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Abstract: *Posttraumatic Growth (PTG), characterized by newfound meaning, perspective, and purpose for trauma survivors, remains enigmatic in its nature. This state is thought to arise from the dynamic interplay of biopsychosocial factors; however, the nature of this interplay is unclear. This study aimed to investigate the intricate relationship between PTG and facial affect dynamics, shedding light on the complex interplay of biopsychosocial factors that underpin this transformative process. We conducted a comprehensive investigation involving 19 wildfire survivors who provided daily self-reported PTG ratings alongside smartphone videos analyzed using Automated Facial Affect Recognition (AFAR) software. Our findings revealed compelling evidence of self-organization within facial affect, as indicated by notably high mean* R^2 *and shape parameter values (i.e., nonlinear indices indicative of structural integrity and flexibility). Further regression analyses unveiled a significant interaction between the degree of facial affect "burstiness" and coping self-efficacy (CSE) on PTG. This interaction suggested that PTG development was a nuanced process intricately linked to the coherence of emotion patterns exhibited by individuals. These insights illuminate the multifaceted dynamics at play in the emergence of PTG and contribute to a broader understanding of its biopsychosocial foundations.*

Key Words: facial affect, posttraumatic growth, nonlinear, disaster, burstiness, self-organization

INTRODUCTION

In contemporary psychology, the concept of resilience is conceptualized through three distinct orientations: trait, outcome, and process. Trait orientation, often referred to as "trait resilience," posits that resilience is an inherent personal trait that equips individuals with the capacity to navigate adversity effectively, facilitating positive adjustment and development. It is akin to considering resilience as an enduring personality characteristic that acts as a protective factor against the impact of adverse or traumatic experiences (Fletcher & Sarkar, 2013).

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Conversely, the outcome orientation views resilience as a measurable behavioral outcome or result, emphasizing its capacity to conquer adversity and enable individuals to recover successfully. This perspective delves into the observable effects of resilience, such as adaptive coping strategies and favorable adaptation (Sisto et al., 2019). Furthermore, the process orientation posits resilience as a dynamic and ongoing process wherein individuals actively engage in adaptation and rapid recovery from significant adversities. This perspective underscores the dynamic nature of resilience, highlighting individuals' active involvement in responding to and rebounding from life challenges (Luthar, Cicchetti, & Becker, 2000; Masten et al., 2021; Rutter, 2012).

These diverse orientations collectively provide a comprehensive framework for understanding resilience, encompassing both inherent traits and observable behavioral outcomes, while emphasizing the dynamic and adaptive processes individuals undertake when confronted with adversity. Researchers are increasingly turning to nonlinear dynamical systems (NDS) theory to understand the dynamic processes associated with human resilience (Kalisch et al., 2017, 2019; Pincus & Metten, 2010; Scheffer et al., 2018). NDS is an umbrella term for a class of models that involve disproportional influences among many variables unfolding in real-time (Guastello, Koopmans, & Pincus, 2009). Biopsychosocial resilience has been identified as an ideal area to apply NDS theory and methods for a few specific reasons: (a) the construct "resilience" is defined as a dynamic process (i.e., "to bounce back"); (b) resilience involves the complex interactions of biopsychosocial parameters; and (c) resilience can unfold in unpredictable ways depending on critical thresholds, timing, and other nonlinear effects. These reasons converge to define resilience as inherently interactive, where its' manifestation is determined by observing differing outcomes among individuals who have undergone substantial stress or adversity.

One's response to trauma, for example, may depend upon the combined functioning of the Hypothalamic-Pituitary-Adrenal (HPA) system on the biological scale, one's coping skills and efficacy beliefs on the psychological scale, and one's levels of social support. With a well-functioning HPA system, positive coping efficacy, and properly attuned support systems, an individual may display *robustness* in response to trauma, with only minor and temporary life disruption even from a major life event. On the other hand, this same individual may head into the same trauma lacking some specific coping ability. This relatively minor psychological difference could hypothetically cascade into dysregulation in HPA functioning over time, social avoidance, and isolation, resulting in low resilience in response to trauma and possibly even symptoms of posttraumatic stress disorder (PTSD). In a third scenario, the same individual could move through the low resilience period only to discover some positive adjustment to their usual mode of coping, resulting in a trajectory toward an anti-fragile response to trauma (Kiefer, Silva, Harrison, & Araújo, 2018; Taleb, 2012) known as posttraumatic growth (PTG; Tedeschi & Calhoun, 2004; Zoellner & Maercker, 2006). Potentially complex interactions among biological, psychological, and social parameters involved in trauma adaptation may be better understood through theoretically derived models designed to understand complex dynamics unfolding in real-time (Benight, Harwell, & Shoji, 2018; Benight, Shoji, & Delahanty, 2017).

Pincus and Metten (2010) proposed that *self-organization* is a good candidate theory under the umbrella of NDS that can ground various modeling strategies applied to human resilience. Self-organization is a process in which systems with sufficient complexity can self-regulate, adapt over time, and exhibit coherence (Bak, 1997; Guastello et al., 2009; Haken, 1988; Kauffman, 1996; Prigogine & Stengers, 2018). Coherence refers to the degree of synchronization or harmony among the various components or elements within a system. It signifies the extent to which these components operate in a coordinated manner, displaying consistent patterns or behaviors over time. In such systems, coherence often reflects the presence of underlying order or organization, where the interactions and relationships between elements lead to stable and predictable dynamics.

Self-organization has been successfully applied to a great variety of systems across the sciences, from physics (e.g., Haken, 1988) to biology (e.g., Kauffman, 1996). It has been applied to human resilience in a wide variety of psychological processes, including menopausal stress dynamics (Taylor-Swanson et al., 2018), personality structure and psychopathology (Pincus, Cadsky, Berardi, Asuncion, & Wann, 2019), behavioral flows involving self-injurious behaviors (Pincus et al., 2014), and interpersonal processes involving conflict (Pincus, 2014). Within each of these biopsychosocial contexts, the common empirical result that has been observed is that resilient systems display two complementary characteristics: (1) flexibility and (2) structural integrity. Flexibility means that a system can adjust to meet demands, while structural integrity means that the critical parameters in the system remain connected under stress. Systems that are both flexible and well-integrated are hypothetically more capable of absorbing a traumatic shock, bouncing back, and perhaps even growing once the shock is removed (Pincus & Metten, 2010).

Emotion is a central psychological factor in understanding human resilience and is an ideal focus for understanding trauma through a systems lens because it cuts across biological (e.g., HPA), psychological, and social dynamics. For example, if one is aware of and able to express fear, anger, and sadness associated with a trauma, he/she should display greater coping flexibility (Bonanno & Burton, 2013; Burton & Bonanno, 2016; Rodin et al., 2017), such as reappraisal combined with, self-care, and letting go of losses. This coping flexibility can lead to more adaptive perspective-taking, a greater sense of personal efficacy, a greater ability to garner social support, and improved HPA regulation. Embedded within this example is flexible yet well-integrated emotion. Positive adaptation from trauma requires the capacity to experience a range of emotional responses (e.g., fear, anger, sadness, disgust) in an integrated manner that allows for effective coping responses and the garnering of social support (Brewin, Andrews, & Valentine, 2000; Zalta et al., 2020). Systemic coping flexibility requires that emotions be well-integrated, with co-regulation occurring among other factors (i.e., coherence) that enable the emergence of healing and the potential for growth (e.g., coping behavior, cognitive factors, self-relations, social support, and HPA functioning). The current study is focused on increasing the understanding of the structure of emotion following severe wildfire disasters and posttraumatic growth (PTG).

Natural Disasters, Trauma, Resilience, and PTG

The research on PTG is filled with contradictions (Hobfoll et al., 2007; Westphal & Bonanno, 2007; Zoellner & Maercker, 2006) and poor methodological design. The bulk of the evidence on PTG has been cross-sectional (Mangelsdorf, Eid, & Luhmann, 2019), looking at relationships between retrospective self-perception of growth and outcome variables such as posttraumatic distress, depression, or anxiety. Many of these studies have found significant positive associations between PTG and these adverse outcomes, whereas others demonstrated significant negative relationships (Mangelsdorf et al., 2019). Scholars have speculated on these equivocal findings, suggesting different solutions such as the Janus Two-Face perspective (Zoellner & Maercker, 2006), the growth with action suggestion (Hobfoll et al., 2007), and an adaptive “coping ugly” self-enhancement perspective (Westphal & Bonanno, 2007).

The Janus-Faced Model of Posttraumatic Growth, introduced by Taku, Calhoun, Cann, and Tedeschi (2008), portrays posttraumatic growth (PTG) as a complex phenomenon encompassing both positive and negative dimensions. Positive PTG reflects personal growth, improved relationships, and an enhanced appreciation for life, whereas negative PTG includes distressing aspects and lingering trauma-related symptoms. This model underscores the coexistence of these dual facets within the PTG experience, emphasizing the need to acknowledge its multifaceted nature. The adaptive “coping ugly” self-enhancement perspective by Westphal and Bonanno (2007) challenges the traditional view of self-enhancement as maladaptive. This perspective suggests that in times of extreme stress, individuals may engage in self-enhancement as an adaptive coping mechanism to protect their psychological well-being. While not always conforming to objective standards, this self-enhancement can serve as a buffer against the negative effects of trauma and stress, promoting resilience. Westphal and Bonanno’s work encourages a nuanced understanding of self-enhancement’s role in coping with adversity. These different models highlight the glaring lack of a clear understanding of how PTG evolves over time.

