American Psychologist

© 2024 The Author(s)
ISSN: 0003-066X

2024, Vol. 79, No. 8, 1076–1091
https://doi.org/10.1037/amp0001315

Resilience to Major Life Events: Advancing Trajectory Modeling and Resilience Factor Identification by Controlling for Background Stressor Exposure

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Resilience has been defined as the maintenance or quick recovery of mental health during and after stressor exposure. One popular operationalization of this concept is to model prototypical trajectories of mental health in response to an adverse event, where trajectories of undisturbed low or rapidly recovering symptoms both comply with the resilience definition. However, mental health responses are likely also influenced by other stressors occurring before or during the observation time window. These "background" stressors may affect a person's assignment to a trajectory class. When using these classes as dependent variables to identify resilience-predictive factors, this may lead to false estimates. A new method to build exposure-controlled trajectories based on time courses of stressor reactivity (SR), rather than pure mental health scores, is demonstrated on a data set of 707 initially healthy participants living in Germany (67.33% female; $M_{\text{age}} = 29.20$, $SD = 8.27$). SR scores express individual deviations from the sample's normative mental health reaction to observed real-life stressors during the observation time window, thus accounting for individual differences in exposure to background stressors. The resulting trajectory models are plausible. In analyses additionally controlling for background stressors occurring before the observation time window (past life events), low SR trajectories are predicted by the well-documented resilience factor sense of coherence, suggesting construct validity. Further, they are associated with lower odds of developing categorical mental health conditions, suggesting predictive validity. Our study provides the first proof of principle for a refined method to identify predictors of resilience to major stressor events.

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This research was funded by the German Research Foundation (DFG CRC 1193, No. 264810226 to Andreas Reif; subprojects B01, C01, C04, C05, C07, Z03, and DFG LORA-Risk, Grant 519365575 to Michael M. Plichta and Andreas Reif), the Stiftung Rheinland-Pfalz für Innovation (MARP program, Grant 961-386261/1080), the Ministry of Science of the state of Rhineland-Palatinate (DRZ program), and the European Union's Horizon 2020 research and innovation program (Grant Agreement Nos. 777084, 667302, 101016127, and 728018). The authors have no conflicts of interest to disclose.

The data are not publicly available. Materials and analysis code for this study are available by emailing the corresponding author. This study was not preregistered.

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Public Significance Statement
Identifying factors that predict resilience is a major goal of mental health science. These factors might be targets for interventions aiming at preventing the development of stress-related mental health problems. To quantify a person's resilience, we must be sure that the individual does not simply show good mental health because they are less exposed to adversity. Our approach to the quantification of resilience tries to exclude this potential confound.

Keywords: stressor reactivity, resilience, *k*-means classification algorithm for longitudinal data, sense of coherence, Longitudinal Resilience Assessment

Supplemental materials: https://doi.org/10.1037/amp0001315.supp

Mental disorders are one of the leading causes of the global burden of disease (GBD 2019 Mental Disorders Collaborators, 2022), with depression and anxiety being the most outstanding contributors (Santomauro et al., 2021). These disorders can have significant personal, economic, and societal costs and are often triggered by stressor exposure during childhood and adulthood (Calcia et al., 2016). The resulting experience of stress is considered a key factor in the onset and persistence of mental disorders. Stress can be triggered by many different stressors ranging from relatively mild but annoying daily hassles (DHs; such as traffic or time pressure) to major life events (LEs; breakups or birth of a child) and (potentially) traumatic events (such as abuse or natural disaster; Liu & Boyatzis, 2021). But not everyone who is exposed to stressors develops a mental disorder, that is, some people are resilient.

Resilience has been defined as the maintenance or quick recovery of mental health during and after times of adversity (Bonanno et al., 2011; Kalisch et al., 2017; Luthar et al., 2000; Zautra et al., 2008). According to this definition, resilience is an outcome of good mental health in the face of stressor exposure, the likelihood of which is increased by the presence of social, psychological, or biological factors ("resilience factors") that facilitate successful adaptation ("resilience processes"; Kalisch et al., 2017).

Per this definition, resilience has to be measured relative to adversity (Infurna & Luthar, 2018; Kalisch et al., 2017; Luthar et al., 2000; Mancini & Bonanno, 2009). One popular operationalization involves modeling the trajectory of mental health upon the experience of a major LE or (potentially) traumatic event or the onset of a difficult life phase with frequent DHs, such as caused by physical disability or the diagnosis of a severe chronic illness (Galatzer-Levy & Bonanno, 2012; Galatzer-Levy et al., 2018). A repeated finding from these studies is that the majority of individuals, often more than 80%, can be assigned to classes of trajectories characterized either by stable mental health across the entire observation period or by rapid recovery following initial, but temporary deterioration (Galatzer-Levy et al., 2018). (Note that ongoing debate surrounds the veridicality and meaning of these class proportions and whether both classes equally indicate resilience; Infurna & Luthar, 2018; Schäfer et al., 2022.)

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Raffael Kalisch and Michael M. Plichta share last authorship.

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Insufficient Consideration of Additional "Background" Stressors

An assumption often implicit in trajectory studies is that the stressor event, to which a mental health trajectory is anchored, is the only stressor that relevantly affects the course of symptoms. However, significant LEs are often preceded or succeeded by additional stressors, such as when divorce follows upon a long period of intensifying marital conflict or when an accident has lasting health and material consequences (Lock et al., 2012; Norris & Uhl, 1993; Stroebe & Schut, 2010). Exposure to these additional adversities may well differ between individuals. Therefore, it cannot be excluded that membership in low-symptom classes (stable or recovering) may rather trivially be explained by relatively less experienced adversity surrounding the anchor stressor. Similar problems could arise if class membership was affected by stressors causally unrelated to the anchor stressor. For instance, one study investigating rescue workers responding to the 9/11 World Trade Center terror attack found that those rescue workers who experienced a smaller number of (potentially) traumatic events before 9/11 were also more likely to show stable mental health after 9/11 (Feder et al., 2016).

