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The Area of Resilience to Stress Event (ARSE): A New Method for Quantifying the Process of Resilience

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Abstract ■ Research on resilience has been wide-ranging in terms of academic disciplines, outcomes of interest, and levels of analysis. However, given the broad nature of the resilience literature, resilience has been a difficult construct to assess and measure. In the current article, a new method for directly quantifying the resilience process across time is presented based on a foundational conceptual definition derived from the existing resilience literature. The Area of Resilience to Stress Event (ARSE) method utilizes the area created, across time, from deviations of a given baseline following a stress event (i.e., area under the curve). Using an accompanying R package ('arse') to calculate ARSE, this approach allows researchers a new method of examining resilience for any number of variables of interest. A step-by-step tutorial for this new method is also described in an appendix.

Keywords ■ resilience, methodology, measurement, stress event. **Tools** ■ R.

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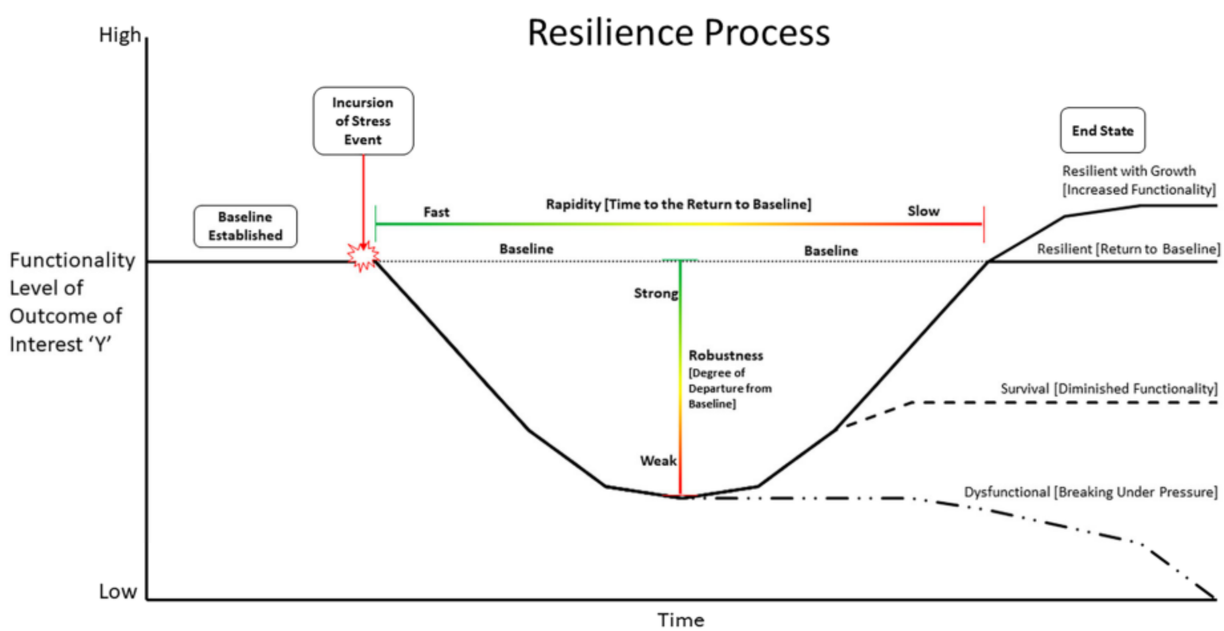
Introduction

As a concept, resilience has inspired a large and diverse literature that crosses many academic disciplines from engineering, childhood development, military psychology, and to the study of organizations. However, assessing and measuring resilience has been challenging; resilience has been characterized using differing terminology (see Meredith et al., 2011) which describe the concept as a state, trait, capacity, process, and an outcome (Britt, Shen, Sinclair, Grossman, & Klieger, 2016; Cacioppo et al., 2015; Egeland, Carlson, & Sroufe, 1993; Estrada, Severt, & Jiménez-Rodriguez, 2016; Masten, 2001; Rutter, 2012; Southwick, Bonanno, Masten, Panter-Brick, & Yehuda, 2014). For instance, Meredith et al. (2011) identified over 100 definitions of resilience in their review of the literature. Yet, taken together, we believe these various conceptual definitions of resilience share certain foundational components that, when organized into a new foundational definition, provide for a novel method of measuring resilience. Thus, the goals of the current work are twofold: (a) to provide a parsimonious definition of the resilience process by identifying its foundational components from the existing literature and (b) using this foundational definition, propose a novel method of measuring and quantifying resilience which can be broadly applied to different disciplines and variables of interest.

Foundational Components of Resilience

In the pursuit of developing a parsimonious conceptualization of the resilience process, and to facilitate measurement, we believed that the construct needed to be defined in terms of its foundational components. To do so, we considered the common themes that are interwoven throughout the wide-ranging resilience literature. From this synthesis, we propose that resilience consists of four essential components: (a) a measured baseline of an outcome of interest 'y' exists for a given entity, (b) the incursion of a stress event occurs for an entity, (c) the degree to which 'y' departs from baseline, and (d) the time it takes 'y' to return to baseline. Thus, our *foundational* definition of resilience is as follows:

Figure 1 ■ The resilience process as a function of robustness and rapidity. Note: In this figure it is assumed that higher values are more desirable for a given outcome of interest where resilience occurs below the baseline and growth occurs above. If lower values were more desirable, then resilience would occur above the baseline and growth would occur below.



> For a given 'y' outcome, resilience is a process, occurring over time, which is characterized by the function of robustness (i.e., the degree of negative departure from the baseline of y) and rapidity (i.e., time to the return to baseline of y) in relation to the incursion of a stress event on an entity.

Importantly, we believe that this foundational definition underlies and supports many prior definitions of resilience (see Meredith et al., 2011). To better explicate this foundational definition, we discuss each of the essential components in turn (see Figure 1).

Component 1: A Pre-Existing Baseline of an Outcome of Interest

The resilience process is directly tied to an outcome of interest. Like similar abstract concepts (e.g., performance[1]), resilience is not a construct independent of a measured outcome, but rather, it is a descriptor of the nature by which a given outcome manifests itself over time after a stress event. Stated differently, any outcome can be subject to resilience (e.g., self-esteem, task performance, mood, confidence, clinical symptoms); it is the pattern in which an outcome fluctuates over time that determines whether resilience has occurred. For example, an individual may go into a meeting with a high level of confidence but during that meeting a senior leader might question that individual's competence to do their job correctly which acts as a stress event on the individual, subsequently bringing their level of confidence down. It is only when the individual confides in a best friend, boosting their confidence back to where it was originally, that the resilience process is complete. In this example, confidence was the outcome of interest and could be interchanged with any number of outcomes (e.g., work satisfaction, positive mood, performance), and still remain a process characterized by resilience. Given that the process of resilience can manifest for any outcome, this allows for the possibility that resilience could occur in one outcome domain but not another. For instance, military Service Members can demonstrate resilience throughout their military careers with training for military-related stressors but once

[1] At the fundamental level, performance can be conceptually defined as the degree to which a given outcome of interest compares to a standard or baseline (e.g., well-performing vs. poor-performing). This characterization of performance is in line with definitions of work performance processes that describe performance as the degree to which actions are relevant to organizational goals (see Campbell, McCloy, Oppler, & Sager, 1993; Koopmans et al., 2011).

they leave that environment for the civilian world (with its own unique set of stressors) they can often have a difficult time adjusting and showing resilience (Bowling & Sherman, 2008; Department of the Army, 2010; Elnitsky, Fisher, & Blevins, 2017).[2] Thus, although entities might not show resilience for a specific outcome of interest, their resilience in another outcome domain or globally across a host of other outcome domains may prove to be very different.

To understand the resilience process, a baseline of the outcome of interest needs to be established or known. The baseline provides a reference point unto which future measurements of the outcome can be compared across time and, importantly, in reference to an occurrence of a stress event. Baselines might be based on agreed upon metrics of an outcome variable, an average, a pre-test measure, or any other assessment that can provide a starting or normal value for the outcome of interest. Without a baseline value, it would be difficult to understand if fluctuations in the outcome are departing from a normal level.

Component 2: Incursion of a Stress Event

The resilience process is preceded by some sort of stress event or adversity. The incursion of a stress event, challenge, adversity, or trauma is a necessary component within the process of resilience; like others have suggested, resilience can only be observed upon the incidence of some sort of stress event (Alliger, Cerasoli, Tannenbaum, & Vessey, 2015; Britt et al., 2016; Hollnagel, 2006; Jensen & Fraser, 2005). Such a stress-laden event is necessary because it is the psychological pressure exerted from the event that triggers a need for the resilience process to be engaged in order to maintain functionality on a given outcome. Given that entities have a strong tendency for routines and to protect accumulated resources to maintain homeostasis (Halbesleben, Neveu, Paustian-Underdahl, & Westman, 2014), the disruption of these routines, via stress events, often negatively impacts functioning (e.g., relative loss of physical, cognitive, and/or emotional resources) that trigger the activation of homeostatic mechanisms to return an entity to a pre-stressor state (Bonanno, 2004; Louis & Sutton, 1991; Morgeson, Mitchell, & Liu, 2015; Ong, Bergeman, Bisconti, & Wallace, 2006; Panter-Brick & Leckman, 2013; Selye, 1974).

Drawing heavily from Event System Theory (EST; see Morgeson et al., 2015), we believe the power of events to influence outcomes can be due to the additive components of an event's strength (e.g., novelty, disruptiveness, criticality), space (e.g., location, context, hierarchical origin), and time (e.g., duration, timing in conjunction with other events). Moreover, EST posits that the weight of events or their impact is determined by answers to three questions: (a) event strength: "How strongly does the event require my attention?", (b) event space: "Where did the event originate in the environment?", and (c) event time: "How long does the event last?" In our conceptual framework, the constellation of these event features additively combine to impact the robustness and rapidity of an entity's response to the stress event. For instance, a student may feel a greater pressure, and subsequently, more difficulty showing a resilience response, from a stressor that is strong (e.g., an unexpected deadline to make a presentation), originating from authority (e.g., senior professor is making the order), and with a big time component (e.g., non-stop 48-hour turnaround) in contrast to one that is weak (e.g., a planned birthday party event for family), originating from someone with less authority (e.g., a child), and with little time concerns (e.g., only lasting a few hours). Furthermore, the nature of the stress event can be agnostic in terms of valence; a stress event can be negative (e.g., loss of a job promotion, loss of a close other), positive (e.g., planning a wedding, winning the lottery), or perhaps even neutral (e.g., too many choices at the supermarket, challenging puzzle to solve). Also, a stress event can vary in terms of duration from a quick event (e.g., sudden unexpected death of a loved one) to one that is more chronic and long-lasting (e.g., constant ridicule by peers at school). Taken together, the stress event marks the triggering point for the resilience process, affecting the subsequent robustness and rapidity of an entity's response to the event.

