Abstract

Emotion regulation (ER) flexibility, defined as shifting regulatory efforts based on contextual demands, has been proposed as central to well-being. However, it remains an elusive construct to capture. In this article, we highlight the promise and challenges of using ambulatory assessment to examine ER flexibility. We consider difficulties in assessing relevant contextual features and ER dynamics using ecological momentary assessment (EMA). The solutions offered include drawing on existing taxonomies of situational characteristics and ER strategies, adopting methods that passively track contextual features and enhance reliability, and leveraging the advantages of various sampling schemes based on target ER dynamics. Studying ER flexibility in vivo, as it naturally unfolds in daily life, is crucial for a comprehensive understanding of the contextual, dynamic nature of ER. Further work is needed developing theories to guide research on how and why specific aspects of the context might call for shifts in regulatory efforts.

Keywords: emotion regulation; flexibility; ambulatory assessment

Time is central to models of emotion regulation (ER; Gross, 2015), but there is little empirical research on the temporal dynamics of ER. Early ER work delineated emotional effects of specific strategies (e.g., reappraisal, suppression), often in experimentally controlled settings (e.g., Gross, 1998). Recent theorizing suggests the utility of strategies depends on the context, and successful ER is thus characterized by flexible adjustment rather than broad deployment of "adaptive" tactics (Aldao, Sheppes, & Gross, 2015). That is, to effectively manage emotions, the regulator must monitor the success of their ongoing ER efforts and make adjustments when necessary (e.g., if goals are not met or contextual features change; Gross, 2015).

Although ER flexibility is proposed as central to well-being (Bonanno & Burton, 2013), it remains an elusive construct. In this article, we highlight the promise of ecological momentary assessment (EMA) for measuring ER flexibility given this method allows tracking of processes within individuals over time across a wide range of contexts. We also delineate key challenges and offer solutions, highlighting the need for theoretical frameworks to guide assessment efforts.

Dynamic Nature of ER Flexibility

ER flexibility is defined as shifting ER efforts based on contextual demands (Aldao et al, 2015). Rather than simply random fluctuation, it is the subset of ER variability that systematically co-varies with contextual features. Individuals are expected to regulate in a more flexible manner if they, 1. Attend to relevant contextual features, 2. Maintain a broad repertoire of strategies, and 3. Respond well to feedback (Bonanno & Burton, 2013). However, ER flexibility per se is better represented as the intraindividual covariation between specific regulation processes (e.g., reappraisal) and contextual features (e.g., controllability).

To capture flexibility, ER needs to be assessed within the same individual under different conditions. Early work conceptualized ER flexibility as the ability to successfully modulate emotion using various instructed tactics (Bonanno et al., 2004). Another approach has been experimentally manipulating contextual features (e.g., intensity) and measuring strategy use (Sheppes et al., 2014). Although experiments allow for causal inferences, it is difficult to represent diverse contexts in the lab. Researchers have therefore begun to assess spontaneous ER fluctuations across daily contexts using EMA to get a comprehensive view of ER flexibility.

The rich time-series data collected in EMA allows for modeling the dynamic properties of ER in various ways. Multilevel modeling can be used to index within-person covariation between strategies and contextual features, with greater flexibility being indicated by stronger covariation. Dynamical systems models could also be applied to better understand how these transactions unfold over time (Ram & Gerstorf, 2009). Work in this area could further benefit from using models that simultaneously estimate associations among large sets of strategies and contextual features (e.g. graphical VAR; Wild et al, 2010), especially approaches combining idiographic and nomothetic elements (e.g. GIMME; Gates & Molenaar, 2012). Person-specific analyses can permit the relevance of specific contextual cues to vary across individuals. Overall, these tools can capture how responsive an individual's ER is to the context (e.g., number and degree of connections), isolate common strategy-context links to target in future work, and test how context-strategy pairing predict relevant outcomes in a concurrent and lagged fashion.

Challenges and Promise of Studying ER Flexibility with EMA

EMA seems ideal for studying ER flexibility because it allows for many observations of the same individual across a wide range of contexts. However, there are several challenges to using EMA to study ER flexibility, which are exacerbated by a lack of guiding theories. We focus on (1) assessing contextual demands, and (2) indexing diverse forms of ER dynamics.

Assessing contextual demands. EMA studies have documented a large proportion of within-person variance in strategy use (e.g., Brans, Koval, Verduyn, Lim, & Kuppens, 2013; Eldesouky & English, 2019). This finding suggests individuals may be tailoring their regulation efforts to the context. However, to differentiate random variability from flexibility, it is necessary to test whether ER varies systematically with contextual features (Catterson, Eldesouky, & John, 2017; English, Lee, John, & Gross, 2017; Haines et al., 2016).