Taken together, trajectory studies may inherently suffer from insufficient consideration of individual differences in exposure to additional "background" stressors (Infurna, 2020; Kalisch et al., 2021; Lowe et al., 2020). This may lead to false results about identified resilience factors, that is, predictors of membership in the stable low or recovering symptom classes. On a more general level, one could argue that the enormous popularity of the trajectory modeling approach, via its natural focus on key events, has promoted a certain bias in resilience research against accommodating more commonplace and chronic types of stressors into resilience operationalizations. Resilience research thereby runs the risk of ignoring the well-documented influence of more mundane LEs (moving house, having a conflict with a close friend, quitting a job, etc.) or also accumulating and repeated DHs (having time pressure, experiencing childcare problems, living in a run-down area, etc.) on mental health (Serido et al., 2004). Such research, however, appears necessary given the high prevalence in the general population of stress-related mental disorders that cannot be linked to single key traumatizing events (GBD 2019 Mental Disorders Collaborators, 2022).

To conclude, the outcome-based conceptualization of resilience as good mental health despite stressor exposure (Kalisch et al., 2017) requires that individual differences in mental health during or after adversity are qualified by the experienced adversity. Normalization of stressor-induced mental health changes to the stressor exposure should achieve that individuals with less pronounced changes (e.g., lower levels of depression developing in Person A than Person B after onset of physical disability) are not automatically qualified as more resilient if they were factually less exposed (e.g., Person A having less financial problems because their affluence allows them to easily pay their increased medical bills or the nonphysical nature of their job allows them to continue working). Normalization should also achieve that individuals with comparable changes are not automatically classified as equally resilient or nonresilient if they were differently exposed (e.g., Persons C and D both develop a similar degree of depression following disability, where C would have less financial difficulties and should therefore ideally be identified as less resilient [more stressor-susceptible] than D). An obvious challenge for normalization is that relevant potential stressors are manifold and of different types and may occur at different points in time within and between individuals (Kalisch et al., 2021). Hence, it is impossible to measure stressor exposure at a single time point or to treat it as a trait. Instead, repeated measurements of the stressors potentially relevant for the study population are necessary.

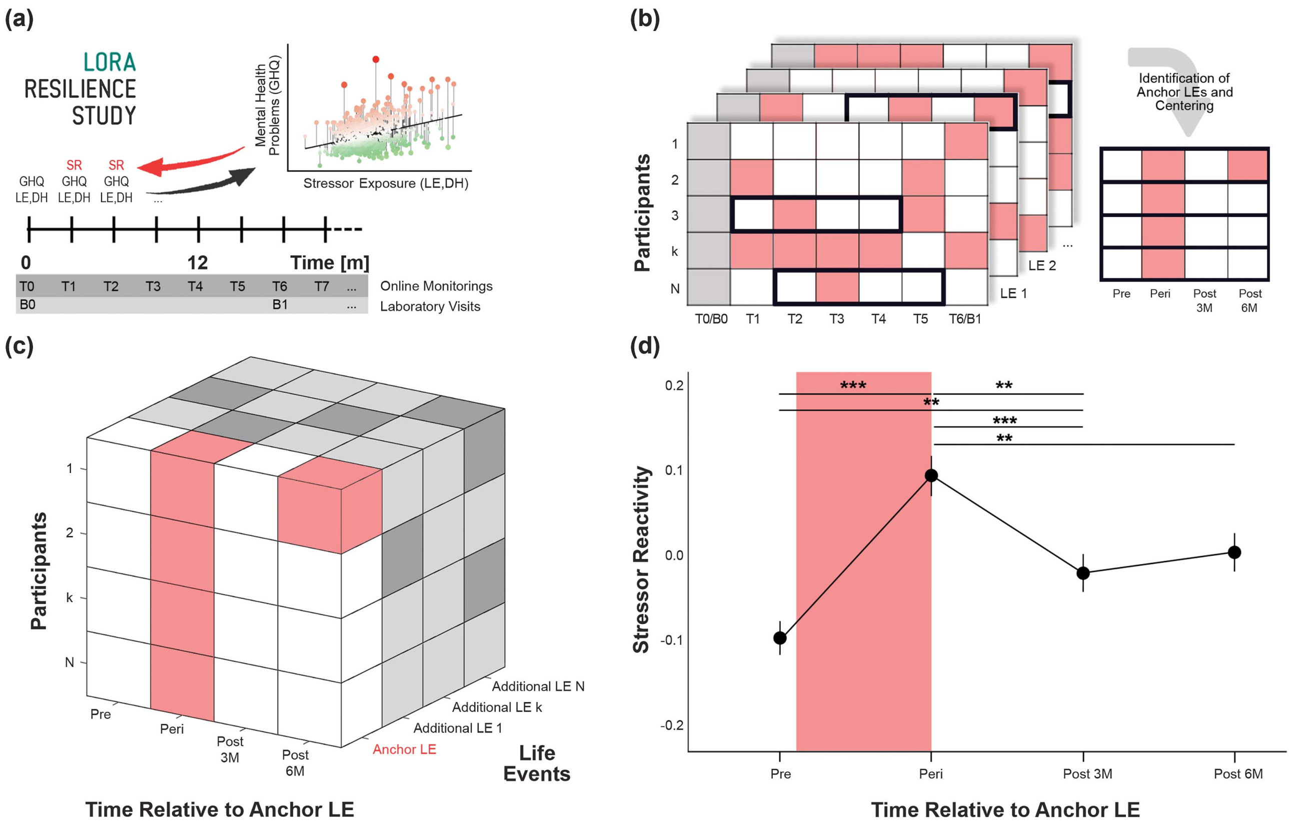
The Longitudinal Resilience Assessment Study