Component 3: Degree of Departure from the Baseline (Robustness)

The resilience process is marked by the degree to which a stress event contributes to a departure from a given outcome's baseline, or robustness. Stress events can be taxing on body, mind, and spirit (Richardson, 2002; Richardson, Neiger, Jensen, & Kumpfer, 1990); being forced to confront a sudden loss, uncertain future, or solve a challenging problem with limited time and resources generates stress that can interfere with normal functioning and start a downward trajectory of sub-optimal functioning. Robustness is the amount a measured outcome departs or bends from the baseline due to the incursion of a stress event (cf. Bruneau et al., 2003). For certain individuals or for certain stress conditions, the departure may be minimal and a strong response is shown for the outcome of interest (i.e., a relatively minimal reduction from the baseline measure). By contrast, in other situations, a weak response to a stress event may be shown indicating that the event has

[2] Research has suggested that persons suffering from post-traumatic stress disorder (PTSD) can show similar resilience as those who do not suffer PTSD (Southwick et al., 2014; Yehuda & Flory, 2007), suggesting that resilience can be dependent upon the domain or outcome of interest.

influenced a relatively large deficit from the measured outcome's baseline (see 'Robustness', Figure 1). Furthermore, the degree to which an entity shows robustness is often dependent on their response to a stress event. An entity must find some sort of response or adjustment (i.e., adaptation) that will enable it to stop its downward trajectory of decline and enable it to return to baseline levels of functioning on an outcome (Burke, Stagl, Salas, Pierce, & Kendall, 2006; Jones, 1991; Masten, 2014; van der Beek & Schraagen, 2015).[3]

Component 4: Time to the Return to Baseline (Rapidity)

The resilience process is also grounded in terms of time and should be defined, depicted, and measured in terms of time (Britt et al., 2016; Meredith et al., 2011). The resilience process is marked by the time it takes for a given outcome to return to baseline, or rapidity. A key feature of resilience is that a recovery or restoration of functionality to the pre-stressor baseline occurs following a stress event. When an entity is able to fully recover from a stress event and return to a normal baseline, they are often described as being able to 'bounce back' from adversity (Meredith et al., 2011; Richardson, 2002; Sawalha, 2015; Sutcliffe & Vogus, 2003; West, Patera, & Carsten, 2009). In contrast to robustness, which is measured in terms of the outcome of interest, rapidity is measured in terms of the time it takes for the measured outcome to return to baseline levels (cf. Bruneau et al., 2003); the time taken for the outcome of interest to return to baseline could range from relatively fast to slow depending on the time scale used (see 'Rapidity', Figure 1). Importantly, if baseline is not reached at some point in time, we believe that this does not constitute a complete process of resilience; normal functionality was not able to be sustained or reestablished (Alliger et al., 2015; Southwick et al., 2014). However, we do believe that when the baseline is exceeded, this represents a resilience process since the baseline is reached and crossed.[4] In this case, growth is occurring and perhaps a new, higher functioning baseline is established (Bartone, 2006; Carver, 1998; Epel, McEwen, & Ickovics, 1998; O'Leary & Ickovics, 1995; Seery, Homan, & Silver, 2010; Wald, Taylor, Asmundson, Jang, & Stapleton, 2006).[5] In contrast, situations in which the baseline is not achieved after a stress event would reflect that an entity has suffered a decrement in functioning and is unable to recover (i.e., survival) or is showing a complete break-down in functioning (i.e., dysfunctional) all together (Carver, 1998; Patterson & Kelleher, 2005; Richardson, 2002; Sawalha, 2015; Wald et al., 2006). In these circumstances, we believe resilience is not observed over a given time period because functioning was not restored following the stress event. Additionally, we want to emphasize that resilience is an on-going process without any true 'end state.' An entity's experience with the resilience process can make future resilience processes more efficient (e.g., stronger robustness and quicker rapidity), feeding into one another, and in exceptional cases, improve overall functionality on a given outcome (e.g., growth). In sum, resilience is a lifelong learning process that is developed continuously over time that always allows room for improvement (see Casey, 2011).

A Two-Dimensional Typology of Resilience

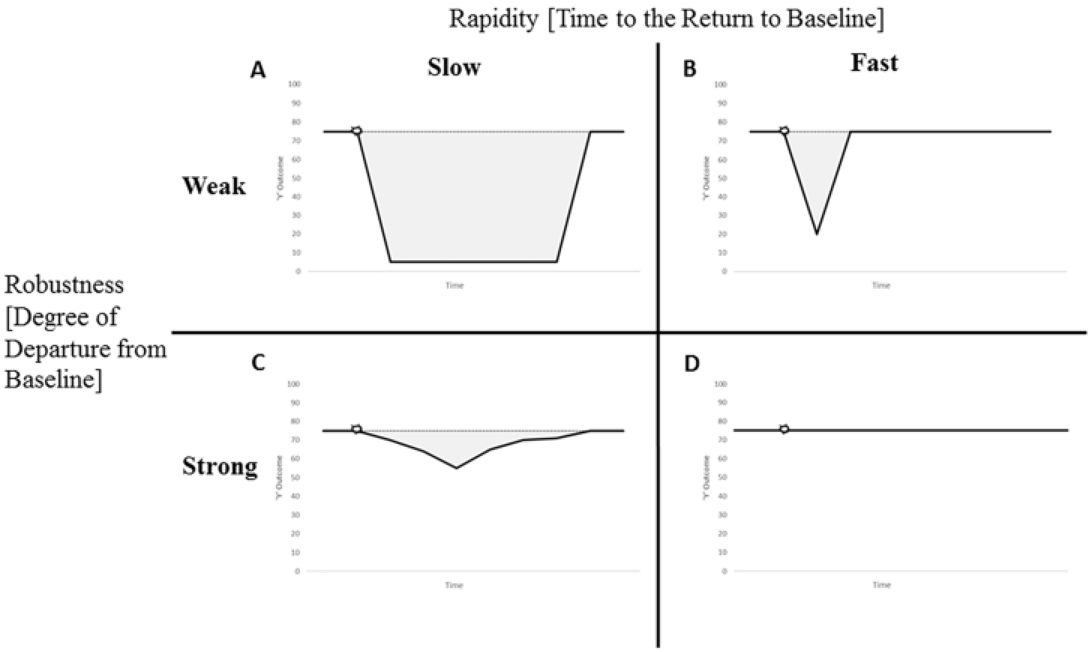
As stated in our foundational conceptualization of resilience, we believe resilience to be a function of two core components: robustness and rapidity. Robustness describes the degree to which a stressor contributes to a departure from the baseline of a given outcome and can conceptually range from strong to weak. Rapidity refers to the time at which a measured outcome returns to baseline following a stressful event and can conceptually range in terms of fast to slow. When considered together, these two dimensions combine to form four theoretically distinct types (categorical exemplars) of resilience processes (see Figure 2). First, in the Weak/Slow quadrant (Figure 2, Panel A), the process of resilience is marked by a deep departure from the baseline in terms of the reduction of the measured outcome and a slow return to baseline level in terms of the passage of time (e.g., after the dissolution of a valued relationship, the loss of a great amount of self-esteem that takes a long time to recover). Second, in the Weak/Fast quadrant (Figure 2, Panel B), the process of resilience is marked by a deep departure from the baseline and a fast return to the baseline level (e.g., a camera flashes in a basketball player's eyes, a brief period of inability to

[3] We do note the possibility that a viable response could be no response (i.e., inaction). In some circumstances, the best thing to do might just be allowing for the passing of time to help remedy a stress event. In this circumstance, the mere passage of time might be enough to decay the impact of a stress event on an entity (e.g., the stressor may remove itself from impacting an entity due to lack of interest or, in the absence of directly experiencing a stress event, the stressor may fade from an entity's memory).

[4] An important point, growth can be occurring above or below the baseline depending on the interpretation of the outcome variable. For instance, if the outcome represents number of widgets assembled in an hour, then higher numbers are indicative of a more desired state. By contrast, if the outcome represents blood pressure during the assemblage of widgets, then lower numbers are indicative of a more desired state. For the sake of language consistency going forward, we refer to growth (and resilience) with the assumption that higher numbers equal a more desired state.

[5] Conducting an After Action Review (AAR) or debriefing can often help entities learn lessons from stress events. By asking what worked and what did not work, and why, entities can learn from their missteps and use that information to inform how to face challenges in the future with a better response. For example, researchers have found that teams that conduct debriefings tend to out-perform other teams by about 25% (see Tannenbaum & Cerasoli, 2013)

Figure 2 ■ A two-dimensional typology of resilience by robustness and rapidity.



shoot the ball is lost before quickly regaining the ability to shoot). Third, in the Strong/Slow quadrant (Figure 2, Panel C), the process of resilience is marked by a shallow departure from the baseline and a slow return to the baseline level (e.g., a team given a sudden deadline implements a strategy that mitigates losses in performance but takes a while to fully implement). Lastly, in the Strong/Fast quadrant (Figure 2, Panel D), the process of resilience is marked by a minimal (or at the theoretical extreme, zero) departure from the baseline and a fast (or zero) time to return to the baseline level (e.g., in the face of a pop quiz, a well-prepared student's heart rate does not change). Although the Strong/Fast type of resilience pictured in Panel D of Figure 2 represents a theoretical extreme archetype, there may be cases in which one is completely prepared for a stress event and does not measurably lose functionality or require time to adapt and return to baseline. Of importance, though the crossing of robustness and rapidity are presented here as discrete categories for ease of depiction, we want to emphasize the continuous nature of both dimensions which allow for any number of patterns to lie in between the four quadrants on a whole host of psychological outcomes.

Overall, this two-dimensional typology provides a comprehensive view of resilience that includes conceptualizations of resilience as a bending process (e.g., Fredrickson, 2001) and those that suggest that resilience is marked by minimal bending in face of adversity (e.g., Bruneau et al., 2003; Omer, 2013). We note that the classification of Strong/Weak or Fast/Slow may be theoretically driven and depend on both the outcome of interest and the type of stress event. For instance, a designation of "strong" or "weak" may be relative to the outcome of interest's normal range (e.g., some outcomes may have tighter tolerances than others) and be relative to the level of impact of the stressor (e.g., a relative decrease in the outcome may appear strong or weak depending on the strength of the preceding stress event). In addition, we note that a resilience process in which growth occurred is not explicitly depicted in Figure 2. Despite this omission, we believe that our two-dimensional model would still be inclusive of cases of growth. In cases of growth, a measurable departure from baseline would occur (fulfilling the robustness component) and the baseline would have been reached (fulfilling the rapidity component) before continuing onward into any sort of growth for the measured outcome (e.g., learning from stress event to further optimize functionality on given outcome). In the section that follows, we offer a few suggestions for how to treat cases in which growth occurs following a stress event.

