J. (2014). Emotion regulation choice: A conceptual framework and supporting evidence. *Journal of Experimental Psychology: General*, *143*, 163–181. https://doi.org/10.1037/a0030831

Shields, G. S., Kuchenbecker, S. Y., Pressman, S. D., Sumida, K. D., & Slavich, G. M. (2016). Better cognitive control of emotional information is associated with reduced pro-inflammatory cytokine reactivity to emotional stress. *Stress*, *19*, 63–68. https://doi.org/10.3109/10253890.2015.1121983

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology*, *4*, 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Shih, C.-H. I., Kowatsch, T., Tinschert, P., Barata, F., & Nißen, M. K. (2016). Towards the design of a smartphone-based biofeedback breathing training: Identifying diaphragmatic breathing patterns from a smartphone's microphone. In *Tenth Mediterranean Conference on Information Systems*. https://aisel.aisnet.org/mcis2016/47/

Short, N. A., Boffa, J. W., Clancy, K., & Schmidt, N. B. (2018). Effects of emotion regulation strategy use in response to stressors on PTSD symptoms: An ecological momentary assessment study. *Journal of Affective Disorders*, *230*, 77–83.

Silk, J. S. (2019). Context and dynamics: The new frontier for developmental research on emotion regulation. *Developmental Psychology*, *55*(9), 2009–2014. https://doi.org/10.1037/dev0000768

Silk, J. S., Pramana, G., Sequeira, S. L., Lindhiem, O., Kendall, P. C., Rosen, D., & Parmanto, B. (2020). Using a smartphone app and clinician portal to enhance brief cognitive behavioral therapy for childhood anxiety disorders. *Behavior Therapy*, *51*, 69–84. https://doi.org/10.1016/j.beth.2019.05.002

Spruijt-Metz, D., & Nilsen, W. (2014). Dynamic models of behavior for just-in-time adaptive interventions. *IEEE Pervasive Computing*, *13*, 13–17.

Spyrou, E., Nikopoulou, R., Vernikos, I., & Mylonas, P. (2019). Emotion recognition from speech using the bag-of-visual words on audio segment spectrograms. *Technologies*, *7*, Article 20. https://doi.org/10.3390/technologies7010020

Steinhubl, S. R., Waalen, J., Edwards, A. M., Ariniello, L. M., Mehta, R. R., Ebner, G. S., Carter, C., Baca-Motes, K., Felicione, E., Sarich, T., & Topol, E. J. (2018). Effect of a home-Based wearable continuous ECG monitoring patch on detection of undiagnosed atrial fibrillation the mSToPS randomized clinical trial. *JAMA*, *320*, 146–155. https://doi.org/10.1001/jama.2018.8102

Stephens, M., & Poorthuis, A. (2015). Follow thy neighbor: Connecting the social and the spatial networks on Twitter. *Computers, Environment and Urban Systems*, *53*, 87–95.

Stevenson, B. L., Blevins, C. E., Marsh, E., Feltus, S., Stein, M., & Abrantes, A. M. (2020). An ecological momentary assessment of mood, coping and alcohol use among emerging adults in psychiatric treatment. *The American Journal of Drug and Alcohol Abuse*, *46*(5), 651–658. https://doi.org/10.1080/00952990.2020.1783672

Stoll, R. D., Pina, A. A., & Gary, K. (2017). Usability of a smartphone application to support the prevention and early intervention of anxiety in youth. *Cognitive and Behavioral Practice*, *24*(4), 393–404. https://doi.org/10.1016/j.cbpra.2016.11.002.

Stone, L. B., Mennies, R. J., Waller, J. M., Ladouceur, C. D., Forbes, E. E., Ryan, N. D., Dahl, R. E., & Silk, J. S. (2019). Help me feel better! Ecological momentary assessment of anxious youths' emotion regulation with parents and peers. *Journal of Abnormal Child Psychology*, *47*(2), 313–324. https://doi.org/10.1007/s10802-018-0454-2

Tamir, M. (2016). Why do people regulate their emotions? A taxonomy of motives in emotion regulation. *Personality and Social Psychology Review*, *20*(3), 199–222.

Tan, P. Z., Forbes, E. E., Dahl, R. E., Ryan, N. D., Siegle, G. J., Ladouceur, C. D., & Silk, J. S. (2012). Emotional reactivity and regulation in anxious and nonanxious youth: A cell-phone ecological momentary assessment study. *Journal of Child Psychology and Psychiatry*, *53*(2), 197–206.