To take a more inclusive approach and specifically to advance the study of resilience against the wear and tear of everyday life stressors in modern, industrialized societies, we have initiated the Longitudinal Resilience Assessment study (LORA; Chmitorz et al., 2021), in which initially healthy adult participants self-report on their exposure to both LEs and DHs and their mental health every 3 months over a period of several years (Figure 1a). LORA thus provides extensive participant characterization in accordance with FRESHMO design recommendations (FREquent Stressor and mental Health MOnitoring; Kalisch et al., 2021). With particular relevance for the present discussion, the LORA data set allows us to take into account the influence of exhaustively measured background stressors when determining individual mental health trajectories in response to demarcated anchor LEs.

Exposure-Controlled Trajectory Approach

Our exposure-controlled trajectory approach comprises the following elements. First, for each 3-monthly monitoring time points T1, T2, T3, and so forth after the initial monitoring at study inclusion T0 (cf. Figure 1a), we build a stressor exposure score summarizing the self-reported occurrence of LEs and DHs in the retrospectively covered time window (3 months between T0 and T1, 3 months between T1 and T2, etc.). Second, for the time window between the two initial laboratory visits (B0/T0 to B1/T6), we regress the self-reported mental health problems on the stressor exposure score, to thus derive a normative *mental health problems–stressor exposure* relationship for the given interval. Individuals' residuals onto the regression line (termed stressor reactivity [SR] score) express to what extent an individual's mental health reacts more (positive SR) or

Figure 1
Method and Design



Note. Design of the LORA study (Panel A): Every 3 months (T0, T1, T2, etc.), exposure to stressors (life events, LEs; daily hassles, DHs) and mental health problems (GHQ) are retrospectively assessed online via self-report. For each time window, GHQ is regressed onto stressor exposure, to derive individual residuals that express a person's mental health reactivity to stressors (stressor reactivity, SR) in the given time window. Every 18 months (B0, B1, etc.), potential social, biological, and psychological resilience factors (e.g., SOC) are measured in a testing battery that also comprises a structured mental health interview (MINI) and, at B0, an LE life history assessment. Panel B: Identification of anchor LEs. For the selection of anchor LEs, four contiguous time points are being searched for, in which a given item from the LE list occurs (black boxes). The only prerequisite for the selection is that the same LE is not preceded (preanchor) by the identical LE. The identified time snippets are centered on the anchor LE. Panel C shows that we allow the occurrence of other LEs (other items from the list) at any time point (gray area). Panel D: As a manipulation check of the data reorganization, the SR response to the anchor LE is averaged over all participants. Consistent with the hypothesis, we see a significant increase in SR to the anchor LE, followed by recovery to postanchor 3M and 6M, that is, 3 and 6 months after the anchor LE. No significant change is seen between 3 versus 6 months postanchor LE. LORA = Longitudinal Resilience Assessment; GHQ = General Health Questionnaire; SOC = sense of coherence; MINI = Mini International Neuropsychiatric Interview. See the online article for the color version of this figure.

less (negative SR) to stressor exposure than would be expected given the sample's normative model. Importantly, in this way, we control for between-participant differences in stressor exposure, thus excluding that differences in mental health in a time window are explained merely by differences in exposure during that time window (Kalisch et al., 2021). We thus use SR scores, rather than raw mental health problem scores, as the basis for trajectory modeling, as discussed and proposed by Schäfer et al. (2022). Third, we identify the first suitable LE reported by a participant to use as the anchor stressor for their SR trajectory. Each trajectory comprises the monitoring time point before the LE report ("preanchor"), the time point when the LE was retrospectively reported ("anchor"), and the time points 3 months ("postanchor 3M") and 6 months ("postanchor 6M") after the LE report. Thereby, the trajectory covers 12 months and shows the immediate reaction to the LE (from preanchor to anchor), as well as its longer term consequences across the next 6 months (at postanchor 3M and 6M; Figure 1b and 1c). Fourth, when testing whether a hypothesized resilience factor measured in the testing battery at LORA study inclusion (T0/B0, in Figure 1a) predicts membership in the thus identified SR trajectory clusters, we control for differences in SR at trajectory baseline (preanchor), for the number of LEs reported at potential LORA monitoring time points before trajectory baseline (between T0 and preanchor), and for LEs prior to study inclusion (reported at T0/B0).

We applied this method to assess the prospective association of sense of coherence (SOC), reported at study inclusion (B0/T0) with trajectory cluster membership. SOC refers to a person's perception of the world as comprehensible, manageable, and meaningful (Antonovsky, 1979). SOC seems to prevail over other resilience factors and shows similar effects across cultural contexts (Eriksson & Lindström, 2006). It is conceptualized as a construct that overlaps with other resilience factors such as optimism and hardiness (Eriksson & Lindström, 2006), and the composite score shows incremental validity beyond other resilience factors, for example, personality and mindfulness (Grevenstein et al., 2018). Not finding a strong and well-validated resilience factor like SOC meaningfully associated with cluster membership would raise doubts about the construct validity (Cahill et al., 2022) of our resilience operationalization.

To assess its predictive validity (Cahill et al., 2022), we asked whether mental health information was read out from a different source, namely the experimenter-led structured interviews conducted as part of the testing batteries at 18-month intervals in the progress of the LORA study (see B1, B2, etc. in Figure 1a), can be predicted by cluster membership in a meaningful way.