Measuring Resilience with the Area of Resilience to Stress Event Method

A common issue in much of the resilience literature is how to measure or quantify resilience. Past research on resilience has typically focused on measuring capacities to show resilience or other indirect proxies of resilience, which are often subjective assessments (Britt et al., 2016; Estrada et al., 2016; Jacelon, 1997; Tusaie & Dyer, 2004). However, directly measuring the resilience process in response to a stress event has received little attention. For example, a recent review found that fewer than 11% of instruments measured resilience directly (see Estrada & Severt, August 2014). Our foundational conceptualization of resilience, being a function of robustness and rapidity, lends itself to a novel, direct method of measurement. We propose that the area beneath (or above, see previous footnote) the baseline of a measured outcome over time that is formed by the function of robustness and rapidity, what we term the *area of resilience to a stress event*, is indicative of the efficiency of the resilience process. The following outlines this new quantitative method for measuring the process of resilience.

Area of Resilience to Stress Event (ARSE)

We believe that the resilience process can be quantitatively assessed by measuring the area created from the relative degree to which functioning negatively deviates from the baseline (i.e., robustness) and the time taken to return to baseline (i.e., rapidity) using x-y Cartesian coordinates. The region beneath the baseline of a measured outcome, what we refer to as the Area of Resilience to Stressful Event or ARSE, is indicative of the efficiency of a given resilience process and can be used for comparison purposes. Specifically, smaller values of ARSE indicate a more efficient resilience process because a smaller area indicates that there was less of a departure from the baseline and/or a shorter amount of time taken to return to baseline levels. By contrast, a larger value of ARSE indicates a relatively less efficient resilience process due to greater departures from baseline and/or longer periods of time with reduced functioning.

To calculate ARSE, the Cartesian coordinates of the data points comprising the perimeter of the region beneath the baseline can be used to calculate the area of the shape that is formed.[6] For example, referring to the top panels of Figure 3, two forms of resilience are shown. In Panel A, the resilience process can be measured with an ARSE value of 223. By contrast, in Panel B, a relatively more efficient resilience process occurs with an ARSE value of 50. Based on the values of ARSE for these two examples, the resilience process in Panel B represents a more efficient form of resilience due to its smaller area.[7] Extrapolating this method further, multiple resilience trials of an entity (e.g., individual or group) could be assessed using ARSE and averaged together to provide a mean level of resilience for a given outcome domain or overall, across multiple outcome domains, using standardized scaling of variables.[8]

Of importance, the ARSE method assumes that the outcome of interest is measured at multiple time points. Ideally, a continuous measurement of the outcome over time would provide the most sensitivity for fluctuations in the outcome of interest. Fewer measured time points often do not allow for the sensitivity necessary to detect quick jumps in an outcome measure. However, assessing an outcome continuously can often be difficult when outcomes do not lend well to continuous measurement (e.g., self-reports) or due to limitations of having access to participants on a continuous basis. Thus, sometimes multiple, discrete time points must be used longitudinally to approximate theoretically continuous processes. To use ARSE as a method for measurement of the resilience process, we recommend at least four measurements over time: one before the stressful event to establish a baseline of the measured outcome, two measures after the stress event, and one final measurement after the stress event to determine the end state (see Table 1). Although three measurement time points would suffice to assess ARSE, researchers would lose detail related to the time taken to return to baseline with just two measurements after the baseline measurement, which is why we are recommending four (or more) total measurements for this method.

Other Methodological Considerations for ARSE: Growth and Non-Resilience

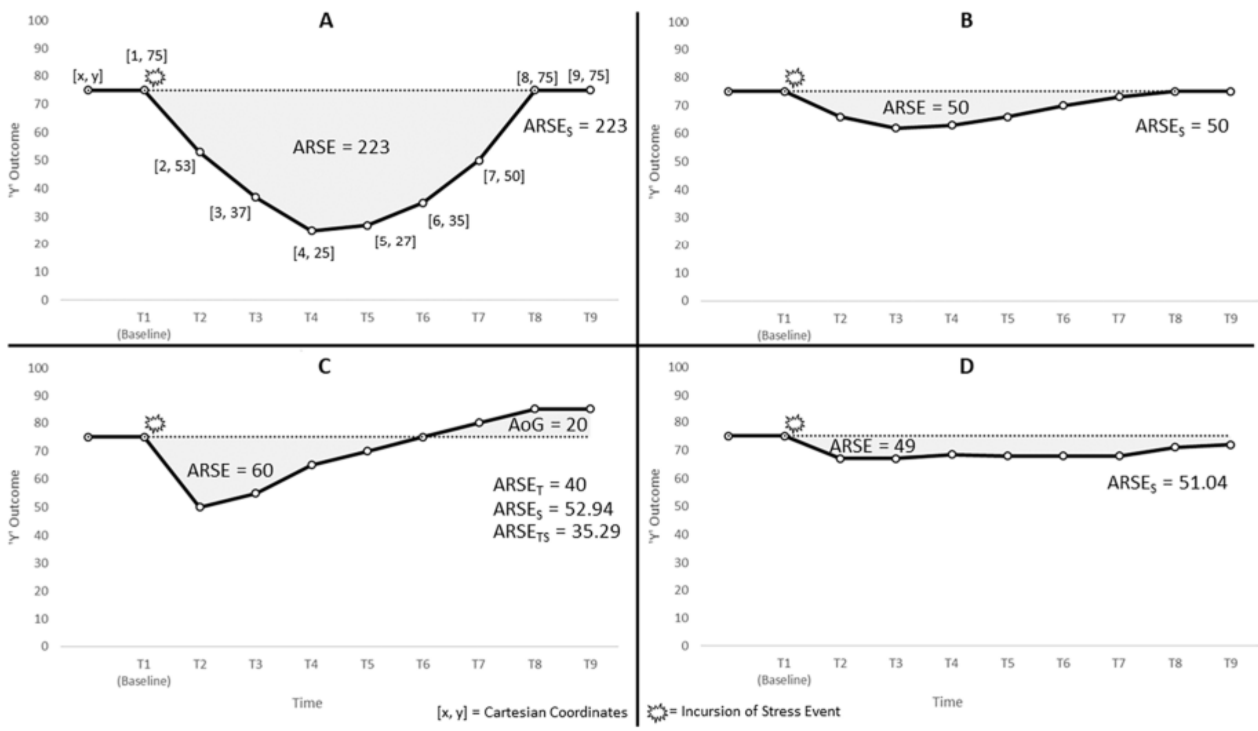
One advantage of using the ARSE method to quantify the resilience process is its utility to assess many different resilience scenarios. However, there may be some scenarios that resilience researchers are interested in that do not perfectly fit with the ARSE method like situations in which growth occurs (i.e., the outcome increases above the baseline) or situations in which resilience was not achieved (e.g., final measure of outcome falls short of reaching the baseline); in some cases, by a small amount or within a margin of measurement error. Each of these scenarios could potentially provide useful information to

[6] Available on CRAN and Github (https://github.com/nr3xe/arse), we developed an R package 'arse' to calculate ARSE and its various forms presented below. Please see Appendix for a step-by-step tutorial of how to use the ARSE method and its associated R package.

[7] For those interested, the values of ARSE for the resilience processes presented in Figure 2 are 420 (Panel A), 55 (Panel B), 55 (Panel C), and 0 (Panel D).

[8] Cross study comparisons would require time intervals to be the same for direct comparisons to be made.

Figure 3 ■ Examples of the Area of Resilience to Stress Event (ARSE) methodology for measurement of resilience. Notes. Smaller numbers are indicative of relatively better resilience. ARSE_T = ARSE total value, ARSE_S = ARSE scaled value, ARSE_TS = ARSE total scaled value, and AoG = Area of Growth.



researchers wanting to draw comparisons between resilience processes.

Growth. A pattern of growth occurs when the measured outcome's end state exceeds the baseline (Carver, 1998; O'Leary & Ickovics, 1995; Wald et al., 2006). We believe that this pattern fits with our conceptualization of resilience since the outcome measure is still showing a return to baseline except with an additional increase. Thus, we believe growth represents an exceptional form of resilience. Using the ARSE method, growth can be accounted for by measuring the area above the baseline, which we call the Area of Growth (AoG). As seen in Panel C of Figure 3, an ARSE total metric (ARSE_T) can be derived for patterns of growth by subtracting the AoG value from the ARSE value. Like measuring resilience without growth, lower ARSE_T values are indicative of better resilience, except with growth, there is a possibility of obtaining negative total values of ARSE_T if the AoG exceeds that of ARSE.

Non-resilience. Another situation that may arise is cases in which a return to an outcome's baseline is not observed by the last time measurement point, or end state (see Figure 3, Panel D). Given our foundational definition of resilience, we do not believe these situations constitute true resilience when facing a stress event since one is operating at reduced functionality and did not fully recover to pre-stressor, baseline levels. But what about situations in which a case 'just misses' the baseline cutoff by a few points? Should these be discarded as not fitting a resilience process? Given the realities of data collection, the final measurement point is not immune to a certain degree of measurement error (i.e., true value end state may reach baseline but not be reflected in last measurement due to measurement error) and this final cut off point can be somewhat arbitrary (i.e., baseline may be reached shortly after last measurement). For these potential scenarios, we offer a few suggestions when using the ARSE method. First, an acceptable baseline region could be established by using statistics related to the precision of measurement of the original baseline (e.g., 95% confidence interval, margin of error, standard deviation). On a per case basis, any endpoint that falls within this region could be considered as fulfilling a return to baseline. This error region could be determined by the use of multiple baseline measurements collected per case, calculated from the baseline measure-

Table 1 ■ Comparison of Outcome Measurement Number and their Associated Inferences

Number of Measurements	Measured Points	Shape	Inference
2	T1: Baseline; T2: End state after stress event	Straight line	Describes whether or not baseline returned or not following stress event
3	T1: Baseline; T2: Measure after stress event; T3: End state after stress event	Triangle	Describes the degree of departure from baseline with little information on rapidity
4+	T1: Baseline; T2 Measure #1 after stress event; T3: Measure #2 after stress event; T4: End state after stress event	Irregular polygon	Describes degree of departure from baseline and rapidity to return to baseline

ment of all cases in a sample, or, possibly, the use of a control group in which a stress event is not introduced and the outcome is measured across all time points free of pressure from a stressor. Furthermore, in certain study designs, the slope of the recovery could be used to extrapolate predicted values of the measured outcome to determine when it would likely cross the baseline and then calculate ARSE. The use of predicted time points may lend itself better to outcomes measured on a continuous basis rather than categorical time points where time may not be equally spaced.

Despite compensating for measurement error or arbitrary end points, some researchers may still want to use the ARSE method to compare cases showing resilience and those that are not. Consider the following scenario: in one resilience case an ARSE value of 50 is observed with a baseline and endpoint of 75 (Figure 3, Panel B), but in another non-resilience case an ARSE value of 49 is observed but the end state is 72, failing to reach the baseline of 75 (Figure 3, Panel D). In these two cases, one achieves resilience but with a greater ARSE value than one that does not achieve resilience but has a smaller ARSE value. Obviously, returning to baseline is a theoretically important distinction between these two cases; returning to the baseline represents fully recovering from a stress event which is categorically different compared to a situation in which minimal functionality is lost but is never fully regained.