One challenge in this area is that there are many ways to categorize "context" (e.g., physical space, discrete event, internal characteristics, such as appraisals; Greenway, Kalokerinos, & Williams, 2018) and it is unclear which contextual features are relevant for ER. Taxonomies of situational characteristics are beginning to emerge (e.g., DIAMONDS, Rauthmann & Sherman, 2015) and these frameworks have been applied successfully using EMA, highlighting their potential utility for studying ER flexibility. However, theoretical models are needed to guide these efforts. Given the central role of goals in ER, cues linked to fundamental human motives (Ryan & Deci, 2000; Tamir, 2016) may provide a useful starting place because effective ER efforts should be sensitive to goal-relevant cues. Although simple strategy-goal mappings are unlikely to apply across all individuals, certain strategies may be more likely to facilitate goal pursuit within a given domain (Eldesouky & English, 2019). For instance, expression-based strategies (e.g., suppression) may fluctuate more with relatedness-cues (e.g., others present, sociality) than competence-related cues (e.g., at work, adversity).

A related challenge is that participants may be unable to provide adequate contextual information because it is not feasible timewise and many features go unnoticed (e.g., partner's emotions, politeness norms). One solution is adopting novel methods that passively track objective contextual features. For example, researchers can collect audio snippets with the electronically-activated recorder (EAR, Mehl et al., 2001), visual recording with wearable cameras (Brown, Blake, & Sherman, 2017), and GPS information with applications installed on smartphones (Timmons et al., 2017). These data can be coded to index various contextual features that may be goal-relevant, including interpersonal elements (e.g., alone or not), activity types (e.g., leisure or work), and physical location (e.g., near or far from home). For example, familiarity of contexts could be inferred from frequency of prior visits based on GPS location.

Finally, in order to sufficiently capture how ER changes with the context, the same (or similar) contexts need to be sampled repeatedly and there should also be diversity in contexts sampled. For instance, an individual would need to report on ER during interpersonal conflict multiple times as well as ER in other contexts. One way to increase the representation of similar contexts is to use event-based sampling, rather than (or in addition to) providing prompts at fixed or random times (i.e., interval- or signal-contingent sampling). Event-based sampling requires participants to provide reports each time they encounter a certain situation (e.g., social interaction). Researchers should consider however, whether the increased participant burden of this approach is offset by its potential benefits (Himmelstein, Woods, & Wright, 2019).

Assessing ER dynamics. Despite increasing precision in defining ER flexibility, there has been less development in flexibility measurement. Various ER flexibility indices have been proposed, such as repertoire of strategies, variability of strategy use across time and contexts, and ability to use a diverse range of strategies (Bonanno & Burton, 2013; Eldesouky & English, 2018). Moving forward, it will be important to remember that variability is not equivalent to flexibility, so measures of ER flexibility necessarily require tracking contextual features along with ER processes. In order to capture the full range of strategies at regulators' disposal, researchers can draw on existing ER taxonomies (e.g. Gross, 2015). Sampling frequency and duration should also be adjusted based on the ER dynamics being targeted. For example, sampling needs to occur intensively to capture fast-acting changes to the environment, whereas sampling across longer intervals may better reveal downstream consequences of flexibility.

As we develop new ways to assess ER flexibility, researchers must be mindful of their psychometric properties. EMA requires using short assessments to keep participant burden manageable. As a result, many EMA studies rely on single-item measures, which raise reliability concerns. Administering items that sufficiently tap ER flexibility may necessitate significant time from participants when it involves assessing a wide range of strategies and contextual features. As noted above, theory development and iterative modeling can aid researchers' efforts in targeting specific contextual features and strategies to minimize burden. Once a focused set of strategies is selected, researchers can adapt validated trait ER measures (e.g., Gross & John, 2003) and incorporate items tapping multiple lower-level tactics (e.g., detached reappraisal) within larger categories (e.g., cognitive change). Future work is needed to determine whether items can also be developed to directly capture ER dynamics (e.g., did you switch strategies?).

Finally, theoretical and computational advancement regarding emotion dynamics (Kuppens & Verduyn, 2017) could be extended to ER flexibility. For example, emotional instability, or reactivity to the environment, has been indexed by mean squared successive difference (MSSD), while inertia, thought to reflect inflexibility of emotion, has been indexed by autocorrelation. Similar dynamic indices could be modeled for ER processes. It is essential, however, to consider how new indices relate to pre-existing ones (Dejonckheere et al., 2019) and uniquely predict relevant criteria (e.g., performance-based flexibility measures: Cheng, 2001; Southward et al., 2018). When considering consequences of flexibility-related indices (Blanke et al., 2019), researchers should also be mindful of EMA's limitations in testing casual inferences.

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