Method

Transparency and Openness

This study was not preregistered. The Longitudinal Resilience Assessment Study is an ongoing longitudinal study, and the data are not publicly available. Full copies of the LORA data files are held by Andreas Reif (reif@med.uni-frankfurt.de). A deidentified data set containing the variables analyzed in this article and the code are available upon request from the corresponding author. Code to calculate the Stressor Reactivity Score can be found in the Supplemental Material.

Longitudinal Resilience Assessment

LORA is a longitudinal study based in Frankfurt and Mainz, Germany, that aims to investigate resilience to modern life stressors in a large convenience sample of initially healthy participants drawn from the general population (Chmitorz et al., 2021). Included participants had to be between 18 and 50 years of age, sufficiently proficient in the German language, able to provide informed consent, and free from mental disorder as assessed through the Mini International Neuropsychiatric Interview (MINI; Ackenheil et al., 1999; Lecrubier et al., 1997; see Chmitorz et al., 2021, for detailed inclusion and exclusion criteria). All participants provided written informed consent. The study adhered to the Declaration of Helsinki (World Medical Association, 2013) and the guidelines by the Ethics Committees in Frankfurt am Main (registration number: 244/16) and Mainz (registration number: 837.105.16[10424]), Germany. Between 2017 and 2019, a total of 1,191 participants (65.9% female, with an average age of 28.59 years [SD = 7.96]) were included in the study.

Following study inclusion and initial monitoring (T0), participants have been followed up at 3-month intervals (T1, T2, etc., see Figure 1a) for current levels of stressor exposure (DHs and LEs) and mental health problems, self-reported online. The additional 18-monthly laboratory visits (B0, B1, etc.) include a testing battery with assessments of potential social, biological, and psychological resilience factors (including SOC), mental health, LE life history (at B0 only), and sociodemographic and lifestyle variables.

Study Design

The current analysis of the LORA data was not preregistered. It only uses data acquired before the COVID-19 pandemic, to ensure that this specific stressor does not influence the results. Data on mental health problems, LEs, and DHs from T0 were discarded because this report only served to familiarize participants with the online reporting procedure.

Anchor LE and Participant Selection

Within this data set, we aimed at describing responses across four monitoring time points (preanchor, anchor, postanchor 3M, postanchor 6M; compare Figure 1b) to the first reported LE that would not be preceded in the previous monitoring time window by a report of the same LE (no identical preanchor LE). Hence, only LEs reported at T2 or later were considered as anchors, provided they were not preceded by the same LE. Note that we allowed the occurrence of other LEs at preanchor, anchor, and postanchor monitoring time points. Additionally, we allowed the occurrence of the same LE as the anchor LE at postanchor 3M and 6M. This was possible because the exposure-based trajectory method is explicitly designed to control for the influence of other stressors than the anchor stressor (see Introduction section). To ensure we did not miss the stressor exposure of a participant, only participants with four complete LE reports from preanchor to selected postanchor 6M were included in the analysis. In the case of two different LEs appearing at two consecutive time points (and both not preceded [preanchor] by the identical LE), the LE with maximum in δ SR (SR at anchor LE minus SR at preanchor) was chosen as anchor LE.

The resulting final sample (N = 707; female = 476, 67.33%) had an average age of 29.20 years (SD = 8.27), identical to the full sample at study inclusion. For demographics, see Table 1. (For a comparison between participants included in the analyses and those not included, revealing a high level of representativeness of the study sample, see Supplemental Table S1.)

Table 1
Overall Demographics

Variable	*M*/*N* ± *SD*/frequency
N	707
Sex	
Female	476 (67.33%)
Male	231 (32.67%)
Age	29.20 (8.27)
Marital status	
Nonmarried	546 (79.48%)
Married	120 (17.47%)
Separated	8 (1.16%)
Divorced	12 (1.75%)
Widowed	1 (0.15%)
Number of persons living in the same household	2.30 (1.22)
Employment status	
Full time	226 (32.85%)
Part time	91 (13.23%)
Part time (health-related)	2 (0.29%)
No employment	15 (2.18%)
No employment (health-related)	1 (0.15%)
Student/in training	353 (51.31%)
Highest level of education	
Certificate of secondary education	15 (2.18%)
School-leaving examination	258 (37.50%)
Completed vocational training	94 (13.66%)
University degree	321 (46.66%)
Nationality	
German	650 (92.07%)
Other European Country	31 (4.39%)
Others (Asia, South America)	25 (3.54%)
Mental health problems (GHQ)	16.67 (7.36)
Sense of coherence (SOC)	149.94 (19.53)
Life events (LE)	2.35 (1.89)
Daily hassles (DH)	62.45 (28.83)

Note. The percentages refer to the frequency of those without missing values on the respective variable. *M* and *SD* for GHQ and SOC were calculated based on the scores of the initial laboratory visits, whereas *M* and *SD* for LE and DH calculations were performed over the observation time window of the trajectories (preanchor to postanchor 6 months). GHQ = General Health Questionnaire.

Measures

All measures used for the current analysis were obtained in German at the 3-monthly online monitoring (T1, T2, etc.), unless otherwise noted.

Life Events. An adapted version of Canli's Life Experiences Questionnaire (Canli et al., 2006), consisting of 27 items, was employed. Participants were asked to report whether an LE occurred in the last 3 months (*occurred*; *did not occur*; *I don't want to answer*) and how straining it was. Following Kalisch et al. (2021), a cumulative score of LE occurrence in the reporting interval was determined by adding all the reported events. Strain data were not used because strain ratings may be more strongly biased than occurrence ratings by the presence of different resilience factors (e.g., different appraisal tendencies) and thus lead to a less objective picture of stressor exposure.