To allow for direct comparisons between resilience and non-resilience (and also growth), we offer the following scaling factor:[9]

$$\mathrm{ARSE_S} = \mathrm{ARSE\ value} \times \frac{\mathrm{Baseline\ value}}{\mathrm{End\ State\ value}}. \tag{1}$$

This scaling factor takes into account the original baseline value and divides it by the end state to provide a metric that accounts for the measured end state to be multiplied with the ARSE. Going back to our two scenarios (see Figure 3), the case in Panel B would have an $\mathrm{ARSE_S}$ value of 50 $[50 \times (75/75)]$; $\mathrm{ARSE_S}$ and ARSE are equivalent when the end state measure of a given outcome is exactly the same as the baseline. For the comparison case in Panel D, it would have an $\mathrm{ARSE_S}$ value of 51.04 $[49 \times (75/72)]$, indicating that the case in Panel B had a smaller area of resilience when factoring in the end state in relation to the baseline. Again, we note that caution should be taken when comparing resilience and non-resilience cases. Theoretical justification may be needed to interpret cases in which resilience was achieved but with a high ARSE value (Figure 3, Panel A) compared to cases in which resilience was not achieved but with a lower $\mathrm{ARSE_S}$ value (Figure 3, Panel D) despite scaling corrections. Future research may need to further explore the relative utility of fully bouncing back (at whatever cost) versus a more efficient non-resilience process where some functionality has been lost but not at a great cost over a comparable time period.

In addition, the scaling calculation can be extended to $\mathrm{ARSE_T}$ values as well (i.e., the area of resilience to stress event total scaled, or $\mathrm{ARSE_{TS}}$). $\mathrm{ARSE_{TS}}$ takes into account the area of growth and scales for the end state value of growth or non-resilience. For this scaling factor, the equation for $\mathrm{ARSE_{TS}}$ is dependent on the values of $\mathrm{ARSE_T}$; when $\mathrm{ARSE_T}$ is greater than or equal to zero,

$$\mathrm{ARSE_{TS}} = \mathrm{ARSE_T\ value} \times \frac{\mathrm{Baseline\ value}}{\mathrm{End\ State\ value}} \tag{2}$$

and when $\mathrm{ARSE_T}$ is less than zero,

$$\mathrm{ARSE_{TS}} = \mathrm{ARSE_T\ value} \times \frac{\mathrm{End\ State\ value}}{\mathrm{Baseline\ value}}. \tag{3}$$

For example, the $\mathrm{ARSE_{TS}}$ value for Panel C in Figure 3 would be 35.29 $[40 \times (75/85)]$. For a summary of ARSE calculation approaches, see Table 2.

[9] This scaling factor can also be used for end state growth cases; for example, the $\mathrm{ARSE_S}$ value for Panel C in Figure 3 would be 52.94 $[60 \times (75/85)]$.

Table 2 ■ Comparison of ARSE Method Calculations

ARSE Method	Calculation	Purpose
ARSE	Use x, y coordinates of vertices formed by the shape created by the baseline of the outcome and the measured resilience response to the stress event (i.e., robustness and rapidity). $\left\lvert \frac{(x_1y_2-y_1x_2)+(x_2y_3-y_2x_3)+\ldots+(x_ny_1-y_nx_1)}{2} \right\rvert$ where x_1 and y_1 are the x and y coordinates of vertex 1 (e.g., baseline) and x_n and y_n are the x and y coordinates of the nth vertex. The last term represents the expression wrapping around back to the first vertex again; this could be the last measurement if it is at the baseline, if not, another point will need to be inferred at the baseline value of y at the same value of x for the last measurement point. In addition, for ARSE, all values that exceed the baseline are reduced down to the baseline value to only calculate the area created beneath the baseline.	Calculates the area of resilience to stress event based on the shape created by the robustness and rapidity of the resilience process in relation to the baseline. The formula for the area of an irregular polygon is used for calculation of the shape from the baseline point until the last measurement of the outcome.
AoG	Same calculation method as ARSE except that all values that fall below the baseline are increased up to the baseline value to only calculate the area created above the baseline.	Calculates the area of growth after stress event to last measurement of the outcome.
ARSE$_\mathrm{T}$	ARSE - AoG	Calculates area of resilience to stress event and takes into account area of growth (i.e., periods where outcome exceeds the baseline).
ARSE$_\mathrm{S}$	$\mathrm{ARSE\ value} \times \frac{\mathrm{Baseline\ value}}{\mathrm{End\ State\ value}}$	Calculates area of resilience to stress event and scales the ARSE value based on the starting baseline value accounting for end state growth or non-resilience.
ARSE$_\mathrm{TS}$	When ARSE$_\mathrm{T}$ is ≥ 0: $\mathrm{ARSE_T\ value} \times \frac{\mathrm{Baseline\ value}}{\mathrm{End\ State\ value}}$; when ARSE$_\mathrm{T}$ is <0: $\mathrm{ARSE_T\ value} \times \frac{\mathrm{End\ State\ value}}{\mathrm{Baseline\ value}}$	A combination of ARSE$_\mathrm{T}$ and ARSE$_\mathrm{S}$. Calculates area of resilience to stress event by accounting for area of growth and for end state growth or non-resilience.

Note. ARSE = Area of Resilience to Stress Event, AoG = Area of Growth, ARSE$_\mathrm{T}$ = Area of Resilience to Stress Event Total, ARSE$_\mathrm{S}$ = Area of Resilience to Stress Event Scaled, ARSE$_\mathrm{TS}$ = Area of Resilience to Stress Event Total Scaled.

An Empirical Example using the ARSE Method

To demonstrate the ARSE method using the 'arse' R package (Ratcliff, Nair, & Goldstein, 2019; Team, 2019), we analyzed data from a publically available repository through the inter-university consortium for political and social research (ICPSR). Specifically, we selected a data set that included a stress event and was followed by repeated measures of heart rate (see Chan et al., 1998).[10] The study investigated the impact of oleoresin capsicum (OC) spray (i.e., pepper spray) on a host of biological functions. Commonly used by law enforcement agencies and the public to subdue violent persons, the goal of the study was to assess the safety of using OC spray on a group of volunteers. The data include 37 volunteers who were recruited from the training staff and cadets of the San Diego Regional Public Safety Training Institute. Demographic data were collected on the participants' age, weight, height, and race. Once participants were informed on the nature of the study, a baseline reading was collected on their heart rate, blood pressure, and respiratory function. For the purposes of this example, we only focus on the heart rate data as an indicator of stress response. Participants participated in four different experimental trials in random order over two separate days in a pulmonary function testing laboratory: (a) placebo spray exposure followed by sitting position, (b) placebo spray exposure followed by sitting position, (c) OC spray exposure followed by sitting position, and (d) OC spray exposure followed by restraint position.

[10] The data set is available through the ICPSR #2961. For a step-by-step tutorial of the ARSE method with a fictitious data set using the arse R package (Ratcliff, Nair, & Goldstein, 2019), please see Appendix.

For this example, we will only be focusing on the OC spray exposure followed by a restraint position trial as it represents the most stressful event for participants. During the trial, participants were asked to be seated with their head in a $5' \times 3' \times 3'$ exposure box that allowed their faces to be exposed to the spray. A one-second spray was administered into the box from the opposite end of the participant's face. The participant's head remained in the box for five seconds and were then restrained in a prone maximal restraint position. Following the OC spray, the participant's heart rate was recorded at one-minute, five-minute, seven-minute, and nine-minute intervals. Participants were then released from their restraint. Eight participants were excluded from the experiment for pre-existing health issues or for not following directions, leaving a final sample of 29 participants (8 females, 21 males, $M_{age} = 32.07, SD = 5.96$; see Chan et al., 1998, for more details).

The data set was organized in wide format with each column representing repeated measurements of heart rate and each row representing a participant. To analyze the data, we organized the heart rate measurements such that the baseline heart rate was followed by the four post-stress event (i.e., OC spray) heart rate measurements in successive order. Five columns were also added to the data set to represent the x-coordinates of the heart rate measurement intervals using '0' for the baseline x-value and '1', '5', '7', and '9' for the subsequent x-values. Using the area of resilience to stress event total scaled (`arse_ts`) function in the arse R package, we specified the x-coordinates and the corresponding y-coordinates for heart rate. Since higher heart rates represent a less desired state, we set the 'yinvert' argument to "TRUE" to invert the y-axis so that values above the baseline would be treated as forming the area of resilience while values below the baseline would be indicative of the area of growth. Once the ARSE_{TS} values were calculated for each participant, we compared the ARSE_{TS} values for participant sex to see if men and women differed in their resilience to the OC spray stress event. Looking at participant sex, women ($M = -19.32, SD = 79.28$) showed better resilience to the OC spray stress event than males ($M = 33.76, SD = 71.79$), however, a t-test revealed that this difference did not reach statistical significance: $t(27) = 1.73, p = .095$, 95% confidence interval (CI) difference [-9.84, 115.99], Cohen's $d = 0.719$, 95% CI effect size [-0.16, 1.59] (see Figure 4).

In sum, this example provides an initial illustration of how the ARSE method can be used to examine resilience using real-world data. Given its flexibility, the ARSE method can be applied to any number of outcome measurements that are repeated over time after the incursion of a stress event.

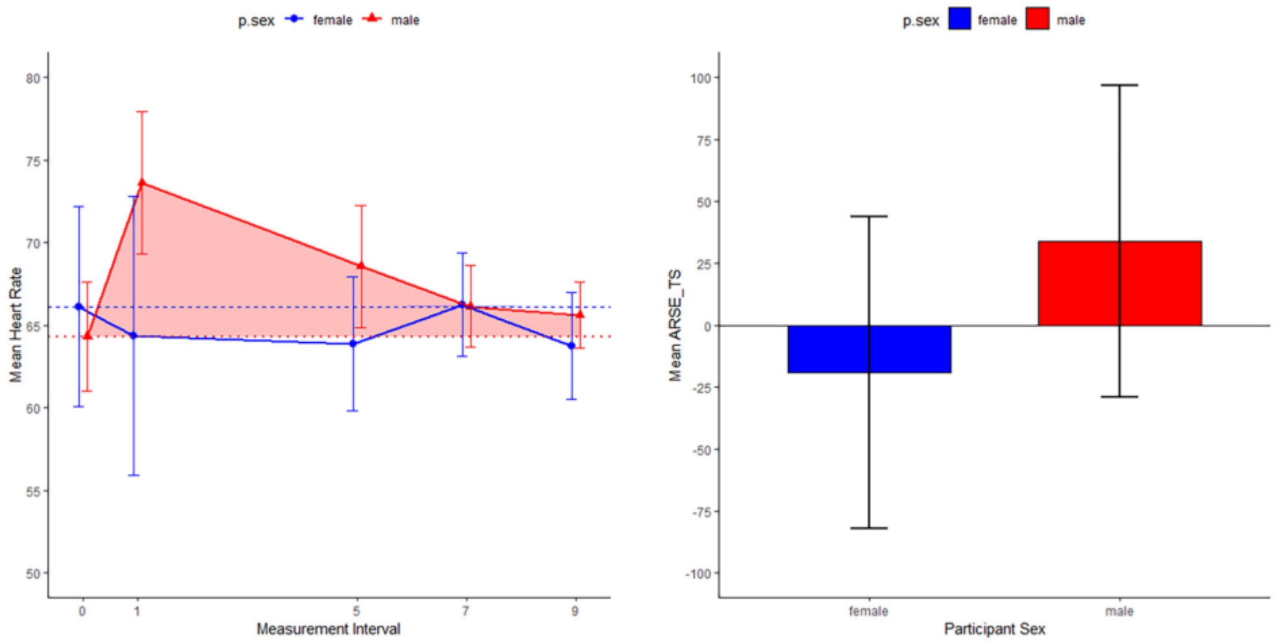
Summary and Conclusions

As stated at the onset, the current work aimed to propose a novel method for measuring resilience. Toward this end, we have documented our explication of the underpinnings of the resilience concept by identifying its fundamental components and, by using a foundational conceptualization, offered a novel way to measure the process of resilience using the ARSE method.