More recent meta-analytic reviews have highlighted the need for a more temporal approach to understanding PTG. Mangelsdorf et al. (2019) evaluated longitudinal research related to negative (i.e., stressful or traumatic), neutral, and positive or post-ecstatic experiences. Findings from this review underscored three critical needs for future research in this area. First, posttraumatic growth should be theorized as a dynamic system response to understand how these changes occur across time, as others have similarly suggested (Cicchetti & Toth, 2009; Masten, 2014, 2015; Overton, 2015). Second, understanding event-driven change needs to be assessed to not solely rely on retrospective self-perceptions of growth. Third, significant amounts of the available longitudinal studies were carried out with medical-related events (e.g., cancer), limiting our understanding of other types of experiences, such as surviving a natural disaster. The present study took a dynamic systems perspective focusing on the self-organization of emotion using facial expression analyses with severe wildfire disaster survivors, thus addressing two out of the three challenges outlined by Mangelsdorf et al. (2019).

Wildfire disasters can best be understood as catastrophic and sudden losses of critical internal and external resources (Hobfoll, 1991). These losses tax the self-regulatory abilities of individuals to a significant degree due to their rapid onset and uncertainty within the post-disaster recovery process. For example, severe wildfires involve the destruction of property (e.g., home, valuables, memorabilia, natural environment) along with post-disaster recovery challenges (e.g., coordinating relocation, dealing with rebuilding efforts and connecting with social support). For some individuals, this challenge proves overwhelming, contributing to the development of intrusive memories, avoidance of disaster reminders, negative alterations in mood and patterns of thinking, as well as increased levels of arousal and reactivity (i.e., PTSD symptomology) (McDermott, Lee, Judd, & Gibbon, 2005; Silveira et al., 2021; Thomas, Butry, Gilbert, Webb, & Fung, 2017). However, for the majority of the population, robust coping self-efficacy beliefs, adaptive coping efforts, and effective utilization of resources result in a more resilient response (Bonanno, 2004; Luszczynska et al., 2009). How PTG functions within the post-disaster recovery process remains unclear. The present study draws from the nonlinear dynamical systems approach to assess how self-organization of emotion relates to PTG to understand this recovery process better. To evaluate this type of evolution over time, we focused on the dynamics of facial affect captured in self-recorded video journals.

Emotion Dynamics

Affect refers to the experiential state of feeling, encompassing emotions and moods (Niven, 2013). Whereas these terms are commonly used interchangeably in everyday language, they fall under the broader category of affect. Emotions are brief and intense reactions typically triggered by specific stimuli, whether spontaneously or following a cognitive evaluation of a stimulus (Eckman, 1992). In contrast, moods are more enduring emotional states that may not be tied to a particular cause or stimulus. For clarity, the remainder of the manuscript will use the term "facial affect" to reference facial expressions of underlying dynamical emotions, whereas the term "emotion" will be used when describing the underlying experience of these states.

Empirical evidence indicates that observations of facial affect provide a reliable means to infer underlying emotional states (Wichers, Wigwam, & Myin-Germeys, 2015). Facial affect represents an available and measurable parameter within the emotional system that involves many densely interactive components (e.g., physiological arousal, behavioral responses, subjective experience, coping-related beliefs, and social factors). Accordingly, facial affect can be concepttualized as the key tapping the self-organizing process as the system (i.e., the trauma survivor) flexibly attempts to self-regulate. The connection between emotional flexibility and positive functioning has been explored by several researchers (Aldao, Sheppes, & Gross, 2015; Bonanno, 2004; Bonanno & Burton, 2013; Burton & Bonanno, 2016; Coifman, Kevrekidis, Lafon, Maggioni, & Nadler, 2008; Fu, Chow, Li, & Cong, 2018). These studies converge to depict emotion as a flexible system that must adapt to attain desired goals.

Adaptive emotional expression is viewed as the selective suppression or manifestation of emotion, depending upon the environmental context, to move individuals toward their goals. For example, Bonanno (2004) conducted an experimental study with first-year college students following the September 11th terrorist attacks, which required them to demonstrate emotional flexibility by suppressing or enhancing various emotions. The researchers found that freshmen who could enhance or suppress their emotions reported significantly less distress at the end of their sophomore year. Of note, these researchers also found that the ability to produce positive emotions within stressful situations was essential to individuals' psychological well-being more than a year after their participation. What remains unclear is whether this same ability is associated with not only psychological well-being but also with posttraumatic growth. It is also unclear whether these findings extend to the context of recovery from a natural disaster.

Emotions vary from one moment to the next, mapping onto a dynamic temporal system (Hoeksma, Oosterlaan, Schipper, & Koot, 2007; Schuldberg & Gottlieb, 2002). Importantly, these fluctuations in emotions have been linked to several psychological health factors and outcomes. Post-natural disaster settings present many challenges for assessing emotions due to practical barriers and competing demands (Pfefferbaum et al., 2012). As such, prior research in this specific area is rare. However, the dynamics of emotional expression are likely to be involved in the recovery process. Relatively coherent yet flexible emotions, as opposed to random and disintegrated emotions, should represent an indicator of resilience. The following section describes some emotional dynamics that underpin emotional flexibility and structural integrity.

Variability

Variability in emotion refers to how the intensity of the emotion state exhibited by a person deviates from their mean level of intensity across time. Emotion variability is typically measured as an individual's standard deviation (SD) or root mean squared successive difference (RMSSD). Standard deviations are computed by calculating the square root of the variance based on each data point's deviance from the average across the series of data points. This metric assumes independence of each observed emotion; therefore, no interpretations can be made regarding the dependence or predictability of emotional states. Despite this limitation, recent research using this metric has revealed important general associations between emotion variability and various psychological outcomes (Houben, Van Den Noortgate, & Kuppens, 2015; Jenkins, Hunter, Richardson, Conner, & Pressman, 2020; Newton & Ho, 2008).

A meta-analysis examining the broader construct of emotion dynamics and mental health outcomes found that higher levels of emotion variability were associated with lower levels of psychological well-being (Houben et al., 2015). Similarly, Jenkins et al. (2020) found that individuals with lower emotion variability generally exhibited more favorable mental and physical health outcomes than individuals with higher emotion variability. In a sample of women with a history of victimization, greater emotional variability was associated with more severe posttraumatic stress symptoms (Newton & Ho, 2008), suggesting that high variability in the intensity of emotion from one's baseline intensity of emotional state is unfavorable for trauma survivors and may indicate poor psychological well-being. These studies highlight the general associations and relationships with relevant outcomes that can be described by assessing variability with standard deviations.

Emotion inertia is another way emotion dynamics have been measured and is computed as the autocorrelation in the emotion state from one moment to the next. High levels of emotion inertia are generally associated with poor psychological well-being and higher levels of psychopathology (Houben et al., 2015; Kuppens, Allen, & Sheeber, 2010; Wang, Schneider, Schwartz, & Stone, 2020). In a study of Operation Iraqi Freedom, Operation Enduring Freedom, and Operation New Dawn veterans, lower negative emotion inertia was associated with lower posttraumatic stress symptoms and more adaptive coping mechanisms (Simons, Simons, Grimm, Keith, & Stoltenberg, 2020). Thus, a low degree of predictability of an emotion state from one moment to the next may indicate better mental health and more effective coping in response to trauma. Researchers suggest that this association may be due, in part, to a negative relationship between inertia and psychological flexibility (De Longis, Alessandri, & Ottaviani, 2020; Houben et al., 2015). Whereas empirical research examining emotion dynamics and psychological well-being is growing, few studies have examined this in the context of posttraumatic adaptation.

Of the studies that have examined emotion dynamics and trauma, Hasmi et al. (2017) used a network approach to examine the interplay between emotion dynamics, childhood trauma, and genetic influence on psychopathology. Although the research team identified a possible link between genetic liability, negative emotional inertia, and psychopathology, findings around the relationship between childhood trauma, emotional inertia, and psychological outcomes were inconclusive. Research has yet to elucidate any relationship between emotion dynamics and posttraumatic growth among trauma survivors. The following section builds upon the emotion dynamics detailed in this section, describing indices that can be used to elucidate the systemic properties of emotion.

Measures of Structural Integrity and Self-Organization

"In self-organizing systems, pattern formation occurs through interactions internal to the system, without intervention by external directing influences" (Camazine et al., 2001). Although self-organizing systems interact with their environment (drawing, for example, energy from their environment or being subjected to various control parameters), their organization is their own.

Taken's theorem (1981) is widely used in the study of nonlinear dynamical systems because it allows for the construction of a state space that is topologically equivalent to a system's state space even when the data stream does not include measurements of all the necessary components. This construction relies on the assumption that there are echoes of the system component in each other system component due to the internal interactions. That is, Taken's theorem can construct a state space because a self-organizing *system* must reflect its self-organization in the behavior of every component. Hence, a researcher studying self-organization has great freedom in the choice of the component to measure; the component may be chosen for such mundane reasons as the availability of data. (Naturally, some components will have better or worse signal-to-noise ratio than others, and that must also be considered.)

Finding measures of self-organization, however, has been a difficult endeavor. Bak et al. (1987) introduced one measure, *power law distribution*, which, when combined with other characteristics of a system (in Bak et al.'s case, the critical slope in a sandpile), is routinely considered to be an indicator of self-organization. More recently, Barabási et al. (2005) introduced *burstiness*, which reflects the "memory" of a self-organizing system. Both these measures have been widely used in literature as indicators of self-organization. Given that these are likely to be unfamiliar in this context, we briefly introduce each in the following sections.