Daily Hassles. The DHs assessment used the Mainz Inventory of Microstressors Scale by Chmitorz et al. (2020), consisting of a 58-item list that asks participants to report the number of days in the past week on which a specific hassle occurred (scale: *did not occur*; *1 day–7 days*), and, if so, how straining it was. As for LEs, a cumulative occurrence score across was calculated, however, by adding all days on which a DH was reported across all items (Kalisch et al., 2021). By repeatedly sampling single weeks from longer time windows, we assume that the covered weeks contain representative information about DH occurrence in the longer window (here 12 months).

Mental Health Problems. Internalizing mental health problems (hypervigilance, worrying, anxiety, psychosocial dysfunctions, despair, hopelessness, depressed mood, somatic tension, exhaustion, pain, irritability) were assessed using the 28-item version of the General Health Questionnaire (GHQ-28; Goldberg & Hillier, 1979; Klaiberg et al., 2004). Items were answered on a 4-point Likert scale and summed to a total score. The cutoff of the GHQ is >23 indicating mental health problems (Sterling, 2011).

Sense of Coherence. The Orientation to Life Questionnaire (SOC-29; Eriksson & Mittelmark, 2017) was administered every 18 months (B0, B1, etc.) to capture Antovosky's (1979, 1993) SOC concept. It consists of 29 items answered on a 7-point Likert scale. To calculate the total score, 12 inverted items were recoded, and the values of the items were summed.

Mini International Neuropsychiatric Interview. To assess whether participants had an axis I mental illness according to the *Diagnostic and Statistical Manual of Mental Disorders, fourth edition* (American Psychiatric Association, 1994) at the beginning of the study or developed it during its course, trained personnel administered the MINI (Lecrubier et al., 1997; German Version 5.0.0 by Ackenheil et al., 1999) every 18 months (B0, B1, etc.).

Data Preprocessing and Statistical Analyses

Data preparation and statistical analyses were performed using R (Version 4.3.0) and SPSS (Version 27).

Stressor Reactivity

Following Kalisch et al. (2021), for the full LORA sample ($N = 1{,}191$), stressor exposure was calculated for each monitoring time window as the mean of the *z* scored LE and DH occurrence counts. In a linear model fit across all time points, combined LE and DH exposure explained more variance in mental health problems ($R^2 = 0.12$, $p < .001$) than either LE exposure ($R^2 = 0.06$, $p < .001$) or DH exposure ($R^2 = 0.10$, $p < .001$) alone, in a predominantly linear relationship.

Individual stressor reactivity (SR) was calculated as the divergence from this norm relationship between mental health problems and the combined stressor exposure score. To this end, individual SR scores were calculated as the residuals from a linear mixed model predicting mental health problems by stressor exposure across the six monitoring time points between the two initial laboratory visits 18 months apart (T1 to B1/T6). As a result, SR reflects the difference between a participant's empirical observation of mental health problems and their normatively predicted mental health problems. To properly account for the hierarchical structure of the data, we incorporated both a random slope and a random intercept, utilizing the fixed effects of the linear mixed model for calculating the SR scores for each participant and time point. The R-Code for these calculations is provided in the Supplemental Material in the R-Code to Compute the Stressor Reactivity (SR) Score section.

SR Trajectory Modeling (Cluster Analysis)

To avoid cluster centers from being driven by extreme outliers (Teuling et al., 2021), before analyses, each time point was checked for extreme outliers (values above Q3 [upper quartile] + 3 × IQR [interquartile range] or below Q1 [lower quartile] − 3 × IQR), and two outliers were detected and omitted from further processing (final n = 707).

To group participants with similar SR trajectories to the same cluster, we employed the KML algorithm via the *kml* package (Version 2.4.1) in R (Genolini et al., 2015; Genolini & Falissard, 2011), a k-means classification algorithm for longitudinal data. This method involves assigning participants to clusters using a hill-climbing algorithm that belongs to the expectation-maximization family. In the expectation phase, seeds for different clusters (centers) are calculated, and in the maximization phase, participants are assigned to the nearest cluster. These steps are repeated until there are no changes in the clusters (Genolini et al., 2015). To initialize the k-means algorithm, to find the optimal partition that maximizes the between-matrix variance, while minimizing the within-matrix variance, the algorithm was run 100 times with varying starting conditions. As a starting condition, we used "allMethod," which is known for its efficiency and combines the starting methods "maxDist," "randomAll," and "randomK" (Genolini & Falissard, 2011). Of those three starting methods, "maxDist" is the most efficient, it selects the two most distant individuals as the first two clusters and then adds subsequent participants that are farthest from the already chosen centers (Genolini et al., 2015). Two to five clusters were calculated. The package provides several quality criteria, of which five are nonparametric (e.g., the Calinski & Harabasz, 1974 criterion, or the Ray & Turi, 2000 criterion). They are used to interpret the separation and compactness of the clusters. Moreover, the Akaike information criterion and the Bayesian information criterion are provided but should not be given too much weight, as they may only be used with normally distributed variables (Genolini et al., 2015).

Prospective Association of SOC With Cluster Membership

Logistic regressions were used to analyze whether cluster membership (dependent variable) was related to differences in SOC at B0 (independent variable). For the obtained two-cluster separation, bivariate logistic regressions were calculated with the glm function from the stats package (Version 4.2.1). For the other separation, the multinom function from the *nnet* package (Version 7.3-18) for multinomial logistic regressions was used. To ensure that detected differences are not better explained by mean differences in SR or by background stressor exposure (see Introduction section), SR at preanchor, lifetime LE exposure, and the number of LEs before preanchor (between T0 and preanchor) were added as covariates, as were age and sex. All variables except sex were standardized. To avoid multicollinearity issues, variance inflation factors (Marquardt, 1970) were ensured for every predictor to be <2. 32 participants had missings on one of the covariates and were therefore excluded from the logistic regressions (final n = 675).