Although our foundational conceptualization is open to further development, we hope that, at the very least, it provides a common foundation from which resilience can be measured as a dynamic process. Areas of need of further examination include understanding how the incursion of multiple stress events at once (i.e., cluster of events) or in a series (i.e., chain of events) might impact the resilience process (cf. Morgeson et al., 2015). To keep things simple, our conceptualization of resilience refers largely to a singular stress event. However, stressors can often occur in tandem with one another before an entity has had a chance to adapt or recover from the last stressor. Research could benefit our understanding of resilience by examining the spacing of stress events to see when an overload might occur, preventing resilience responses. Moreover, in a similar vein to research on allostatic load (McEwen, 1998; Ong et al., 2006), it may be possible that an entity could show resilience in one domain at the cost of functioning in another area given a limited amount of physical and cognitive resources. Therefore, research should also investigate whether too much resilience in a single domain can come at a cost to other, non-related domains.

A two-dimensional typology of resilience was outlined given the conceptualization of resilience as a function of an entity's robustness and rapidity to a stressful event. In past research, robustness and rapidity serve as central components of resilience (Adger, 2000; Bruneau et al., 2003; Kantur & Iseri-Say, 2012; Linnenluecke & Griffiths, 2012). Importantly, we believed that the function of both of these dimensions together can describe different 'categories' of resilience; the crossing of robustness (weak vs. strong) and rapidity (slow vs. fast) form a theoretical four-quadrant matrix. Thus, a given resilience outcome can vary (continuously) in terms of either how strong or weak it is and how fast or slow it took the outcome to return to the baseline. We believe this typology covers a comprehensive range of resilience scenarios allowing for instances in which resilience is characterized by no bending or loss in functionality (strong robustness/fast rapidity; cf. Bruneau et al., 2003; Omer, 2013) and instances in which some functionality is temporarily lost on an outcome (e.g., somewhat weak robustness/slow rapidity). Future research and theory should further explore the relationship between ro-

Figure 4 ■ Left Panel: Mean heart rates for each measurement interval grouped by participant sex. Area formed above the baseline represents ARSE (shaded) with a smaller area indicative of better resilience. Unshaded regions below the baseline represents areas of growth. Error bars represent 95% correlation-adjusted confidence intervals for repeated measures data (Cousineau, 2017; Morey, 2008). Right Panel: Mean $\mathrm{ARSE}_{\mathrm{TS}}$ grouped by participant sex. Values above zero indicate the area of resilience was larger than the area of growth while values below zero indicate the area of growth was larger than the area of resilience. Error bars represent 95% confidence intervals using pooled variance.



bustness and rapidity, especially in terms of which dimension may be more critical in certain situations. Is the relative decrement in the outcome or the speed at which an entity returns to the baseline more vital to an outcome? What about situations in which resilience was not achieved but only a minimal amount of functionality was lost (strong robustness)? How can these be compared to situations in which a large decrement in an outcome is observed but the baseline is eventually reached? Is merely the end state of returning to baseline all that matters or does the relative functionality that was lost during the time in between the stressful event and the return to baseline matter? Similarly, it might also be interesting to explore if certain domains of resilience have a more restricted expression of the process. For instance, in high stakes occupations (e.g., members of the military, surgeons) there may be relatively little room for resilience to be expressed as anything but strong given that a loss of too much functionality on a desired outcome would have grave consequences for an entity. Taken together, from this typology, we believe there is much that theorists can add and expand upon to better understand the interplay of robustness and rapidity.

Of importance, we introduced a novel way of directly measuring the process of resilience. We proposed that the area created by the function of robustness and rapidity (i.e., ARSE) reflects the efficiency of the resilience process where smaller areas are more indicative of better resilience. Unlike past approaches that tended to focus on measuring the capacities for resilience rather than the actual process (Britt et al., 2016; Estrada et al., 2016; Estrada & Severt, August 2014; Southwick et al., 2014; Windle, Bennett, & Noyes, 2011), the proposed ARSE method for resilience measurement provides researchers a means to quantitatively assess the resilience process directly. Using ARSE, researchers are able to quantify the resilience process in a manner that allows for more direct and meaningful comparisons. However, the ARSE methodological approach is not without some lingering questions that could be addressed by future research. For instance, how does the strength of a stressor impact interpretations of the subsequent resilience process and ARSE? The relative size of a stressor might have a big impact on how the response to the stressor is interpreted; a major stressor (e.g., death of a loved one) might show a less efficient ARSE than a lessor stressor (e.g., loss of cell phone) but the response made to the major stressor might be a 'good one' considering the circumstances. This situation may underline the importance of only comparing ARSE measurements when the event is the same or, at the least, from a similar domain. Researchers who do want to make comparisons across events might want to consider controlling for these differences by weighting the scenarios in terms of their severity or strength, such as with third-party raters.

Another big question pertains to how to compare resilience versus non-resilience responses, if at all. Ideally, the ARSE method works best when a resilience response has been observed (i.e., at the last time point the outcome has, at minimum, returned to the original baseline), though we acknowledge this may not always be practical given the realities of data collection. Thus, we presented a few ways to account for these types of comparisons when calculating ARSE (e.g., $ARSE_S$, $ARSE_{TS}$). However, future research should further examine whether, over comparable timeframes, resilience responses (a return to baseline) with high levels of functioning loss after a stressor are superior to responses in which resilience was never fully achieved (end state results in some functioning loss) but minimal levels of functioning were lost over the same period of time after a stress event. Stated differently, is the resilient end state that matters, at all cost, or should the relative loss of outcome functionality over time be the important criterion, regardless of final measured end state? These are largely theoretical and philosophical questions, but important ones for future theoretical development surrounding resilience.

In conclusion, with further development by future research efforts, we believe the ARSE method and the associated arse package for R might open up many new and interesting ways to study resilience, providing more substantive conclusions about resilience which has often been difficult to make using more indirect measures. We also hope that our foundational definition of resilience adds clarity to the measurement of resilience that is often a complex construct to assess.

Authors' note

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Appendix A: Tutorial of ARSE Method using Fictitious Data

This appendix is intended to serve as a step-by-step guide to using the area of resilience to stress event (ARSE) method of quantifying the resilience process using the `arse` R package. As described in the main text, the resilience process is conceptualized as the function of robustness (i.e., the degree of negative departure from the baseline of y) and rapidity (i.e., time to the return to baseline of y) in relation to the incursion of a stress event on an entity. To use this method, three things must be in place: (a) a baseline value (before the stress event) of a variable of interest `y` needs to be known, (b) an incursion of a stress event needs to occur on an entity (e.g., individual, group), and (c) the variable of interest `y` needs to be measured repeatedly after the incursion of a stress event. The combination of robustness and rapidity form a series of points that can be connected into an irregular polygon from which an area can be derived. It is this area, ARSE, that is indicative of how much resilience is demonstrated to a stress event where smaller values of ARSE indicate better resilience and larger values indicate poorer resilience. It should be noted that we refer to decreases as a default way of discussing departures from baseline levels, however, for variables in which higher numbers are characterized as less desirable (e.g., blood pressure), negative departures from the baseline would be increases from the baseline. The ARSE functions discussed below have an option `yinvert` that accommodate cases in which higher values are not desirable. For the purposes of this tutorial, we assume that higher values are more desirable and that decreases from the baseline level are not. In addition to the real data example presented in the main text, the following presents a step-by-step guide to analyzing ARSE using a fictitious data set.

Installation of arse R Package

To install arse, use install.packages("arse") in R or RStudio. Alternatively, the development version of the arse package can be downloaded from github using `devtools::install_github("nr3xe/arse")`. In addition, for this tutorial you will need to install the following packages: dplyr, pracma, tidyr, ggplot, car, and Rmisc.

Load arse Package, Dependent Packages (dplyr, pracma), and the `stress_appraisal` Data Set

```
# Required R packages that need to be loaded to use arse
library(arse)
library(dplyr)
library(pracma)
# Required R packages for this tutorial
library(tidyr)
library(ggplot2)
library(car)
```

Description of stress_appraisal Data Set Embedded in arse Package

A Fictitious data set (embedded in arse package) was used to demonstrate the calculation of ARSE. In this data set, there are 50 fictitious "subjects" split into two groups with 25 members each (i.e., 'group' variable). The Control condition represents subjects in which training was not given before a stress event. In the Appraisal_Training condition, subjects were given a training to help cognitively reappraise a stressful situation and think of strategies to adapt to a stressor. Before random assignment to group condition, a baseline `tby` is measured on the subject's ability to place 100 colored-pegs in a specified patterned grid in one minute. Following baseline measurement, a stress event occurs for all subjects where they are asked to dip their hand in a bath of ice cold water for one minute (or as long as they can stand). Following the stress event, the subjects are asked to perform the peg task four more times with different patterns to match. subjects perform the peg task at three minute intervals. The fourth time the subject performs the task `t4y` represents the subject's end state at the end of the fictitious experiment. In the data set, `t#x` values represent time on the x-axis using x-coordinates.