Burstiness

Bastien, Vallières, and Morin (2001) noted that many human situations are governed by dynamics that result in *bursty* data. Burstiness is understood to represent the degree to which events are clustered or random over time. Quantitatively, Barabási, Goh, and Vazquez (2005) defined the burstiness parameter, $B = (\sigma - \tau)/(\sigma + \tau)$, where σ and τ are the inter-event time standard deviation and mean, respectively; B can range from -1 to 1. A value of $B = -1$ can only occur when σ equals zero and indicates an exactly repeating pattern of events. Values of B between -1 and 0 indicate that the inter-event times follow an exponential or Poisson distribution (Karsai et al., 2018). Both the exponential and Poisson distributions of inter-event times are *memoryless*. That is, in those distributions, the amount of time until the next event is, on average, independent of how long it has been since the previous event. Values of B greater than zero, however, indicate that the inter-event times display a "memory" of previous events (resulting in events that are more likely to be clustered together than in the memoryless case) and that the distribution of inter-event times is a "fat-tailed" (e.g., inverse power law) distribution. Such fat-tailed distributions are commonly taken as indicators of self-organization in a system (Karsai et al., 2018). Following previous literature (Berardi, Pincus, Walker, & Adams, 2021; Pincus & Metten, 2010; and Pincus et al., 2019), we will use self-organization as a measure of structural integrity in a system.

Kim and Jo (2016) introduced a refined definition of the burstiness parameter, which works much better with short sequences. The interpretation of *B* is unchanged, but the equation for *B* incorporates the total number of events, *n*, in the sequence. Writing $r = \tau/\sigma$, Kim and Jo's burstiness parameter is:

$$\mathrm{B} = \frac{\sqrt{n+1}r - \sqrt{n-1}}{(\sqrt{n+1} - 2)r + \sqrt{n-1}} \quad (1)$$

We used this refinement in our calculations.

Inverse Power Law Distributions

Previous work in psychosocial systems (Berardi et al., 2021; Pincus et al., 2019; Pincus et al., 2014) has found that an *inverse power law* (IPL) distribution is a sign of self-organization within psychosocial systems as it has in other systems across the sciences (Prigogine & Stengers, 2018; e.g., Kauffman, 1996), and that features of the distribution may reflect aspects of functioning, such as readiness for habit change (e.g., Berardi et al., 2021), self-injurious behavior (e.g., Pincus et al., 2014), and psychopathology (Pincus et al., 2019). An inverse power law distribution is one that follows the form $P \sim x^b$, where *P* is the probability distribution function, *x* is the *rank* of the frequency of an occurrence, and *b* is the *shape parameter*.

An example may be instructive. Consider a set of simulated categorical data representing three different emotion states in a time sequence:

A, A, A, A, A, A, A, B, A, A, C, A, A, A, B, B, A, A

We see that there are 14 As, 3 Bs, and 1 C. Hence, the rank of A is 1 (i.e., most common), the rank of B is 2 (i.e., second most common), and the rank of C is 3 (i.e., least common). In this example, the three data points to be fit by a power-law distribution would be (1,14), (2,3), and (3,1). Several approaches to fitting the data to estimate the shape parameter have been used. Importantly, one must be careful when interpreting the shape parameter, as it is defined differently in different disciplines. Those coming from a physics background, such as Clauset, Shalizi, and Newman (2009), define *P* with a negative sign in the exponent, whereas social scientists usually define *P* without the negative sign. Furthermore, Clauset et al.'s (2009) approach to estimating the exponent from data works with the cumulative distribution function rather than the probability distribution function, which results in further differences in shape parameter between approaches. Because Clauset et al.'s (2009) maximum likelihood approach can be shown to produce an unbiased estimate, it will be used in this study.

In addition to demonstrating self-organization, Pincus et al. (2016) described how the shape parameter can be used to measure systemic flexibility. IPL distributions reflect an exponential relationship between size and frequency. For example, Pincus et al. (2014) found that the recurrence size of behavioral patterns of individuals observed during 150-minute periods showed IPL distributions. There were exponentially more patterns that occurred only once or twice than patterns repeated up to 15 or more times. Higher recurrence levels, in this case, indicate greater structure or rigidity, a flatter distribution (i.e., a "fatter" tail), and a lower absolute value for *b*. Less repetition produces a steeper distribution (i.e., larger mode and a "thinner" tail), less rigidity, and a higher value for *b*. In this study, lower *b* (more behavioral rigidity) was associated with higher levels of self-injury during the 150-minute period. Equivalent results have been found between conflict and rigidity in small group dynamics (Pincus, 2014) and rigid response-time distributions on personality inventories and psychopathology (Pincus et al., 2019).

Once the shape parameter has been estimated (if possible, some empirical distributions cannot be fit by a power-law), a correlation between the predicted and actual values can be used to compute an *R*-squared (R^2) value; this value measures how closely the data match an IPL distribution. Systems whose distributions result in larger R^2 values are considered to be more organized (e.g., have more self-organized structural integrity) than systems with small (or non-existent) R^2 values (Berardi et al., 2021; Pincus et al., 2016).

The Current Investigation

The present investigation studied wildfire disaster survivors to elucidate the dynamic evolution of emotion and PTG. By turning to NDS theory to understand PTG as a possible positive aspect of human resilience, we are heeding the recommendation that PTG is a dynamic process rather than a static outcome related to adversity (Cicchetti & Toth, 2009; Masten, 2014, 2015; Overton, 2015). Understanding emotion dynamics provides an opportunity to increase our understanding of PTG and mental health outcomes following trauma. Affective facial computing (i.e., automatic computerized facial expression detection) allows for furthering our understanding of emotion and psychological processes (Cohn et al., 2019). Affective facial computing has been used successfully to assess the occurrence and severity of depression and outcomes following treatment for obsessive-compulsive disorder (Cohn et al., 2018; Ding et al., 2020) and may help assess psychological outcomes following trauma. Furthermore, understanding the dynamics of facial expressions may provide useful information in helping to predict risk for PTSD and help monitor outcomes following trauma.

Systems that are both flexible and well-integrated are not only considered more capable of shifting toward coherence in response to trauma but also capable of returning to flexibility again (even growth) once the actual trauma has ended (Pincus & Metten, 2010). We first hypothesize that the facial affect data will exhibit IPL structure, with exponentially more low recurring patterns than high recurring patterns being observed, suggesting that there is a structure underlying the recurrence of the observed patterns. We also hypothesize that measures of self-organization (i.e., burstiness, R-squared, and shape parameter) for facial affect will positively correlate with self-report ratings of PTG. This hypothesis stems from our conceptualization of these indices as being indicative of structural integrity and flexibility. Taken together, we predict that both structure and flexibility are needed to facilitate growth under changing conditions (i.e., the post-disaster environment) throughout the temporal process of recovery. We further hypothesize that measures of facial affect self-organization will significantly predict posttraumatic growth and traumatic distress ratings at the 6-week and 6-month follow-up timepoints. Our sample was collected from survivors of one of the worst wildfire disaster seasons in the country's history. From December 2017 through November 2018, California experienced a series of wildfires (and severe mudslides), causing a total loss of more than 1.8 million acres. A total of 103 people were killed, and more than 24,000 structures were destroyed (NIFC, 2018).

METHODS

Sample

The study was conducted using data (n = 19) from a large sample of participants (N = 161) exposed to various natural disasters that occurred in California between December 2017 and November 2018 (i.e., the Thomas Fire and Mudslide, Montecito Complex Fire, Carr Fire, Paradise Fire, and Woolsey Fire). To participate, individuals were required to have been significantly affected by a respective disaster, own an updated smartphone, and be able to speak and respond to questions in English. Participants were deemed "significantly affected" by the disaster if they reported either having resided in a disaster-affected neighborhood (e.g., within three blocks of damaged or destroyed homes), experienced property damage, or known someone who was injured or died due to the disaster. A total of 100 participants (i.e., 62% of the sample) experienced significant property damage. Only 53 individuals participated in the 30-day ecological momentary assessment (EMA) app portion of the study. Of these 53 individuals, 19 elected to upload videos and were thus included in the study. These 19 individuals submitted a total of 112 videos. Longer-term (6-week and 6-month) follow-up surveys were requested of all participants. Of the 19 individuals studied here, only 12 participated in the 6-week follow-up data collection, and only 11 participated in the 6-month follow-up data collection.

Participants

The majority of participants were female (73.68%), and 26.32% identified as ethnic minorities, primarily Hispanic. Additionally, 36.84% of the participants reported being married or living with a partner, and 68.42% were home renters. On average, participants were assessed 277.88 days (SD = 99.36) since the disaster occurred. On the study-developed disaster exposure measure, participants exhibited an average score of 6.79 (SD = 2.42), indicating moderate exposure to life-threatening disaster situations. Participants reported moderate traumatic distress levels (Impact of Events Scale-Revised; IES-R; M = 1.70, SD = 0.87) and moderate trauma coping capability perceptions (Trauma Coping Self-efficacy; CSE-T; M = 5.12, SD = 0.97). Furthermore, participants reported an average score of 2.43 (SD = 1.40) on the Posttraumatic Growth Inventory - Short Form (PTGI-SF), suggesting that they perceived small to moderate levels of posttraumatic growth.