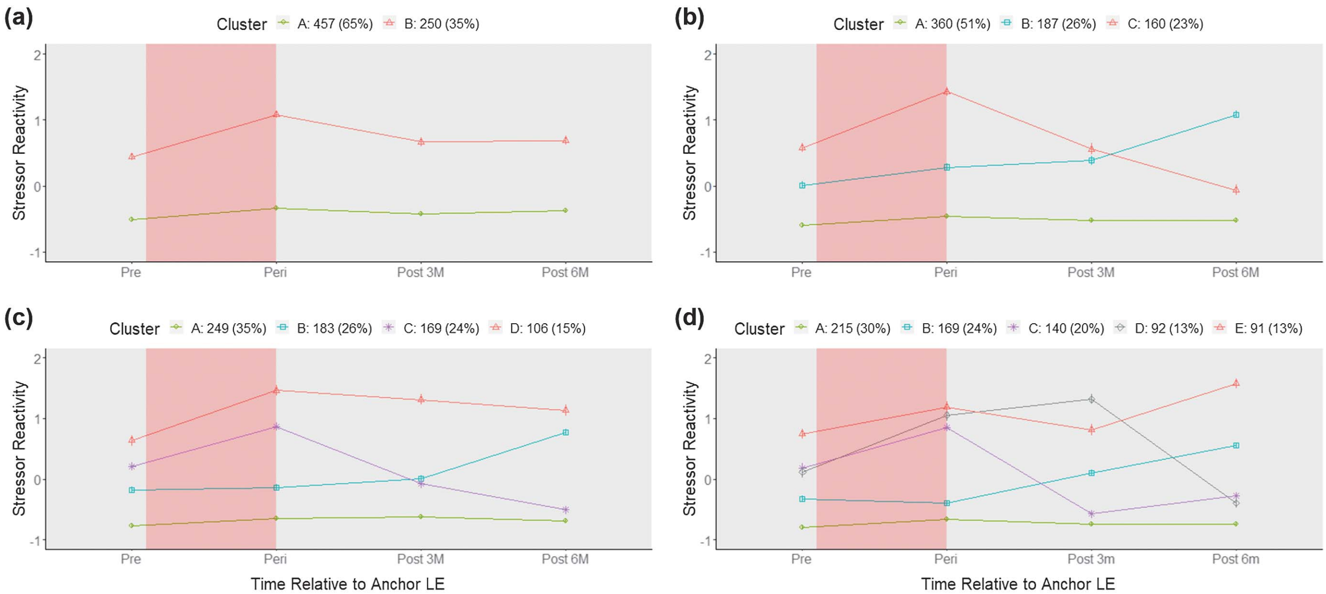
Relationship Between Clusters and Mental Dysfunction

To predict the presence of mental dysfunction indicated by the MINI interviews conducted after study inclusion (B1, B2, and/or B3), chi-square tests of independence, with MINI as dependent and cluster membership as the independent variable, were used. This was followed by pairwise Fisher's exact test as a post hoc test to compare each cluster combination with p values, corrected using the Bonferroni correction. Here, 79 participants were removed (final n = 628) due to missing MINI assessments. Results were confirmed by logistic regressions, accounting for the number of MINI interviews (since, depending on the time of study inclusion, not every participant has already completed all follow-ups), age, sex, preanchor SR, and lifetime LE exposure.

Results

Figure 1d illustrates the participants' average SR responses to their individual anchor LE. On average, SR increases from the monitoring time point before the event (preanchor) to the time point at which the event was reported (anchor), then diminishes again at the time points 3 and 6 months after the occurrence of the anchor LE (postanchor 3M and 6M), yet does not completely return to the baseline level. Repeated measures analysis of variance showed an effect of time, $F(3, 2118) = 19.73$, $p < .001$. Separate post hoc t tests with Bonferroni adjustment showed that SR was increased at anchor compared to preanchor ($p_{adj.} < .001$) and compared to postanchor 3M ($p_{adj.} < .001$). This suggests the events were on average stressful and had a negative impact on participants' mental well-being.

Figure 2
Trajectories of Different Cluster Separations Generated by KML



Note. Error bars represent standard error. (a) Two-cluster separation. (b) Three-cluster separation. (c) Four-cluster separation. (d) Five-cluster separation. $N =$ 707. LE = life event; KML = *k*-means Classification Algorithm for Longitudinal Data. See the online article for the color version of this figure.

SR-Based Trajectory Modeling (Cluster Analysis)

The cluster separations (see Figure 2) all featured one most frequent cluster (green trajectory A in Figure 2) that was characterized by very low initial SR at preanchor and a largely absent response to the LE as well as one least frequent cluster (red) with a very high initial SR at preanchor and a pronounced immediate response to the anchor LE (at time point anchor). Other clusters had intermediate initial SR values and showed different trajectories.

According to the quality criteria comparison (Table 2), the best cluster separation is either the parsimonious two-cluster separation or the least parsimonious five-cluster separation (Figure 2). Both separations had an appreciable number of participants in the least frequent cluster (in particular 13% in Cluster E of the five-cluster separation; see Figure 2). Inspection of Figure 3, overlaying the cluster trajectories onto the corresponding individual time courses, suggests that the five-cluster separation is an adequate description of within- and between-subject variance. Hence, the following analyses to assess the criterion and predictive validity of the cluster separations are based on the two-cluster and five-cluster separations (see Supplemental Tables S2 and S3 for comparative sociodemographics).