Theofanopoulou, N., Isbister, K., Edbrooke-Childs, J., & Slovák, P. (2019). A smart toy intervention to promote emotion regulation in middle childhood: Feasibility study. *JMIR Mental Health*, *6*, Article e14029. https://doi.org/10.2196/14029

Torous, J., & Nebeker, C. (2017). Navigating ethics in the digital age: Introducing connected and open research ethics (CORE), a tool for researchers and institutional review boards. *Journal of Medical Internet Research*, *19*, Article e38. https://doi.org/10.2196/jmir.6793

Trifan, A., Oliveira, M., & Oliveira, J. L. (2019). Passive sensing of health outcomes through smartphones: Systematic review of current solutions and possible limitations. *JMIR MHealth and UHealth*, *7*(8), Article e12649. https://doi.org/10.2196/12649

Troy, A. S., Saquib, S., Thal, J., & Ciuk, D. J. (2019). The regulation of negative and positive affect in response to daily stressors. *Emotion*, *19*(5), 751–763. https://doi.org/10.1037/emo0000486

Trull, T. J., & Ebner-Priemer, U. W. (2020). Ambulatory assessment in psychopathology research: A review of recommended reporting guidelines and current practices. *Journal of Abnormal Psychology*, *129*, 56–63. https://doi.org/10.1037/abn0000473

Valliappan, N., Dai, N., Steinberg, E., He, J., Rogers, K., Ramachandran, V., Xu, P., Shojaeizadeh, M., Guo, L., Kohlhoff, K., & Navalpakkam, V. (2020). Accelerating eye movement research via accurate and affordable smartphone eye tracking. *Nature Communications*, *11*(1), Article 4553. https://doi.org/10.1038/s41467-020-18360-5

Wadley, G., Smith, W., Koval, P., & Gross, J. J. (2020). Digital emotion regulation. *Current Directions in Psychological Science*, *29*, 412–418. https://doi.org/10.1177/0963721420920592

Waller, J. M., Silk, J. S., Stone, L. B., & Dahl, R. E. (2014). Co-rumination and co-problem-solving in the daily lives of adolescents with major depression. *Journal of the American Academy of Child and Adolescent Psychiatry*, *53*, 868–878.

Wang, C., Li, X., Hu, H., Zhang, L., Huang, Z., Lin, M., Zhang, Z., Yin, Z., Huang, B., Gong, H., Bhaskaran, S., Gu, Y., Makihata, M., Guo, Y., Lei, Y., Chen, Y., Wang, C., Li, Y., Zhang, T., . . . Xu, S. (2018). Monitoring of the central blood pressure waveform via a conformal ultrasonic device. *Nature Biomedical Engineering*, *2*, 687–695. https://doi.org/10.1038/s41551-018-0287-x

Wasil, A. R., Venturo-Conerly, K. E., Shingleton, R. M., & Weisz, J. R. (2019). A review of popular smartphone apps for depression and anxiety: Assessing the inclusion of evidence-based content. *Behaviour Research and Therapy*, *123*, Article 103498. https://doi.org/10.1016/j.brat.2019.103498

Weisel, K. K., Fuhrmann, L. M., Berking, M., Baumeister, H., Cuijpers, P., & Ebert, D. D. (2019). Standalone smartphone apps for mental health—A systematic review and meta-analysis. *npj Digital Medicine*, *2*, Article 118. https://doi.org/10.1038/s41746-019-0188-8

Wilson, S. T., Chesin, M., Fertuck, E., Keilp, J., Brodsky, B., Mann, J. J., Sönmez, C. C., Benjamin-Phillips, C., & Stanley, B. (2016). Heart rate variability and suicidal behavior. *Psychiatry Research*, *240*, 241–247. https://doi.org/10.1016/j.psychres.2016.04.033

Wisniewski, H., Liu, G., Henson, P., Vaidyam, A., Hajratalli, N. K., Onnela, J.-P., & Torous, J. (2019). Understanding the quality, effectiveness and attributes of top-rated smartphone health apps. *Evidence-Based Mental Health*, *22*(1), 4–9. https://doi.org/10.1136/ebmental-2018-300069

Wolfers, L. N., & Schneider, F. M. (2021). Using media for coping: A scoping review. *Communication Research*, *48*(8), 1210–1234. https://doi.org/10.1177/0093650220939778

Wu, D., Sharma, N., & Blumenstein, M. (2017). Recent advances in video-based human action recognition using deep learning: A review. In *2017 International Joint Conference on Neural Networks* (pp. 2865–2872). Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/IJCNN.2017.7966210

Yang, C. H., Huh, J., Mason, T. B., Belcher, B. R., Kanning, M., & Dunton, G. F. (2020). Mother-child dyadic influences of affect on everyday movement behaviors: Evidence from an ecological momentary assessment study. *International Journal of Behavioral Nutrition and Physical Activity*, *17*, Article 56. https://doi.org/10.1186/s12966-020-00951-6

Zhang, H.-B., Zhang, Y.-X., Zhong, B., Lei, Q., Yang, L., Du, J.-X., & Chen, D.-S. (2019). A comprehensive survey of vision-based human action recognition methods. *Sensors*, *19*(5), Article 1005. https://doi.org/10.3390/s19051005

Zhang, Y., & Tao, T. H. (2019). Skin-friendly electronics for acquiring human physiological signatures. *Advanced Materials*, *31*, Article 1905767. https://doi.org/10.1002/adma.201905767

Zimmer-Gembeck, M. J., & Skinner, E. A. (2011). The development of coping across childhood and adolescence: An integrative review and critique of research. *International Journal of Behavioral Development*, *35*(1), 1–17. https://doi.org/10.1177/0165025410384923