Measures and Data Collection

All participants completed a baseline survey online through Qualtrics, which included measures of disaster exposure, traumatic distress, coping self-efficacy (CSE), PTG, other psychological constructs, and demographics. After completing this survey, individuals were given the option to participate in the EMA portion of the study. Participants who opted-in to this portion of the study downloaded and used the *Mema* smartphone app and specified an ideal time to receive daily survey notifications. These participants were notified to complete brief surveys through the app (approximately 5 minutes long) daily for a month. The brief daily surveys included questions related to traumatic distress, CSE, PTG, and positive and negative affect. After completing a survey, participants were asked to record a video in response to the prompt, "how are you doing today?" Participants were also instructed to complete an "on-demand" survey if they perceived a significant shift in their level of distress or functioning. All participant app data, including videos, were uploaded to a secure cloud server and retrieved later for analysis.

The delivery and composition of measures varied between the longer baseline survey and the brief daily app survey. Measures of disaster exposure, CSE, PTG, and traumatic distress were collected in their entirety at baseline. Participants answered rotating subsets of items within each larger measure to substantially reduce participant burden during the month-long EMA app phase of the study. For example, on the six-item measure of traumatic distress (i.e., the Impact of Events Scale-Revised 6 (IES-R; Weiss, 2007), participants answered three items on day one and the remaining three items on day two. A detailed breakdown of the adjusted EMA question delivery structure is detailed in Table 1. Previous EMA studies have used comparable procedures for restructuring study measures and total score calculations without significantly affecting their psychometric properties (Dunton et al., 2014).

Table 1. EMA Sum Score Overview.

- Day 1
    - CSE Total = Sum of items 1, 4, 7
    - IES Total = Sum of items 1, 3, 5
    - PTGI Total = Sum of items 1, 3, 5, 7, 9
- Day 2
    - CSE Total = Sum of items 2, 5, 8
    - IES Total = Sum of items 2, 4, 6
    - PTGI Total = Sum of items 2, 4, 6, 8, 10
- Day 3
    - CSE Total = Sum of items 3, 6, 9
    - IES Total = Sum of items 1, 3, 5
    - PTGI Total = Sum of items 1, 3, 5, 7, 9

Note: CSE = Trauma Coping Self-efficacy total score, IES = Impact of Events total score, PTGI = Posttraumatic Growth Inventory total score.

Trauma Coping Self-Efficacy

The Trauma Coping Self-Efficacy Scale (CSE-T; Benight et al., 2015)) assessed the respondent's perception of trauma-related CSE across nine items. Respondents were asked to rate their perceived capability to manage various posttrauma demands (e.g., control thoughts). Ratings were scored using a 7-point Likert scale ranging from 1 ("I'm not capable at all") to 7 ("I'm totally capable"). The internal consistency (α = .93), test-retest reliability, and convergent validity of this scale have been validated with three separate samples, including disaster survivors (Benight et al., 2015). Participants answered three questions per day for the EMA app portion of the study, answering all nine questions over three days.

Traumatic Distress

The Impact of Events Scale-Revised 6 (IES-R; Weiss, 2007) is a six-item measure that assesses the presence and severity of posttraumatic distress. The scale corresponds to the B, C, and D criteria of the PTSD diagnosis in the DSM-5. Two questions relate to intrusions (criterion B), two items relate to avoidance (criterion C), and two items relate to hyperarousal (criterion D). For each question, respondents rated the severity of an item using a 5-point Likert scale ranging from 0 ("not at all") to 4 ("extremely"). The scale demonstrated adequate concurrent validity, discriminant validity, and short-term test-retest validity (Bienvenu, Williams, Yang, Hopkins, & Needham, 2013). This scale was shown to have good internal consistency when validated using a sample of sexual assault and motor vehicle accident survivors (α = .93; Cieslak, Benight, & Caden Lehman, 2008). Participants answered three questions per day for the EMA app portion of the study, answering all six questions over two days. Each day the participants were prompted to answer one question corresponding to criteria B, one corresponding to criteria C, and one corresponding to criteria D.

Positive and Negative Affect

The PANAS (Watson, Clark, & Tellegen, 1988) is a 20-item measure that produces two subscales (i.e., positive and negative affect), each consisting of ten adjectives. Participants responded based on how they felt during the past week for the baseline measure. Participants responded based on how they felt during the previous 24 hours for the daily app surveys. Respondents rated their feelings relative to a target word for each item on a 5-point Likert scale ranging from 1 ("very slightly") to 5 ("very much"). For the EMA portion of the study, participants answered four items per day, answering all 20 questions over five days. Each day, participants rated two items relative to positive affect and two items relative to negative affect.

Posttraumatic Growth

The Posttraumatic Growth Inventory Short Form (PTGI-SF; (Cann et al., 2010) is a 10-item measure of perceived positive changes in five domains following a trauma (i.e., relating to others, personal strength, new possibilities, appreciation of life, and spiritual change). For this investigation, respondents were asked to rate their agreement with items on a 6-point Likert scale ranging from 1 ("I did not experience this change as a result of the disaster") to 6 ("I experienced this change to a great degree as a result of the disaster"). Higher scores are indicative of greater positive change. For the EMA portion of the study, participants completed five items per day, each corresponding to one of the five domains of possible growth. Over two days, participants answered all ten of the PTGI-SF items.

Disaster Exposure Severity and Resource Loss

This measure was developed for the study and included 17 items referring to the exposure to life threats (e.g., seeing smoke or fire, being physically injured, knowing someone who died as a result of the disaster) and lost resources (e.g., destroyed home, finances, loss of employment). The responses had a yes/no format. This data was only assessed during the baseline questionnaire.

Demographics

Participants also completed a demographic questionnaire at baseline that inquired about gender, race, age, socio-economic status, and education. Demographic data was only assessed during the baseline questionnaire.

Self-Video Data

In addition to the EMA data, 19 participants contributed one or more self-recorded videos to this study; a total of 177 videos were contributed. These videos included facial images and the subject's verbal description of their emotions following a prompt to describe how they were doing that day. Two independent raters assessed the quality of each video to determine whether they were acceptable for analysis. Before independent assessment of video quality, exclusion criteria were set by study personnel. Exclusion criteria included wearing sunglasses, lighting too dark to observe facial features, and recording a participant's environment rather than their face. Based on these criteria, 65 videos were considered unfit for analysis, leaving 112 videos analyzed as part of the study.

AI Coding of Facial Affect

The Automatic Facial Affect Recognition (AFAR) toolbox software was used for automated facial affect recognition and *action unit* (AU) detection (Ertugrul et al., 2019b) of these video data. AUs are anatomically based facial movements that, when combined, comprise facial expressions of emotions such as happiness, fear, and disgust (Du, Tao, & Martinez, 2014). AFAR produces a normalized face video from the original video data at a frame rate of 30 frames per second and detects the probability of 12 AUs simultaneously. AU probabilities are detected at the frame level such that an output of probabilities for each AU is produced per frame of video. AFAR is licensed for free, non-commercial use and available through the software hosting platform GitHub. Various implementations of automatic facial affect recognition have been used in multiple studies, but the process is "very much in its infancy in psychology" and is known to currently have limited statistical power (Wyman & Zhang, 2023). Nevertheless, previous studies have demonstrated its usefulness (see, for example, Dupré et al. (2020) and Ertugrul et al. (2019)), and so we feel justified in using it here.

Combinations of the 12 AUs capable of being detected by the AFAR system were used to identify six total emotion states within the smartphone videos recorded by participants. These six emotion states included: happy, sad, angry, happily surprised, sadly angry, hatred, and angrily disgusted, and were based on algorithms described by Du et al. (2014). Figure 1 depicts the combinations of AUs used to form the six emotion states identified by the software. Emotion was only coded as present when the AFAR system detected each AU within a combination above a detection probability of 0.60. If no identifiable emotion states were identified in a given frame, the emotion state was labeled as neutral. The lack of accuracy of the AFAR system resulted in a large majority of frames (i.e., 89.2%) being labeled as neutral; this limits the sensitivity of the analyses. (The AFAR author recommends starting with a value of 0.50 and adjusting as appropriate; lower values increase the number of frames assigned into nonsensical hybrid categories (e.g., {happy + sadly angry}), thereby increasing the noise, while higher values reduce the number of non-neutral frame assignments. The relatively low quality of the video recordings necessitated using a slightly higher parameter value. Choosing a non-optimal parameter value in either direction will reduce the *B* estimate.) Frames could be labeled as neutral for two reasons: either a lack of AFAR sensitivity, or the emotion at the frame not aligning with one of the seven emotion states capable of being detected (e.g., being a neutral expression).