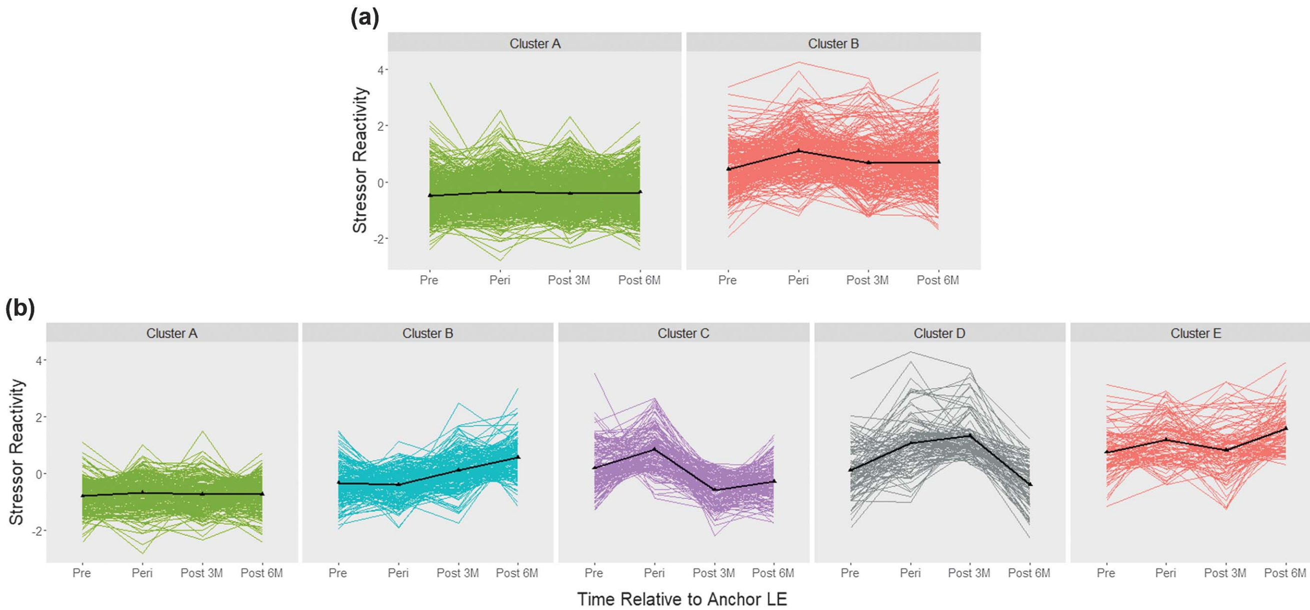
To explore whether cluster assignment might be driven by the nature of anchor LEs, we grouped the anchor LEs into eight thematic categories, based on theory and supported by principle component analysis. Supplemental Figure S4 shows that the relative frequencies of anchor LEs from the eight categories in each cluster of the different separations were comparable to their frequencies in the whole sample, speaking against an association of cluster assignment and LE type.

Table 2
Quality Criteria

Quality criterion	Two-cluster	Three-cluster	Four-cluster	Five-cluster
Calinski and Harabasz (1974)	**312.87**	220.12	212.43	189.27
Calinski and Harabatz by Kryszczuk and Hurley (2010)	0.44	0.63	0.91	**1.08**
Calinski and Harabatz by Genolini et al. (2015)	312.87	311.30	367.94	**378.57**
Ray and Turi (2000)	**−0.13**	−0.20	−0.18	−0.18
Davies and Bouldin (1979)	**−1.42**	−1.54	−1.46	−1.46
BIC; Schwarz (1978)	**−7713.73**	−7789.39	−7744.77	−7784.13
AIC; Akaike (1974)	**−7672.94**	−7730.09	−7767.23	−7688.35

Note. Every criterion should be maximized for the best fit, as the R package *kml* has redefined each criterion that needs to be minimized (Genolini & Falissard, 2011). The best fit for cluster separation is bolded for each criterion. BIC = Bayesian information criterion; AIC = Akaike information criterion.

Figure 3
Individual Time Courses Underlying Cluster Trajectories



Note. (a) Two-cluster separation: Cluster A = 65% and Cluster B = 35%. (b) Five-cluster separation: Cluster A = 30%, Cluster B = 24%, Cluster C = 20%, Cluster D = 13%, and Cluster E = 13%. LE = life event. See the online article for the color version of this figure.

Comparison With Growth Mixture Modeling

An alternative approach to identifying prototypical response trajectories that is frequently used in the literature is growth mixture modeling (GMM; Muthén & Muthén, 2000). GMM requires to predefine the shape of potential temporal trends (e.g., linear or quadratic) to be found in the data (Wickrama et al., 2016). GMM analysis of our data, see Supplemental Material in the Growth Mixture Modeling (GMM) section, identified a three-class solution as optimal, based on fit indices. The solution featured qualitatively different trajectories (Supplemental Figure S1) than the three-cluster solution identified with KML (Figure 2b), and inspection of the individual trajectories in Supplemental Figure S2 suggested the separation is (similar to the two-cluster KML separation) mainly driven by mean value differences and less by differential trends. As shown in Supplemental Tables S8–S11, the classes obtained by GMM also show construct and predictive validity. Regardless of the method used, meaningful unobserved classes/clusters can be extracted. At this early stage of the development of the SR trajectory method, the data-driven and exploratory approach to KML appeared more intuitive, which is why we focused on the KML results. Further research may find prototypical trajectories across different populations that can be adequately described with both GMM and KML.

Prospective Association of SOC With Cluster Membership

To test the construct validity of the two-cluster and five-cluster KML separations, we tested whether SOC measured at study inclusion (B0) predicted cluster membership in a meaningful way. Because the most frequent Cluster A with low stable SR scores (green in Figure 2) could be safely classified as representing a resilient response in both separations, we compared SOC in A relative to all other clusters using logistic regression, controlling for starting values (preanchor SR), other potential background stressors (lifetime LE exposure, number of LEs before the preanchor time point), age, and sex (see Table 3).