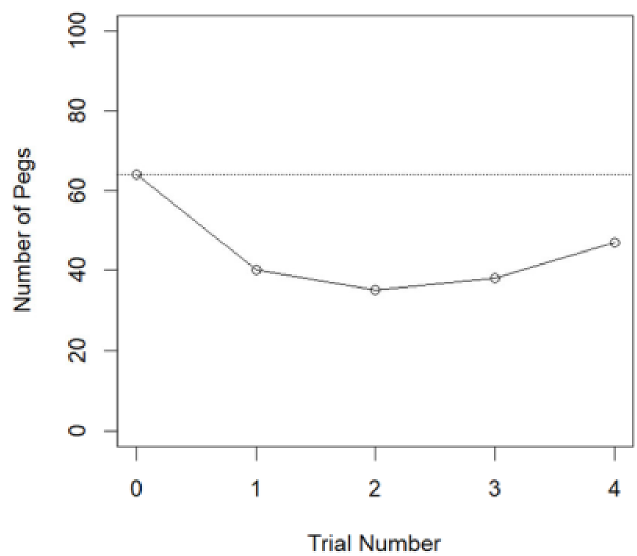
```
# Dataframe of stress\_appraisal fictitious data set showing first five rows
head(stress_appraisal, 5)
##   subj              group tbx t1x t2x t3x t4x tby t1y t2y t3y t4y
## 1    1            Control   0   1   2   3   4  64  40  35  38  47
## 2    2 Appraisal_Training   0   1   2   3   4  59  57  64  60  57
## 3    3            Control   0   1   2   3   4  41  28  20  19  28
## 4    4 Appraisal_Training   0   1   2   3   4  62  70  75  67  61
## 5    5            Control   0   1   2   3   4  43  41  42  43  43
```

stress_appraisal Layout

Viewed above, the stress_appraisal data set has 12 columns and 50 rows that represent individual subjects. Each of the columns represent the following

- subj = subject number
- group = experimental condition
  - Control = Control group receiving no training
  - Appraisal_Training group = Experimental condition receiving training
- tbx = x-coordinate of baseline measure of peg performance

Figure 5 ■ For subject #1, you can see that the baseline is 64 and that, in this case, resilience was not achieved since the end state is below the baseline at a value of 47.



- t1x–t4x = x-coordinates of additional measured peg performance measure (t4x = end state x-coordinate)
- tby = baseline measure of peg performance (0–100 scale)
- t1y–t4y = y-coordinates of additional measured peg performance measure (t4y = end state y-coordinate)

Data Organization

To organize the data set, the baseline x-coordinate should be the first column of x-coordinates. Accordingly, the baseline y-coordinate value should be the first column of the y-coordinates. The functions within the arse package will default to the first column of y-coordinates as the baseline value.

ARSE Plot of Subject #1

To plot an example case of ARSE, the plot_arse function provides a rough picture of the pattern of resilience. To plot a single case of arse, the plot_arse function requires a vector of x-coordinates and a vector of y-coordinates. The baseline value defaults to the first column of the y-coordinates but can be specified with the ybase = argument. Below, we indicate where in our dataframe the x- and y-coordinates are located and enter them as vectors using the as.integer() prefix. The lower and upper limits of the displayed scale are specified using the ll = and ul =, respectively. Figure 5 shows the result of these commands.

```
# Plot of ARSE for single subject
plot_arse(xcoord = as.integer(stress_appraisal[1,3:7]),
          ycoord = as.integer(stress_appraisal[1, 8:12]),
          ll=0, ul=100, xlab = "Trial Number", ylab = "Number of Pegs")
```

Calculating ARSE for Subject #1

To calculate ARSE from our example case, the arse function is used. The arse function requires three arguments: data, xcoord, and ycoord. For data, indicate the dataframe that is being used, in our example this would be stress_appraisal. For xcoord, a dataframe of x-coordinates is required with the first column having the x-coordinate of the baseline value of `y`. For ycoord, a dataframe of y-coordinates is required with the first column having the baseline value of `y`. The baseline value defaults to the first column of the y-coordinates but can be specified with the ybase = argument (we strongly suggest that users rely on the default using the first column of x- and y-coordinates). The arse function only calculates the area below the baseline; any points above the baseline (i.e., growth) are set to the baseline level to only calculate the area beneath the baseline. The arse function, as well as the related ARSE functions, will provide interpolation points for x-coordinates where the line between two points crosses the baseline at a point not measured in the data (using a function analogous to the getintersectx function in the arse package (see help for more details). In the example below, the first row of the dataframe is selected with the corresponding columns for the x- and y-coordinates. To calculate ARSE, an implementation of the shoelace formula (Gauss's area formula) for the area of irregular polygons is used with the (polyarea()) function from the pracma package.

The arse function also has two additional arguments that can be specified: yinvert and saveout. The yinvert argument can be used to calculate ARSE depending on how the range of values of y are to be interpreted. By default, yinvert = FALSE and assumes that higher values of y are more desirable or positive. However, if higher values of y are not desirable and lower values are, then yinvert = TRUE will calculate ARSE assuming that values above the baseline represent resilience and values below the baseline represent growth. Lastly, the saveout argument is set to FALSE by default and will just return a vector of values for the ARSE calculation. When set to TRUE, saveout will return the original dataframe and add a column of the calculated ARSE values.

```
# Returns area of resilience to stress event (ARSE) for single subject
arse(data = stress_appraisal, xcoord = stress_appraisal[1, 3:7],
     ycoord = stress_appraisal[1, 8:12])
## [1] 87.5
```

The Result of ARSE for Subject #1

The function returns an ARSE value of 87.5. This area was calculated by using the x- and y-coordinates that form an irregular polygon. Since resilience was not achieved in this example (i.e., the end state value did not return or exceed the baseline), an additional point is interpolated at the same x-coordinate as the end state value with a y-coordinate value at the baseline (i.e., x = 4, y = 64). Doing so completes the appropriate shape to calculate ARSE (see Figure 5).

Calculating AoG for Subject #4

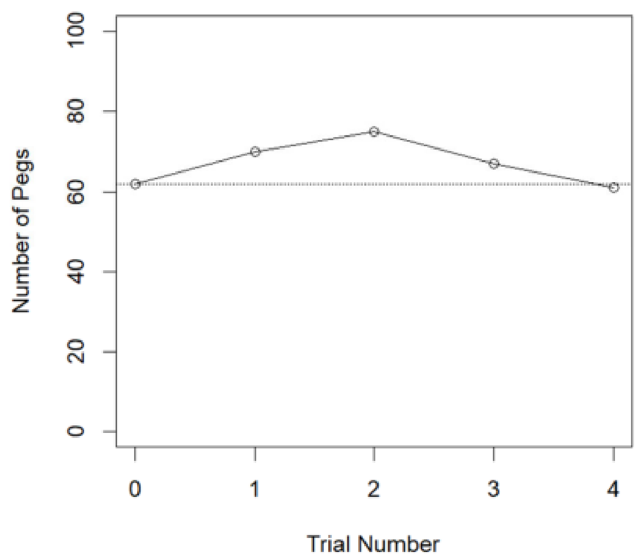
In some cases, users may want to know how much growth a subject might have experienced (see Figure 6 below).

```
# Plot of area of growth (AoG) for single subject
plot_arse(xcoord = as.integer(stress_appraisal[4,3:7]),
          ycoord = as.integer(stress_appraisal[4, 8:12]),
          ll=0, ul=100, xlab = "Trial␣Number", ylab = "Number␣of␣Pegs")
```

To calculate areas of growth, the aog function is used. This function is exactly the same as the arse function above except that instead of setting values above the baseline to the baseline, aog sets values below the baseline to the baseline to only look at the area above the baseline.

```
# Returns area of growth (AoG) value for single subject
aog(data = stress_appraisal, xcoord = stress_appraisal[4, 3:7],
    ycoord = stress_appraisal[4, 8:12])
## [1] 25.58333
# Returns area of resilience to stress event (ARSE) value for single subject
arse(data = stress_appraisal, xcoord = stress_appraisal[4, 3:7],
     ycoord = stress_appraisal[4, 8:12])
## [1] 0.08333333
```

Figure 6 ■ The plot shows that Subject #4 experienced growth (i.e., y values above the baseline) after the incursion of a stress event.



The Result of AoG and ARSE for Subject #4

The result of aog returns a value of 25.58 indicating the area of growth for Subject #4. However, since the subject had an end state value below the baseline (t4y = 61), arse can also be calculated and return a value of 0.08. In this case, more growth was achieved for the subject with a small area of resilience, indicating a good response to the stress event.

Calculating ARSE$_\mathrm{T}$ for Subject #4

In some cases, users may want to take into account both resilience and growth. There is also a function, arse_t, that calculates the area of resilience (arse) and area of growth (aog) and takes their difference (i.e., $ARSE_\mathrm{T} = ARSE - AoG$) to get a total area value for resilience. In these cases, ARSE can be positive and negative depending on whether the area of resilience or area of growth is larger.

```
# Returns area of resilience to stress event total (ARSE_T) value for single subject
arse_t(data = stress_appraisal, xcoord = stress_appraisal[4, 3:7],
       ycoord = stress_appraisal[4, 8:12])
## [1] −25.5
```

The result of ARSE$_T$ for Subject #4

The result of arse_t returns a value of -25.5 which reflects the subtraction of ARSE (0.08) from AoG (25.58). A negative returned value indicates that the area of growth was larger than the area of resilience.

Calculating ARSE$_\mathrm{S}$ for Subject #1

In some cases, users may want to account for the end state being above the baseline (growth) or below the baseline (non-resilience). The `arse_s` function provides a scaling factor that accounts for the end state where $\mathrm{ARSE_S} = \mathrm{ARSE} \times \mathrm{Baseline/EndState}$. When the end state is below the baseline, the scaling factor will make ARSE larger and when the end state is above the baseline, the scaling factor will make ARSE smaller.

```
# Returns area of resilience to stress event scaled (ARSE_S) value for single subject
arse_s(data = stress_appraisal, xcoord = stress_appraisal[1, 3:7],
       ycoord = stress_appraisal[1, 8:12])
## [1] 119.1489
```

The Result of ARSE$_\mathrm{S}$ for Subject #1

The result of arse_s returns a value of 119.15. Recall that the arse value for this subject was 87.5 with a baseline value of 64 and an end state value of 47. Thus, $\mathrm{ARSE_S} = 87.5 \times (64/47)$ or $\mathrm{ARSE_S} = 87.5 \times 1.36$ which returns a larger area (vs. the un-scaled ARSE) of 119.15.

Calculating ARSE$_\mathrm{TS}$ for Subject #4

In some cases, users may want to account for both growth and the end state value; the arse_ts function combines aspects of both arse_t and arse_s. Specifically, arse_ts is calculated as follows: for arse_t values that are >= 0, $\mathrm{ARSE_{T \cdot S}} = \mathrm{ARSE_T} \times (\mathrm{Baseline}/\mathrm{EndState})$ while for arse_t values that are < 0, $\mathrm{ARSE_{T \cdot S}} = \mathrm{ARSE_T} \times (\mathrm{EndState}/\mathrm{Baseline})$. The two different calculations are needed to account for scaling positive and negative values of arse_t. For instance, if arse_t is negative and the end state is above the baseline, then the end state value needs to be in the numerator so that the scaling factor can make a negative value larger (versus smaller when arse_t is zero or positive).

```
# Returns area of resilience to stress event total scaled (ARSE_TS) for single subject
arse_ts(data = stress_appraisal, xcoord = stress_appraisal[4, 3:7],
        ycoord = stress_appraisal[4, 8:12])
## [1] −25.08871
```

The Result of $\mathrm{ARSE_{TS}}$ for Subject #4

The result of arse_ts returns a value of -25.09. Recall that arse_t for this subject was -25.5 with a baseline of 62 and an end state of 61. Thus, $ARSE_{T \cdot S} = -25.5 \times (61/62)$ or $ARSE_{TS} = -25.5 \times (0.98)$ which returns a smaller negative value (vs. un-scaled ARSE$_\mathrm{T}$) of -25.09.