Analysis of Time Series Data

We use three data series in our analysis. The first series is a categorical time series resulting from the AFAR process. There is a one-to-one correspondence between the video frame and category (e.g., happy, sad). The second series is *event-based* rather than time-based. An event-based series is derived from a time-based series by collapsing consecutive identical codes into a single code. That is, a time-series such as …, B, A, A, A, A, B, C, A.... would be collapsed into the event-based series …, B, A, B, C, A... where the four consecutive "A" codes are treated as a single event. This event-based series is also a categorical time series. The day-to-day sequences of EMA responses form the third set of time series; these sequences consist of ordinal data. We note that each of these series has a different *characteristic time*. The time-series created by the AFAR processes have characteristic inter-element times of 1/30th second, the frame rate of the video. The event-based series consists of elements that may last from one to several tens of frames, so the most typical inter-element time for the event-based series is on the order of seconds. EMA data were collected daily, so those data have a characteristic inter-element time of one day. Numerous

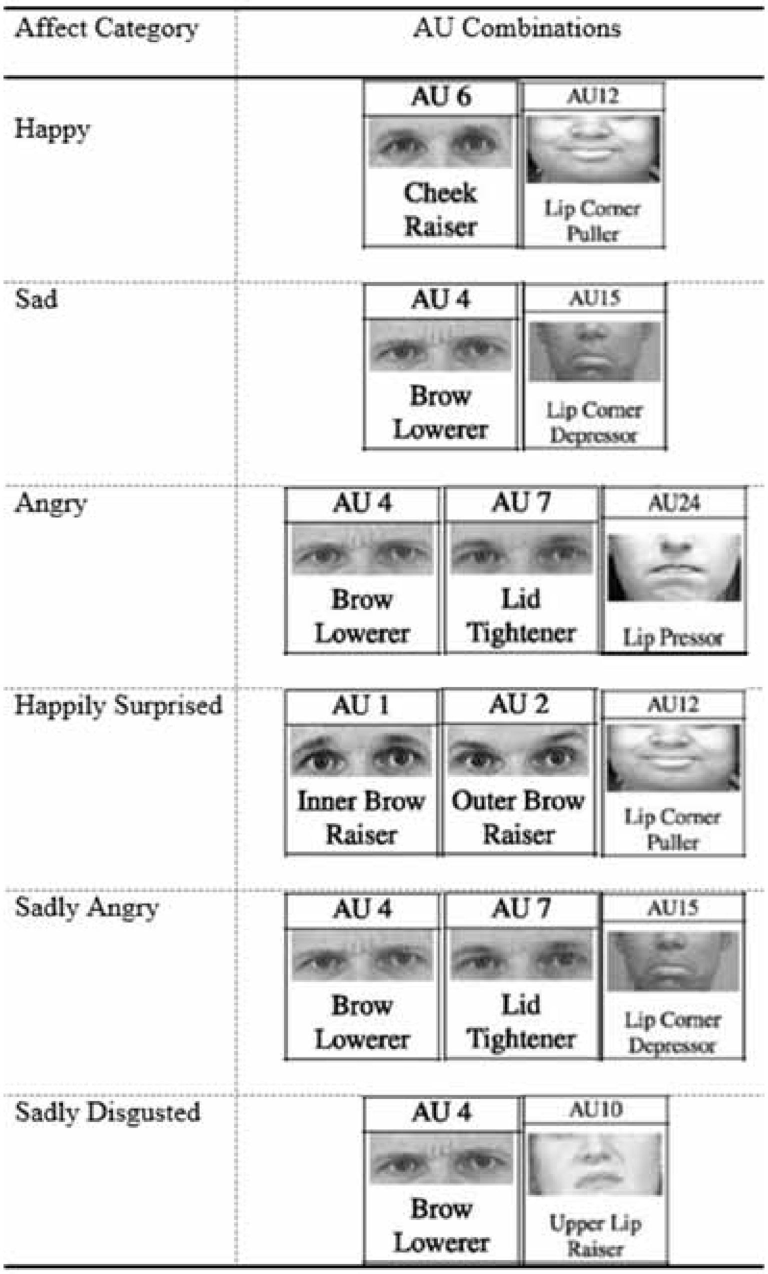

Fig. 1. AUs observed in each detected affect category. AU = Action Unit.

approaches exist to analyze time-series data; we chose two that are both empirically supported (Bak et al., 1987; Barabási et al., 2005) and that meet the analytic needs of studying self-organization: *burstiness* and *system integrity*.

Burstiness

We estimated burstiness, B, parameters for each of the AFAR time series. We expect that B should correlate with the PTGI-SF score (Berardi et al., 2021). Because self-efficacy is conceptually similar to, although not identical to, self-organization, we also expected CSE to be moderately correlated with B and tested that possibility.

Self-regulation shift theory (SRST, Benight et al., 2017) posits that CSE will predict both posttraumatic distress and growth. Because of the expected correlation between CSE and B, a predictive model of PTGI depending upon CSE, B, and their interaction was tested. A similar predictive model of traumatic distress was also investigated.

System Integrity

Orbital decomposition (Guastello, Peressini, & Bond, 2011) is designed to identify "dynamical patterns in categorical data" (p. 499). These dynamic patterns can indicate important patterns within the data. In particular, orbital decomposition uses topological entropy to identify the length, coefficient of determination (C_{OD}), of the longest immediately recurring pattern that is statistically significant. We can use C_{OD} to create a frequency distribution of pattern recurrences and, from that distribution, estimate a measure of *system integrity* (Pincus, 2014) by fitting the distribution to a power law. An example will be helpful.

Consider a (fictitious) categorical time-series A, B, B, D, A, E, F, G, A, B, B, D. Suppose that an orbital decomposition of this series indicates the appropriate maximum pattern length, C_{OD} is 2. We can use that information to create a distribution of pattern repetitions as follows: the first pattern of length 2 is AB (starting from the first element of the pattern), while the second is BB (starting from the second element of the pattern), and so on. We can see that some patterns (AB, BB, BD) occur twice in the data, while the other five patterns occur only once. Hence, we can say that the distribution of pattern repetitions is that five patterns occur once, and three patterns that occur twice.

Pincus et al. (2014) proposed that the coefficient of determination value, R^2, from a *power-law* fit ($y \sim x^b$) to the distribution is a measure of system integrity (a power-law fit is used because self-organizing systems typically display power-law distributions for many of their properties). In layperson's terms, the value of R^2 reflects the fit of the C_{OD} to a power-law distribution. Lower R^2 values may indicate maladaptive processes (either too rigid or too chaotic), and higher R^2 values may indicate better adaptive ability. Although Pincus et al. (2014) studied small group dynamics, we expect the same principle, that structural integrity underlies resilience, to be applicable here. Hence, higher R^2 values indicate a better growth trajectory, and therefore, higher R^2 values should be reflected in higher CSE scores and *increasing* PTGI-SF scores. Stated more practically, we expect the *change* in PTGI-SF scores between one day and the next to be correlated with the R^2 value of the earlier day. We used orbital decomposition on the event-based data to determine a C_{OD} value for each sequence. We used event-based data because we are more interested in the transitions between events than in the length over which an emotion state is expressed.

Correlations and Modeling

Having estimated three measures of system integrity from the AFAR sequences - burstiness, shape parameter, and R^2 (for the power-law fit) -, we used those measures as predictors of EMA data (e.g., CSE, PTG, traumatic distress). Daily correlations between the measures were conducted to get an overall picture of the relationships between the variables.

In addition to correlations, we used predictive and inferential models to test our hypotheses. We began by performing a permutation ANOVA for significant differences in traumatic distress, CSE, positive affect, and negative affect when divided into two groups: those participants who provided videos and those who did not. A permutation ANOVA was chosen because it was expected that the data would deviate substantially from a normal distribution. A second significance test for each variable was performed using groupings depending on system integrity. (Those whose AFAR sequences showed sufficient system integrity (as demonstrated by a minimum length of the longest immediately repeating pattern) comprised the first group, and those whose AFAR sequences showed a lack of sufficient system integrity (as demonstrated by shorter immediately repeating patterns) comprised the second group.) It was determined that a multilevel model would not have been appropriate as the non-video condition did not have subgroups equivalent to the subgroups in the video case.

We investigated the interaction between CSE and system integrity in predicting PTG by building a linear model using CSE, burstiness, shape parameter, and R^2 as predictors and including an interaction term between CSE and the measures of system integrity and burstiness. The initial predictive model used was:

$$\begin{aligned} PTGI(SF) = {} & \beta_0 + \beta_1 PTGI(SI) + \beta_2 * CSE.T + \beta_3 * R2 \\ & + \beta_4 * \alpha + \beta_5 * B + \beta_6 * CSE.* R^2 \\ & + \beta_7 * CSE.T * \alpha + \beta_8 * CSE.T * B + \varepsilon \end{aligned} \tag{2}$$

Non-significant terms in the initial predictive model were dropped sequentially from the initial model to produce a final model (Hastie & Pregibon, 2017). Akaike information criteria (AIC) and ANOVAs were used to evaluate the models relative to the initial model.

Lastly, we investigated the ability of CSE, again in interaction with system integrity measures and burstiness, to predict short- (i.e., next EMA report) and long-term (i.e., 6-week and 6-month) outcomes of traumatic distress (IESR) and PTG.

Short-term predictions were made using one day's EMA measurements and video data to predict the subsequent EMA measurement. Given that not all participants completed all 30 days of EMA, the subsequent EMA measurement may have been more than one day in the future from the predictor measurements. Although the missing data can create issues with statistical power and interpretation (see Discussion below), this approach was chosen as the best possible exploration that could be undertaken in the face of likely missing data. The short-term equation for the prediction of traumatic distress is:

$$\begin{aligned} IESR_{next} = {} & \beta_0 + \beta_1 * IESR + \beta_2 * PTGI + \beta_3 * CSE.T \\ & + \beta_4 * R2 + \beta_5 * \alpha + \beta_6 * B + \beta_7 * CSE.T * R^2 \\ & + \beta_8 * CSE.T * \alpha + \beta_9 * CSE.T * B + \varepsilon \end{aligned} \tag{3}$$

where all of the values of *IESR*, *PTGI*, *CSE.T*, R^2, α, and *B* on the right-hand side of the equation are evaluated at the earlier day of EMA collection, and the left-hand side value of *IESR* is evaluated at the next date with *IESR* data.

The baseline values of CSE, traumatic distress, and PTG were used as predictors for the long-term models. The 30-day average of R^2, the shape parameter, and burstiness values also were used as predictors. The initial models for those who had usable system integrity and burstiness values were:

$$\begin{aligned} PTGI_{6-week} = {} & \beta_0 + \beta_1 * PTGI_{base} + \beta_2 * CSE.T_{base} + \beta_3 * R2 \\ & + \beta_4 * \alpha + \beta_5 * B + \beta_6 * CSE.T * R^2 \\ & + \beta_7 * CSE.T * \alpha + \beta_8 * CSE.T * B + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned} PTGI_{6-month} = {} & \beta_0 + \beta_1 * PTGI_{base} + \beta_2 * CSE.T_{base} \\ & + \beta_3 * R2 + \beta_4 * \alpha + \beta_5 * B + \beta_6 * CSE.T * R^2 \\ & + \beta_7 * CSE.T * \alpha + \beta_8 * CSE.T * B + \varepsilon \end{aligned} \tag{5}$$

$$\begin{aligned} IES_{6-week} = {} & \beta_0 + \beta_1 * IES_{base} + \beta_2 * CSE.T_{base} + \beta_3 * R2 \\ & + \beta_4 * \alpha + \beta_5 * B + \beta_6 * CSE.T * R^2 \\ & + \beta_7 * CSE.T * \alpha + \beta_8 * CSE.T * B + \varepsilon \end{aligned} \tag{6}$$

$$\begin{aligned} IES_{6-month} = {} & \beta_0 + \beta_1 * IES_{base} + \beta_2 * CSE.T_{base} \\ & + \beta_3 * R2 + \beta_4 * \alpha + \beta_5 * B + \beta_6 * CSE.T * R^2 \\ & + \beta_7 * CSE.T * \alpha + \beta_8 * CSE.T * B + \varepsilon \end{aligned} \tag{7}$$

(Note that Eqs. 4 and 6 are 6-week follow-ups while Eqs. 5 and 7 are 6-month follow-ups.) Non-significant terms in the initial predictive model in Eqs. 3-7 were dropped stepwise from the initial model to produce a final model (Hastie & Pregibon, 2017). Akaike information criteria (AIC) and ANOVAs evaluated the intermediate models relative to the initial model.

RESULTS

Usable Videos

Of the 112 submitted videos, only 102 were used for system integrity measures. Five of the excluded videos were submitted on the same day as another video by the same participant. Only the video submitted in response to the prompt was used in these cases. One video was submitted and attributed to a participant, but no other information about the video (e.g., the date of submission) was recorded. That video was also excluded. An additional four videos were excluded because the AFAR analysis discerned no non-neutral emotion states in them. (This resulted in removing one participant whose only submitted video fell into this category.)

A total of 11 videos submitted by one participant were excluded from further analysis. None of the 11 videos from this participant displayed any immediately repeating patterns (as identified through orbital decomposition), and seven of those videos exhibited the only seven negative burstiness coefficients estimated from any usable videos. Because of the almost complete inability of our procedure to discern patterns, we suspect that either the participant's camera or video environment or the AFAR system made this participant's video data inappropriate to use. Hence, we excluded these 11 videos, leaving 91 usable videos and 18 participants.

Orbital Decomposition and IPL Analyses

Orbital decomposition determined that 81 of 91 (87%) usable videos contained immediately recurring patterns. Of the 91 usable videos, 75 have $C_{OD} \geq 4$, 66 of them have $C_{OD} \geq 6$, and 48 have $C_{OD} \geq 8$. In the absence of further guidance regarding how to compare subsequences, we chose to use only the 66 videos with $C_{OD} \geq 6$, as that seems to be a reasonable balance between the length of the longest immediately recurring pattern and the statistical power that comes from increasing the number of examples. For those sequences with $C_{OD} \geq 6$, a power-law fit was performed on the resulting subsequence length distribution, and an R^2 value was calculated from the correlation of the fit with the data.

Self-Organization

Results revealed evidence for self-organization in facial affect across the sample, demonstrated by a high mean R-squared value ($R^2 = 0.84$) and a high mean shape parameter value ($b = 1.94$). Burstiness coefficients from analysis of the emotion states in the videos ranged from 0.01 to 0.67, with a mean of 0.33, a median of 0.31, and two missing values. Because positive burstiness coefficients indicate some level of self-organization, we take these results as evidence that the participants display self-organization in their videos.

Table 2. Study Variable Correlations with Confidence Intervals.

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. CSE							
2. IES	.27** [.07, .45]						
3. PTGI	-.11 [-.31, .10]	.63** [.48, .74]					
4. PANAS_NE	.53** [.37, .66]	.49** [.31, .63]	.32** [.12, .50]				
5. PANAS_PE	.34** [.14, .51]	.83** [.75, .88]	.59** [.44, .71]	.50** [.33, .64]			
6. Bursty	-.23* [-.42, -.02]	.21* [.00, .40]	.43** [.24, .58]	-.23* [-.42, -.02]	.14 [-.07, .34]		
7. Shape	.01 [-.25, .26]	.03 [-.23, .29]	-.06 [-.31, .20]	-.04 [-.29, .22]	.06 [-.20, .31]	-.23 [-.44, .02]	
8. R^2	.07 [-.19, .32]	-.08 [-.33, .18]	-.16 [-.40, .10]	-.06 [-.31, .20]	-.15 [-.39, .11]	-.05 [-.29, .20]	-.55** [-.70, -.35]

Note: CSE = Trauma Coping Self-efficacy, IES = Impact of Events, PTGI = Posttraumatic Growth Inventory, PANAS_NE = negative affect, PANAS_PE = positive affect, Bursty = burstiness, Shape = shape parameter. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). *p < .05. **p < .01.

Table 3. Study Variable Means and Standard Deviations.

Variable	*M*	*SD*
CSE	18.69	5.79
IES	5.56	3.40
PTGI	14.87	8.52
PANAS_NE	6.57	3.41
PANAS_PE	3.26	2.28
Bursty	0.26	0.29
Shape	1.94	0.20
R^2	0.84	0.08

Note: M and SD are used to represent mean and standard deviation, respectively. CSE =Trauma Coping Self-efficacy, IES = Impact of Events, PTGI = Posttraumatic Growth Inventory, PANAS_NE = negative affect, PANAS_PE = positive affect, Bursty = burstiness, Shape = shape parameter.

Correlations

Table 2 is a correlation matrix for PTGI-SF, IES, CSE, PANAS-Positive, PANAS-Negative, burstiness, and the two IPL measures. Variable means and standard deviations are reported in Table 3. Correlations were calculated using only the data from complete cases where the day contained a usable video submission and a complete set of EMA data.

Table 4. Permutation Analysis of Variance for IES, PANAS, and CSE.

Variable	IES *Fit*	IES *Residuals*	PANAS-PE *Fit*	PANAS-PE *Residuals*	PANAS-NE *Fit*	PANAS-NE *Residuals*	CSE *Fit*	CSE *Residuals*
Df	1	78	1	78	1	78	1	78
R Sum Sq	19	947	5	442	14	926	0	2951
R Mean Sq	19.4	12.1	5.4	5.7	13.8	11.9	0	37.8
Iter	479	-	51	-	678	-	51	-
Pr (Prob)	0.2	-	0.8	-	0.1	-	1	-

Note: Df = degrees of freedom, R Sum Sq = residual sum of squares, R Mean Sq = residual mean square, Iter = number of iterations, Pr (Prob) = probability value. CSE = Trauma Coping Self-efficacy, IES = Impact of Events, PANAS_NE = negative affect, PANAS_PE = positive affect.

Table 5. Regression Results Using PTGI as the Criterion.

Predictor	*b*	*b* *95% CI* *[LL, UL]*	sr^2	sr^2 *95% CI* *[LL, UL]*
(Intercept)	-2.72	[-206.46, 201.02]		
CSE	1.42	[-8.85, 11.70]	.00	[-.01, .01]
Bursty	55.52*	[7.83, 103.20]	.07	[-.04, .19]
R^2	33.07	[-121.13, 187.26]	.00	[-.02, .02]
Shape	-18.25	[-65.72, 29.22]	.01	[-.03, .05]
CSE:Bursty	-2.08	[-4.85, 0.70]	.03	[-.04, .10]
CSE:R^2	-2.46	[-10.38, 5.45]	.01	[-.03, .04]
CSE:Shape	0.90	[-1.33, 3.13]	.01	[-.03, .05]

Note: A significant b-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. CSE = Trauma Coping Self-efficacy, Bursty = burstiness, Shape = shape parameter, CSE:Bursty = interaction between CSE and burstiness, CSE:R^2 = interaction between CSE and burstiness, CSE:Shape = interaction between CSE and burstiness. *$p < .05$. **$p < .01$.

Table 6. Regression Results Using PTGI as the Criterion.

Predictor	*b*	*b* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]
CSE	0.73*	[0.04, 1.42]	.04	[-.03, .11]
Bursty	55.91**	[18.66, 93.16]	.08	[-.02, .18]
CSE:Bursty	-2.18*	[-4.01, -0.34]	.05	[-.03, .13]

Note: A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. CSE = Trauma Coping Self-efficacy, Bursty = burstiness, CSE:Bursty = interaction between CSE and burstiness. *$p < .05$. **$p < .01$.

Significance Tests

We tested the EMA data for significant differences between videos that had the longest immediately repeating patterns of length ≥ 6 (n = 66) and those that did not (n = 25).