Calculating ARSE for Entire Sample

Calculation of ARSE and the ARSE family of functions for the entire sample is the same as for individual cases.

```
# Returns area of resilience to stress event (ARSE) for entire sample with
# modified data set including calculated ARSE values
# The head function is set to ‘5’ to limit to the first five subjects for display purposes
# The mutate_if function from the dplyr package is used to limit decimals of ARSE output
head(
  mutate_if(
    arse(data = stress_appraisal, xcoord = stress_appraisal[,3:7],
           ycoord = stress_appraisal[,8:12], saveout = TRUE),
    is.numeric, round, digits = 4), 5)
##    subj              group tbx t1x t2x t3x t4x tby t1y t2y t3y t4y    arse
## 1     1            Control   0   1   2   3   4  64  40  35  38  47 87.5000
## 2     2 Appraisal_Training   0   1   2   3   4  59  57  64  60  57  1.9524
## 3     3            Control   0   1   2   3   4  41  28  20  19  28 62.5000
## 4     4 Appraisal_Training   0   1   2   3   4  62  70  75  67  61  0.0833
## 5     5            Control   0   1   2   3   4  43  41  42  43  43  3.0000
```

Calculating ARSE$_\mathrm{T}$ for Entire Sample

```
# Returns area of resilience to stress event total (ARSE_T) for entire sample
```

```
# with modified data set including calculated ARSE_T values ( first five subjects shown)
head(
  mutate_if(
    arse_t(data = stress_appraisal, xcoord = stress_appraisal[,3:7],
       ycoord = stress_appraisal[,8:12], saveout = TRUE),
    is.numeric, round, digits = 4), 5)
##   subj              group tbx t1x t2x t3x t4x tby t1y t2y t3y t4y arse_t
## 1    1            Control   0   1   2   3   4  64  40  35  38  47   87.5
## 2    2 Appraisal_Training   0   1   2   3   4  59  57  64  60  57   -3.0
## 3    3            Control   0   1   2   3   4  41  28  20  19  28   62.5
## 4    4 Appraisal_Training   0   1   2   3   4  62  70  75  67  61  -25.5
## 5    5            Control   0   1   2   3   4  43  41  42  43  43    3.0
```

Calculating ARSE$_S$ for Entire Sample

```
# Returns area of resilience to stress event scaled (ARSE_S) for entire sample
# with modified data set including calculated ARSE_S values ( first five subjects shown)
head(
  mutate_if(
    arse_s(data = stress_appraisal, xcoord = stress_appraisal[,3:7],
             ycoord = stress_appraisal[,8:12], saveout = TRUE),
    is.numeric, round, digits = 4), 5)
##   subj              group tbx t1x t2x t3x t4x tby t1y t2y t3y t4y   arse_s
## 1    1            Control   0   1   2   3   4  64  40  35  38  47 119.1489
## 2    2 Appraisal_Training   0   1   2   3   4  59  57  64  60  57   2.0209
## 3    3            Control   0   1   2   3   4  41  28  20  19  28  91.5179
## 4    4 Appraisal_Training   0   1   2   3   4  62  70  75  67  61   0.0847
## 5    5            Control   0   1   2   3   4  43  41  42  43  43   3.0000
```

Calculating ARSE$_{TS}$ for Entire Sample

```
# Returns area of resilience to stress event total scaled (ARSE_TS) for entire sample with
# modified data set including calculated ARSE_TS values ( first five subjects shown)
head(
  mutate_if(
    arse_ts(data = stress_appraisal, xcoord = stress_appraisal[,3:7],
              ycoord = stress_appraisal[,8:12], saveout = TRUE),
    is.numeric, round, digits = 4), 5)
##   subj              group tbx t1x t2x t3x t4x tby t1y t2y t3y t4y  arse_ts
## 1    1            Control   0   1   2   3   4  64  40  35  38  47 119.1489
## 2    2 Appraisal_Training   0   1   2   3   4  59  57  64  60  57  -3.1053
## 3    3            Control   0   1   2   3   4  41  28  20  19  28  91.5179
## 4    4 Appraisal_Training   0   1   2   3   4  62  70  75  67  61 -25.9180
## 5    5            Control   0   1   2   3   4  43  41  42  43  43   3.0000
```

Calculating ARSE$_{TS}$ for Entire Sample and Comparing Mean Group Differences with a t-test

In this example, we first calculate values of arse_ts for the entire sample and create a new column `arse_ts` by saving the new dataframe as a new object `data1`. Second, we perform a t-test by comparing the control and appraisal_training groups under the `group` factor.

```
# Returns area of resilience to stress event total scaled (ARSE_TS) for entire sample with
# modified data set including calculated ARSE_TS values
data1 <- arse_ts(data = stress_appraisal, xcoord = stress_appraisal[,3:7],
                 ycoord = stress_appraisal[,8:12], saveout = TRUE)
# Levene's Test for equal variances
leveneTest(arse_ts ~ group, data = data1)
## Levene's Test for Homogeneity of Variance (center = median)
##       Df F value  Pr(>F)
## group  1  5.8471 0.01945 *
##       48
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
detach("package:car", unload=TRUE)
t.test(data1$arse_ts ~ data1$group, var.equal = FALSE)
##
##  Welch Two Sample t-test
##
## data: data1$arse_ts by data1$group
## t = -2.5177, df = 26.175, p-value = 0.01826
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -160.99391 -16.29634
## sample estimates:
## mean in group Appraisal_Training          mean in group Control
##                         21.27067                      109.91580
```

The subsequent code produces the plot shown in Figure 7.

```
# Summary table of means and MoE for control and appraisal training groups
ggplot_bsci <- Rmisc::summarySE(data1, measurevar = "arse_ts", groupvars = "group")
# Bar plot of mean ARSE_TS for control and appraisal training groups
ggplot(ggplot_bsci, aes(x = group, y = arse_ts, fill = group)) +
  geom_bar(stat = "identity", width = .65, color = "black") +
  geom_errorbar(aes(ymin = arse_ts - ci, ymax = arse_ts + ci), width = .15, size =
   0.85) +
  labs(x = "Experimental Condition", y = "Mean ARSE_TS") +
  coord_cartesian(ylim = c(-50, 190)) +
  theme_classic() +
  scale_fill_manual(values = c("blue","red")) +
  scale_y_continuous(breaks = c(-50, -25, 0, 25, 50, 75, 100, 125, 150, 175)) +
  geom_hline(yintercept = 0, linetype = "solid", color = "black") +
  theme(legend.position = "top")
```

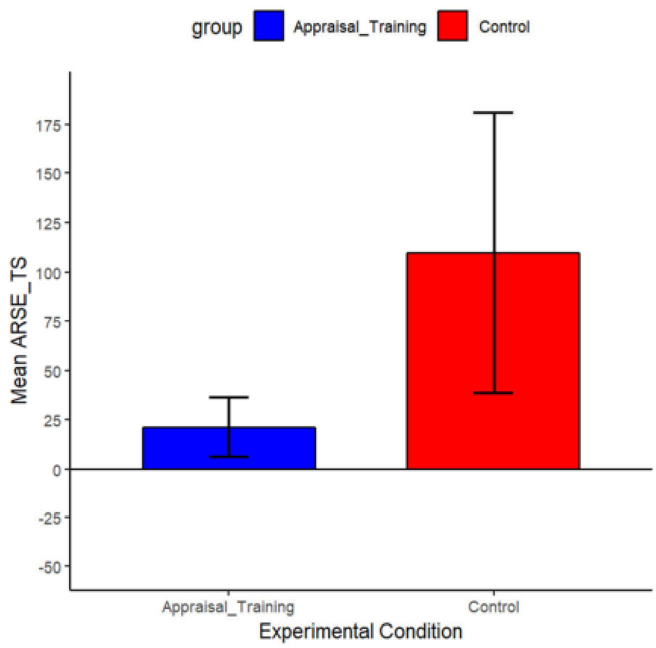
The Result of t-test comparing the Control Group to Appraisal Training Group

The result of the t-test reveals a significant difference between the two groups at an alpha level of 0.05. Specifically, subjects in the appraisal training condition had smaller ARSE$_{\mathrm{TS}}$ values ($M = 21.27$) compared to the control condition ($M = 109.92$). Plotting Mean ARSE of Control and Appraisal Training Groups

Plotting ARSE of Control Group Using Mean Values of Y-Coordinates

```
# Plots the mean values of y across x-coordinates for the control group
stress_appraisal_group1 <- subset(stress_appraisal, group == "Control",
                                  select = c("subj", "group",
```

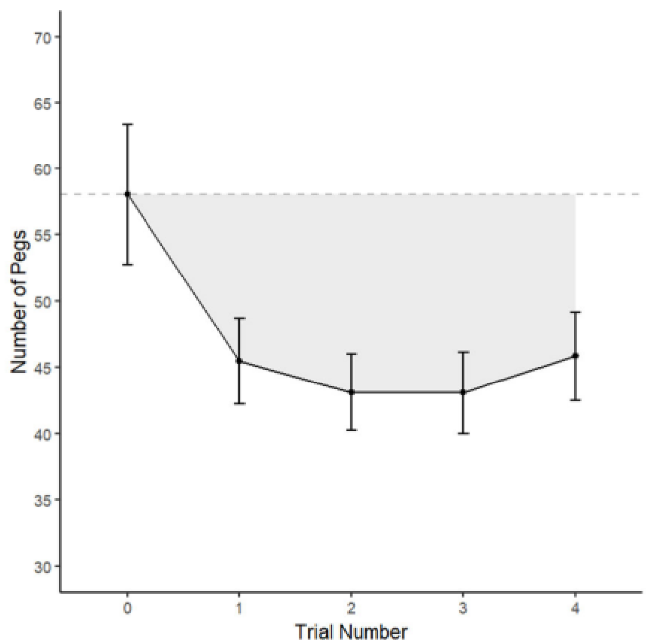
Figure 7 ■ Mean $ARSE_{TS}$ grouped by experimental condition. Error bars represent 95% confidence intervals.




```
                                            "tbx", "t1x", "t2x", "t3x", "t4x",
                                            "tby", "t1y", "t2y", "t3y", "t4y"))
# Transform dataframe to be in long form
stress_appraisal_group_long1 <- stress_appraisal_group1 %>%
  gather(trial, pegs, tby:t4y)
# Recode trial labels to be numbers: 0-4
stress_appraisal_group_long1$trial <- as.factor(recode(stress_appraisal_group_long1
    $trial,
                                            tby = "0", t1y = "1",
                                            t2y = "2", t3y = "3", t4y = "4"))
stress_appraisal_group_long1$subj <- as.factor(stress_appraisal_group_long1$subj)
# Cousineau-Morey within-subject confidence interval correction
gplot_wsci1 <- Rmisc::summarySEwithin(stress_appraisal_group_long1, measurevar = "
    pegs",
                                     withinvars = "trial", idvar = "subj")
# See print out of means to identify baseline peg value for trial '0'
head(gplot_wsci1, 5)
##   trial  N  pegs        sd       se       ci
## 1     0 25 58.04 12.914946 2.582989 5.331028
## 2     1 25 45.44  7.829166 1.565833 3.231721
## 3     2 25 43.08  6.899275 1.379855 2.847881
## 4     3 25 43.04  7.464081 1.492816 3.081021
## 5     4 25 45.80  8.082130 1.616426 3.336140
```

From the output table you will be able to extract the mean baseline value to input in the `ggplot` code below to create a baseline graphic using `geom_hline` (i.e., 58.04) in `ggplot` (see Figure 8). The means at each trial time point are displayed here to be used as inputs for shading the area of resilience using `geom_ribbon` (i.e., min: 58.04, 45.44,

Figure 8 ■ The plot reflects the mean values of the y variable at each time interval to show the average shape of the ARSE for subjects in the control group. The shaded area represents the average ARSE of the control condition. Error bars represent 95% correlation-adjusted confidence intervals for repeated measures data (Cousineau, 2017; Morey, 2008).