The results of these tests are shown in Table 4 for the variables IES, PANAS-PE, PANAS-NE, and CSE.T, respectively. A permutation analysis of variance model was conducted to compare the IES scores for videos with long (length ≥ 6, M = 6.2, SD = 3.8) immediately repeating patterns and those without a long pattern (M = 4.9, SD = 1.8), p = 0.12. A permutation analysis of variance model was conducted to compare the PANAS-PE scores for videos with long (length ≥ 6, M = 3.7, SD = 2.6) immediately repeating patterns and those without a long pattern (M = 2.8, SD = 1.2), p = 0.096. A permutation analysis of variance model was conducted to compare the PANAS-NE scores for videos with long (length ≥ 6, M = 6.1, SD = 3.8 immediately repeating patterns and those without a long pattern (M = 6.5, SD = 2.2), p = 0.65. A permutation analysis of variance model was conducted to compare the CSE.T scores for videos with long (length ≥ 6, M = 18.2, SD = 7.0) immediately repeating patterns and those without a long pattern (M = 18.7, SD = 1.8), p = 0.98. A post-hoc power analysis indicated that the study was underpowered for all four of these empirical effect sizes, so the non-significant results are not unexpected.

Short-Term Predictive Modeling of PTGI and CSE

Table 5 shows the results of the initial modeling of PTGI as a function of CSE, system integrity, and burstiness (Eq. 2). The initial model was stepwise reduced to this model:

$$PTGI(SF) = \beta_0 + \beta_1 * CSE.T + \beta_4 * B + \beta_7 * CSE.T * B + \varepsilon \quad (8)$$

The model of Eq. 8 was significant, with a model R^2 of 0.233 and a 95% confidence interval of [.07, .36]; see Table 6. Additionally, all three coefficients of Eq. 8 - for CSE, burstiness, and the interaction between CSE and burstiness - were significant predictors of PTGI. The significant interactions between CSE and burstiness for these models are depicted in Figs. 2 and 3.

Table 7 shows the results of the initial modeling of IES as a function of CSE, system integrity, and burstiness (Eq. 3). The initial model was stepwise reduced to this model:

$$IESR = \beta_0 + \beta_1 * CSE.T + \beta_4 * B + \beta_7 * CSE.T * B + \varepsilon \quad (9)$$

The model of Eq. 9 was significant, with a model R^2 of 0.239 and a 95% confidence interval of [.08, .36]; see Table 8. Additionally, all three coefficients of Eq. 9 - for CSE.T, burstiness, and the interaction between CSE and burstiness - were significant predictors of IES. The significant interactions between CSE and burstiness for these models are depicted in Figs. 4 and 5.

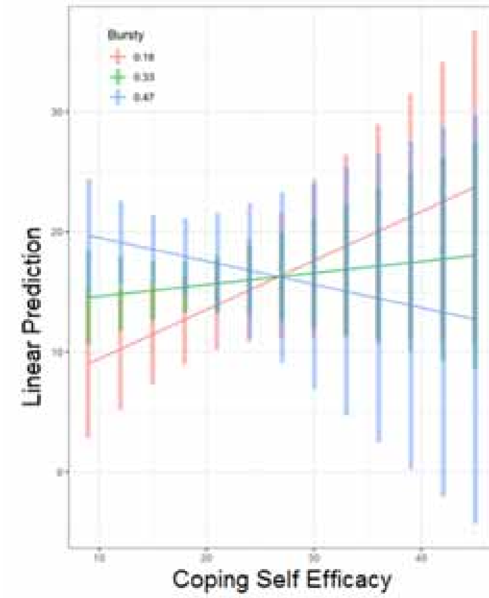

Fig. 2. Interaction figure for Table 5. Bursty = burstiness.

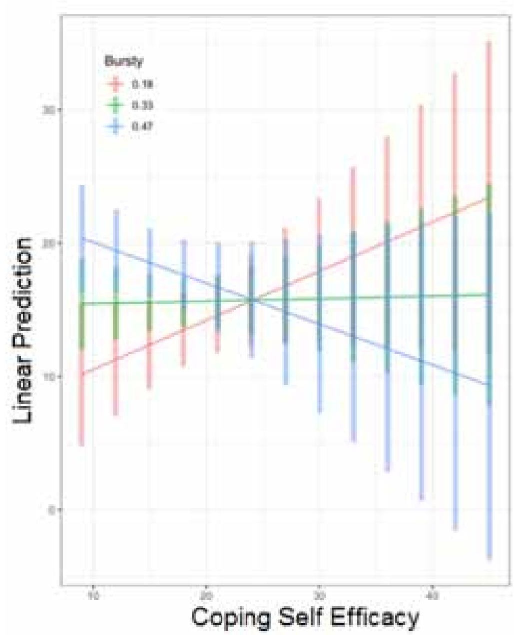

Fig. 3. Interaction figure for Table 6. Bursty = burstiness.

Table 7. Regression Results Using IES as the Criterion.

Predictor	*b*	*b* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]
CSE	2.93	[-1.10, 6.95]	.03	[-.04, .09]
Bursty	35.92**	[17.24, 54.60]	.17	[.02, .33]
R^2	16.87	[-43.54, 77.28]	.00	[-.02, .03]
Shape	14.80	[-3.80, 33.40]	.03	[-.04, .10]
CSE:Bursty	-1.96**	[-3.04, -0.87]	.15	[.01, .30]
CSE:R^2	-0.98	[-4.08, 2.12]	.00	[-.02, .03]
CSE:Shape	-0.72	[-1.60, 0.15]	.03	[-.04, .10]

Note. A significant *b*-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. CSE = Trauma Coping Self-efficacy, Bursty = burstiness, Shape = shape parameter, CSE:Bursty = interaction between CSE and burstiness, CSE:R^2 = interaction between CSE and burstiness, CSE:Shape = interaction between CSE and burstiness. *$p < .05$. **$p < .01$.

Table 8. Regression Results Using IES as the Criterion.

Predictor	*b*	*b* 95% CI [LL, UL]	sr^2	sr^2 95% CI [LL, UL]
CSE	0.58**	[0.31, 0.86]	.16	[.03, .30]
Bursty	25.66**	[10.84, 40.49]	.11	[-.01, .22]
CSE:Bursty	-1.11**	[-1.84, -0.38]	.08	[-.02, .18]

Note. A significant b-weight indicates the semi-partial correlation is also significant. *b* represents unstandardized regression weights. sr^2 represents the semi-partial correlation squared. *LL* and *UL* indicate the lower and upper limits of a confidence interval, respectively. CSE = Trauma Coping Self-efficacy, Bursty = burstiness, CSE:Bursty = interaction between CSE and burstiness.* $p < .05$. **$p < .01$.

Long-Term Predictive Modeling

None of the long-term predictive models, Eqs. 4 - 7, were significant. Long-term predictive modeling was hampered by the relatively few participants who provided long-term data and those videos that could not produce power-law fits. The result of missing data was that only 10 (for the six-week) and 9 (for the six-month) cases were available for modeling. Post-hoc power tests for long-term measures of PTGI and IESR indicate that all four Eqs. 4 - 7 lack sufficient power to provide significant models or to produce significant estimates of the β coefficients. Stepwise reduction of the equations (using AIC) typically resulted in a reduction to include only the CSET baseline and system integrity measures. However, these reduced equations were non-significant as well.

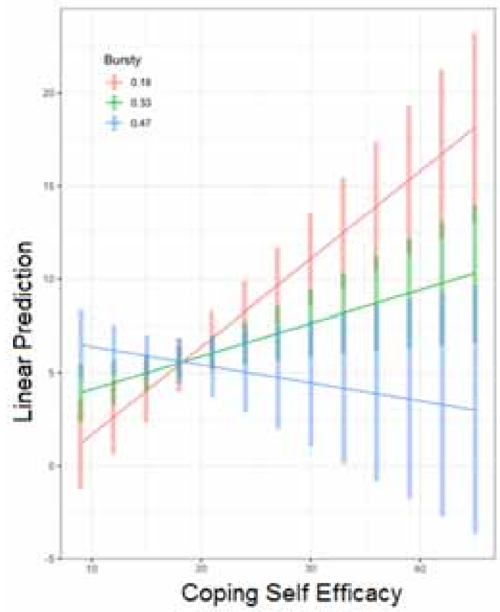

Fig. 4. Interaction figure for Table 7. Bursty = burstiness.

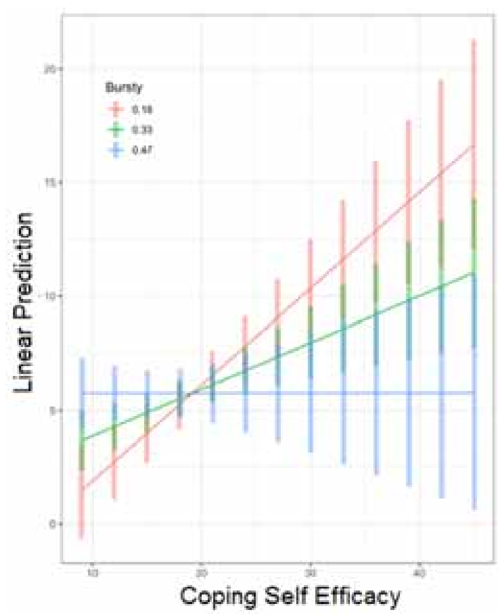

Fig. 5. Interaction figure for Table 8. Bursty = burstiness.

DISCUSSION

The current study used a novel application of a theory-based nonlinear technique to examine how facial affect dynamics are associated with PTG over time. Self-organization theories suggest that effective self-regulation requires a delicate balance of flexibility and structural integrity (Pincus & Metten, 2010). Our investigation detected evidence of these systemic features within the facial affect of wildfire survivors, extending support for their relevance within posttraumatic recovery. Several findings are noteworthy from the investigation.