43.08, 43.04, 45.80; max: 58.04) in ggplot. Although not apparent in this example, if a point would have been observed above the baseline (e.g., 65.01), the geom_ribbon function should be coded so that any points above the baseline do not create a shaded area so that readers can see the shaded area as ARSE and non-shaded areas as AoG.

```
# Plot of ARSE using ggplot for control group
ggplot(gplot_wsci1, aes(x = trial, y = pegs, group = 1)) +
  geom_ribbon(ymin = c(58.04, 45.44, 43.08, 43.04, 45.80),
              ymax = 58.04, color = NA, fill = "grey",
              alpha = .3) +
  geom_point() +
  geom_line() +
  geom_errorbar(width = .1, aes(ymin = pegs - ci, ymax = pegs + ci)) +
  labs(x = "Trial Number", y = "Number of Pegs") +
  coord_cartesian(ylim = c(30, 70)) +
  geom_hline(yintercept = 58.04, linetype="dashed", color = "grey") +
  scale_y_continuous(breaks = c(30, 35, 40, 45, 50, 55, 60, 65, 70)) +
  theme_classic()
```

Plotting ARSE of Appraisal Training Group Using Mean Values of Y-Coordinates

```
# Plots the mean values of 'y' across x-coordinates for the appraisal training group
stress_appraisal_group2 <- subset(stress_appraisal, group == "Appraisal_Training",
                                  select = c("subj", "group",
                                             "tbx", "t1x", "t2x", "t3x", "t4x",
                                             "tby", "t1y", "t2y", "t3y", "t4y"))
```

```
# Transform dataframe to be in long form
stress_appraisal_group_long2 <- stress_appraisal_group2 %>%
  gather(trial, pegs, tby:t4y)
# Recode trial labels to be numbers: 0-4
stress_appraisal_group_long2$trial <- as.factor(recode(stress_appraisal_group_long2
    $trial,
                                                       tby = "0", t1y = "1",
                                                       t2y = "2", t3y = "3", t4y = "4"))
stress_appraisal_group_long2$subj <- as.factor(stress_appraisal_group_long2$subj)
# Cousineau-Morey within-subject confidence interval correction
gplot_wsci2 <- Rmisc::summarySEwithin(stress_appraisal_group_long2, measurevar = "
    pegs",
                                      withinvars = "trial", idvar = "subj")
# See print out of means to identify baseline peg value for trial '0'
head(gplot_wsci2, 5)
##   trial  N  pegs       sd        se       ci
## 1     0 25 59.32 7.258937 1.4517874 2.996342
## 2     1 25 52.80 5.246157 1.0492315 2.165507
## 3     2 25 53.60 4.740042 0.9480084 1.956593
## 4     3 25 54.32 5.066689 1.0133377 2.091426
## 5     4 25 58.08 4.101585 0.8203170 1.693051
```

The subsequent code, shown in Figure 9 produces the plot for the appraisal training group.

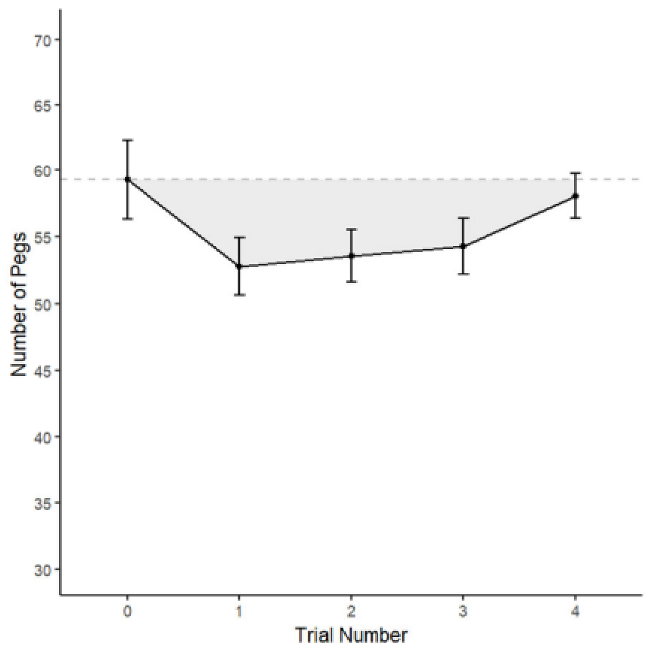
```
# Plot of ARSE using ggplot for appraisal training group
ggplot(gplot_wsci2, aes(x = trial, y = pegs, group = 1)) +
  geom_ribbon(ymin = c(59.32, 52.80, 53.60, 54.32, 58.08),
              ymax = 59.32, color = NA, fill = "grey",
              alpha = .3) +
  geom_point() +
  geom_line() +
  geom_errorbar(width = .1, aes(ymin = pegs - ci, ymax = pegs + ci)) +
  labs(x = "Trial Number", y = "Number of Pegs") +
  coord_cartesian(ylim = c(30, 70)) +
  geom_hline(yintercept = 59.32, linetype="dashed", color = "grey") +
  scale_y_continuous(breaks = c(30, 35, 40, 45, 50, 55, 60, 65, 70)) +
  theme_classic()
```

Ploting ARSE of Control and Appraisal Group in Combined Graph

The subsequent commands combined in a single plot both groups, as seen in Figure 10.

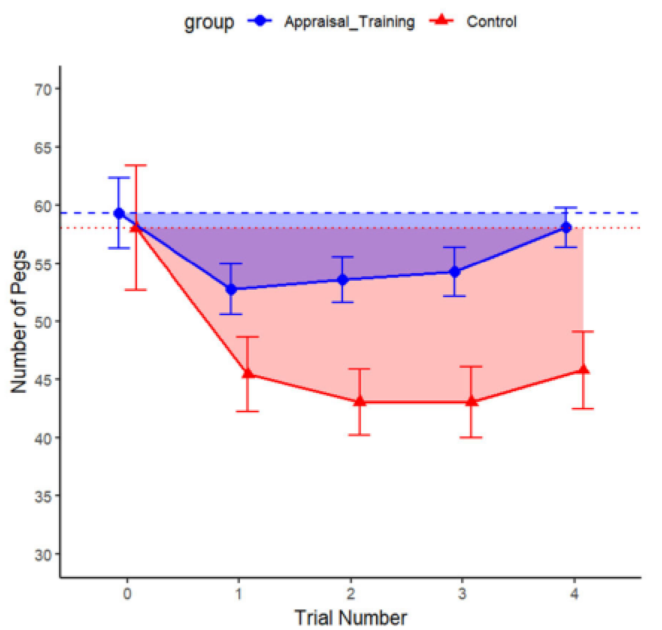
```
# Combine the aggregated summaries of the control and appraisal training group
gplot_wsci_combine <- bind_rows(gplot_wsci1, gplot_wsci2)
# Add back in factor names to output
gplot_wsci_combine <- mutate(gplot_wsci_combine, group =
                             as.factor(c("Control", "Control", "Control",
                                         "Control", "Control", "Appraisal_Training"
    ,
                                         "Appraisal_Training", "Appraisal_Training"
    ,
                                         "Appraisal_Training", "Appraisal_Training"
    )))
# Plot combined output with shaded regions
```

Figure 9 ■ The plot reflects the mean values of the y variable at each time interval to show the average shape of the ARSE for subjects in the appraisal training condition. The shaded area represents the average ARSE of the appraisal training group. Error bars represent 95% correlation-adjusted confidence intervals for repeated measures data (Cousineau, 2017; Morey, 2008).




```
# For shaded areas (geom_ribbon), input the means across time points and place NaN to
# fill out the vector expecting inputs the length of the combined dataframe (e.g., 10)
ggplot(gplot_wsci_combine, aes(x = trial, y = pegs, group = group,
                               colour = group, shape = group)) +
  geom_ribbon(ymin = c(58.04, NaN, 45.44, NaN, 43.08, NaN, 43.04, NaN,
                       45.80, NaN), ymax = 58.04, color = NA, fill = "red",
              alpha = .25, position = position_dodge(width = .3)) +
  geom_ribbon(ymin = c(59.32, NaN, 52.80, NaN, 53.60, NaN, 54.32, NaN,
                       58.08, NaN), ymax = 59.32, color = NA, fill = "blue",
              alpha = .3, position = position_dodge2(width = .3)) +
  geom_point(size = 2.5, position = position_dodge(width = .3)) +
  geom_line(size = .75, position = position_dodge(width = .3)) +
  geom_errorbar(width = .4, position = position_dodge(width = .3),
                aes(ymin = pegs - ci, ymax = pegs + ci)) +
  labs(x = "Trial Number", y = "Number of Pegs") +
  coord_cartesian(ylim = c(30, 70)) +
  geom_hline(yintercept = 58.04, linetype = "dotted", color = "red") +
  geom_hline(yintercept = 59.32, linetype = "dashed", color = "blue") +
  theme_classic() +
  scale_color_manual(values = c('blue','red')) +
  scale_y_continuous(breaks = c(30, 35, 40, 45, 50, 55, 60, 65, 70)) +
  theme(legend.position = "top")
```

Figure 10 ■ The plot reflects the mean values of the y variable at each time interval to show the average shape of the ARSE for subjects in both the control and appraisal training group. The two shaded areas reflect the average ARSE for each group. Error bars represent 95% correlation-adjusted confidence intervals for repeated measures data (Cousineau, 2017; Morey, 2008).



Open practices

The *Open Data* badge was earned because the data of the experiment(s) are available on the journal's web site.

Citation

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