First, a high mean *R*-squared (M = 0.84, SD = 0.08) and a mid-range mean shape parament value (M = 1.94, SD = 0.20) were observed for the facial affect data. Additionally, this investigation also found a positive mean burstiness value (M = 0.26, SD = 0.29). Taken together, these findings demonstrate that self-organization of facial affect was evident within the videos analyzed for this study. Emotional complexity, often assessed via R^2 and shape parameter values, is commonly associated with psychological health and flexibility instead of maladaptive rigidity. Prior studies of self-organization have observed similar values when investigating physical activity, psychopathology, and personality (Berardi et al., 2021; Pincus et al., 2019). This was the first investigation to evidence self-organizational properties of trauma survivors' facial affect captured via smartphone video.

Apart from finding that means of the systemic facial affect properties (i.e., *R*-squared, shape parameter, and burstiness values) were consistent with self-organization, the secondary IPL-related hypothesis was not supported. The *R*-squared and shape parameter values for facial affect did not positively correlate with PTG. Of note, no study variables correlated with *R*-squared or shape parameter values. Furthermore, these values were also not correlated with burstiness. Taken together, this may suggest that the lack of correlations may have been due to the nature of the data. The facial affect data included shorter series, with the majority of the patterns being simple alternations of some emotion and neutral. The data was analyzed using an event-based approach (i.e., collapsing across time points that do not represent a transition from the prior time point). Data analyzed in this way more closely aligned with the study aims and allowed for more meaningful analysis of the transitions between discrete emotion states. However, when analyzed in this manner, information regarding the time intervals of emotion state transitions is not considered. It is possible that without this information, *R*-squared and shape parameter values were less related to the variables of interest.

Prior literature has struggled to explain the nature of the relationship between traumatic distress, CSE, and PTG (Cieslak et al., 2009). Similarly, the correlational analyses depicted an interesting picture of how these variables related to one another. For example, CSE and traumatic distress demonstrated a positive association (.27), whereas CSE and PTG demonstrated a negative association trending toward significance (-.11). This suggests that greater perceived coping capabilities may coincide with more severe traumatic stress symptoms but lesser perceptions of growth from a trauma. The results of this investigation suggest that burstiness may represent a key factor needed to further explain the dynamic relationship between PTG, traumatic distress, and CSE over time.

As hypothesized, burstiness emerged as a robust predictor of both PTG and traumatic distress, explaining 8% and 11% of the variance, respectively. Burstiness values help indicate the degree of self-organization that a system exhibits. Higher burstiness values are often considered "healthy" within human research, equating to a lower degree of randomness (Pincus et al., 2019). The series of regressions examining burstiness, CSE, and PTG provide novel insights into the dynamic recovery of trauma survivors. Particularly important are the significant interaction terms revealed by these analyses.

The significant interaction between burstiness and CSE helped to explain how bursty facial affect interacted with CSE to influence PTG for this disaster survivor sample. For individuals who exhibited low levels of affective burstiness (i.e., indicative of poor self-organization), greater perceived coping capabilities were associated with higher ratings of PTG. For individuals who exhibited moderate levels of affective burstiness (i.e., indicative of average self-organization), greater perceived coping capabilities were not associated with PTG. For individuals who exhibited high levels of affective burstiness (i.e., indicative of good self-organization), greater perceived coping capabilities were associated with lower ratings of PTG. The significant interaction between burstiness and CSE revealed by regression analysis helped to explain how bursty facial affect interacts with CSE to influence traumatic distress. For individuals who exhibited low to moderate levels of affective burstiness (i.e., indicative of poor self-organization), greater perceived coping capabilities were associated with heightened traumatic distress levels. However, individuals who exhibited high affective burstiness (i.e., indicative of good self-organization) and greater perceived coping capabilities were not associated with traumatic distress levels.

These two significant interactions tell a compelling story of how emotion patterns and coping perceptions are embedded within divergent recovery and growth processes following a trauma. Trauma survivors who exhibit highly bursty emotions may not experience significant growth from trauma due to lower distress levels. The authors of this paper speculate that individuals who display more regulated emotion patterns experience less distress, and therefore, they do not have sufficient distress to warrant growth. However, individuals who display more random emotion patterns are more likely to experience more chronic and severe traumatic distress. Interestingly, these same individuals (who exhibited less organized emotions) are also more likely to report lofty coping capability perceptions and greater PTG. It may be the case that individuals who display less organized emotions are more prone to experience the pseudo-confident effect. This interpretation may provide unique insight into prior work demonstrating that higher PTG can co-occur with chronic courses of traumatic distress (Zoellner & Maercker, 2006), pointing toward the emotion quality of burstiness as a critical factor to consider.

These interaction findings are noteworthy given that they highlight potential answers to important theoretical questions that remain unanswered about the underpinnings of PTG. As mentioned earlier, some scholars have positioned the Janus-face model of PTG as a possible explanation for discrepant findings between changes in PTG and traumatic distress levels (Zoellner & Maercker, 2006). However, this model presents many challenges in that, historically, it does not pinpoint targetable aspects of experience that can be accurately observed. Instead, it relies primarily on self-report, which is wrought with confounds such as motivation, insight, and mood. The current study addressed this shortcoming by identifying facial affect as a more objectively measured construct that enables a greater understanding of PTG as a dynamic process. Our findings suggest that individuals who flexibly exhibit emotion governed by attempts to self-regulate, even without conscious awareness, are more likely to report positive changes in their sense of purpose and meaning in life.

Additionally, the findings of this study highlight the utility of using video data to refine our understanding of posttraumatic phenomena such as PTG. The majority of the US population (i.e., 68% in 2015) now owns a smartphone capable of recording videos (Anderson, 2015), making this data much more accessible. Within the context of disaster research, participants often are displaced, relocate, and encounter barriers that make traditional research methods more of a challenge. The current smartphone study afforded participants greater mobility, heeding (Kazdin & Blase, 2011) call to reduce participant burden by allowing for greater reach and access to this population. The video data collected and analyzed as part of this study is arguably less invasive for the subject, quicker, and can automate calls for intervention.

Limitations

The current study provides important contributions to the fields of nonlinear dynamics and traumatic stress, but it is not without its limitations. Whereas the current study assessed 112 different videos, the data came from a small sample of 18 participants. A larger sample would help improve the likelihood that the findings of this study closely approximate the population of wildfire survivors. Another limitation of this study was that it was based on data from survivors of four different wildfires. These wildfires varied in longevity, location, and destruction. Such variability could have significantly influenced constructs not assessed within the current study (e.g., social support), indirectly affecting individual pathways toward traumatic recovery and growth. Conversely, the significant results found within this heterogeneous group of wildfire survivors suggest greater generalizability.

Another limitation is that the timing of study enrollment following disaster exposure was not uniform across participants. Enrollment dates ranged from 112 days to 380 days post-disaster. By definition, the dimension of time is central to the recovery process. Furthermore, relevant theories of PTG and dynamic systems suggest that timing represents a critical feature needed to understand internal processes and external behavior (Schaefer & Moos, 1998;

Tedeschi & Calhoun, 2004; Thelen, 2005). For example, a survivor one month removed from a wildfire may still be displaced, seeking employment, and experiencing several intrusive memories. Alternatively, a survivor nine months removed from a wildfire may have secured housing and new employment but experience a persistent depressed mood and hold rigid negative beliefs about their safety. One survivor is dealing with more immediate stressors and may be less capable of experiencing or perceiving growth.

Outside of disaster research, scholars have observed that time since a life-threatening medical event (i.e., a stroke) moderates the correlation between PTG and several outcomes (e.g., anxiety and depression) (Gangstad, Norman, & Barton, 2009). These researchers found that earlier measurements produced nonsignificant results, whereas later measurements yielded significant correlations between PTG and other variables. Whereas the time since disaster was statistically controlled for within the present study, precise time-based predictions could not be generated due to variable study enrollment with the small sample. Furthermore, after initial disaster exposure, inadequate time may have passed to allow for post-disaster turmoil to dissipate and reduce the risk of illusory coping strategies. However, this investigation does provide insight into the systemic processes that may underlie the eventual emergence of PTG.

The demonstrated utility of AFAR, a free public-use facial affect detection software, within this study represents a major strength. The cost and feasibility of research are major concerns of any scientific discipline, and the AFAR system reduces the burden of both. However, the AFAR system is limited in that it has not been used to investigate trauma survivors and can only detect 12 out of 44 possible AUs based on the Facial Action Coding System (FACS; Ekman & Friesen, 1978). The system is also still in the earlier stages of empirical support, and a Google Scholar search revealed that, to date, four peer-reviewed articles report usage. If similar results were found using a comparable software program, the efficacy of AFAR and the validity of our results would be further supported. The retrospective self-report of PTG used in this study also represented a noteworthy limitation. A significant point of contention within the research domain of PTG centers on whether self-reported growth genuinely represents personal development or serves as a coping mechanism (Frazier et al., 2009).

Future Research

The discussed limitations point toward some critical directions for future research. Future studies should assess the degree to which nonlinear facial affect dynamics (e.g., burstiness) captured during shorter EMA protocols are associated with relevant future outcomes. Simplistic time series that capture alternations between emotion states appear well suited for computing burstiness. Given the additional systemic information that burstiness values provide, researchers should consider its inclusion along with other measures of self-organization. Additionally, the window of time assessed during this study may not have been large enough to infer that the participants were in a new steady state by the end of the study. Following up with participants periodically months or years after the

EMA portion could yield new insights into how these facial affect dynamics predict PTG, PTSD, or other psychological states. Lastly, expansion of the AFAR software to detect additional AUs would be helpful to improve the sensitivity of the approach used in this study. More AUs would allow for additional emotion states to be coded, possibly yielding more robust and complex emotion patterns.

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