In the two-cluster separation, participants in Cluster A (green) exhibited significantly higher baseline levels of SOC compared to those in Cluster B (red), who demonstrated consistently increased stressor reactivity. In the five-cluster separation, Cluster A (green) showed a significantly higher SOC compared to Clusters D (gray) and E (red), which both exhibited the highest levels of stressor reactivity.

Relationship Between Clusters and Mental Dysfunction

To test the predictive validity of the two separations, we tested whether cluster membership is associated with the

Table 3
Construct Validity

Variable	*B*	*p*	*OR*	95% CI
Two-cluster separation			A versus B	
Intercept	**1.34**	**<.001**	**0.25**	**[0.17, 0.36]**
SOC	**−0.57**	**<.001**	**0.57**	**[0.46, 0.70]**
Sex (female)	**0.90**	**<.001**	**2.45**	**[1.60, 3.82]**
Age	0.02	.847	1.02	[0.82, 1.27]
Preanchor SR	**1.27**	**<.001**	**3.58**	**[2.81, 4.55]**
Lifetime LE exposure	−0.08	.460	0.92	[0.73, 1.15]
LEs between the initial laboratory visit and preanchor	0.16	.104	1.17	[0.97, 1.42]
Five-cluster separation			A versus B	
Intercept	−0.12	.561	0.89	[0.59, 1.33]
SOC	−0.25	.056	0.78	[0.60, 1.01]
Sex (female)	**0.69**	**.004**	**1.98**	**[1.24, 3.17]**
Age	−0.06	.625	0.94	[0.74, 1.20]
Preanchor SR	**1.10**	**<.001**	**3.02**	**[2.14, 4.26]**
Lifetime LE exposure	−0.08	.507	0.92	[0.72, 1.18]
LEs between the initial laboratory visit and preanchor	0.10	.317	1.10	[0.88, 1.37]
Five-cluster separation			A versus C	
Intercept	−0.28	.216	0.76	[0.49, 1.18]
SOC	−0.20	.171	0.82	[0.61, 1.09]
Sex (female)	**0.54**	**.044**	**1.72**	**[1.01, 2.92]**
Age	−0.12	.380	0.88	[0.67, 1.17]
Preanchor SR	**1.96**	**<.001**	**7.10**	**[4.87, 10.35]**
Lifetime LE exposure	0.05	.724	1.05	[0.79, 1.40]
LEs between the initial laboratory visit and preanchor	−0.12	.398	0.89	[0.67, 1.17]
Five-cluster separation			A versus D	
Intercept	**−0.93**	**<.001**	**0.39**	**[0.23, 0.67]**
SOC	**−0.50**	**.002**	**0.60**	**[0.44, 0.83]**
Sex (female)	**0.90**	**.004**	**2.46**	**[1.33, 4.54]**
Age	−0.10	.535	0.91	[0.67, 1.23]
Preanchor SR	1.83	<.001	6.29	[4.20, 9.40]
Lifetime LE exposure	0.03	.867	1.03	[0.75, 1.41]
LEs between the initial laboratory visit and preanchor	−0.03	.854	0.97	[0.73, 1.30]
Five-cluster separation			A versus E	
Intercept	**−2.15**	**<.001**	**0.12**	**[0.06, 0.24]**
SOC	**−0.90**	**<.001**	**0.41**	**[0.29, 0.57]**
Sex (female)	**1.54**	**<.001**	**4.69**	**[2.23, 9.86]**
Age	−0.06	.743	0.94	[0.67, 1.34]
Preanchor SR	**2.59**	**<.001**	**13.36**	**[8.62, 20.70]**
Lifetime LE exposure	−0.22	.228	0.80	[0.56, 1.15]
LEs between the initial laboratory visit and preanchor	0.16	.317	1.17	[0.86, 1.59]

Note. Bold values indicate statistical significance level at $\alpha = .05$. $N = 675$. SOC = sense of coherence; SR = stressor reactivity; LE = life event.

occurrence of a categorical mental disorder during the study, measured with the MINI at B1 (18 months after B0), B2 (36 months after B0), and B3 (54 months after B0). We again used Cluster A as a reference, as it should have the smallest odds of developing clinical problems (Kalisch et al., 2021). The chi-square test of independence was performed to examine the relationship between cluster membership and mental disorder in the upcoming years. For the two-cluster separation, the relation was significant, $\chi^2(1, N = 628) = 11.08$, $p \leq .001$, but small, Cramer's $V = .13$. Participants assigned to Cluster B (red) are more likely to have a mental disorder in the future than participants assigned to Cluster A. For the five-cluster separation, the chi-square test of independence showed also a small significant effect, $\chi^2(4, N = 628) = 20.231$, $p \leq .001$, Cramer's $V = .18$. Fisher's exact post hoc tests (see Supplemental Table S4) showed a below-average frequency of mental health conditions in Cluster A (green) compared to the Clusters D ($p_{adj.} = .022$) and E ($p_{adj.} = .005$). This pattern was confirmed by binary logistic regressions controlling for the number of MINI interviews, age, and sex (see Supplemental Table S5).

In a final confirmatory analysis additionally controlling for whether the effects persisted over the difference in SR scores at preanchor (see Supplemental Table S6), there was no longer an association between mental illness and cluster for the two-cluster separation. This could imply that this separation is mainly dominated by baseline SR differences but offers little relevant information about temporal response profiles. By contrast, odds ratios for the two risk clusters in the five-cluster separation were as high as 2.51 (D) and 2.94 (E), suggesting that a more fine-grained separation of participants indeed provides an adequate and meaningful description of the data.

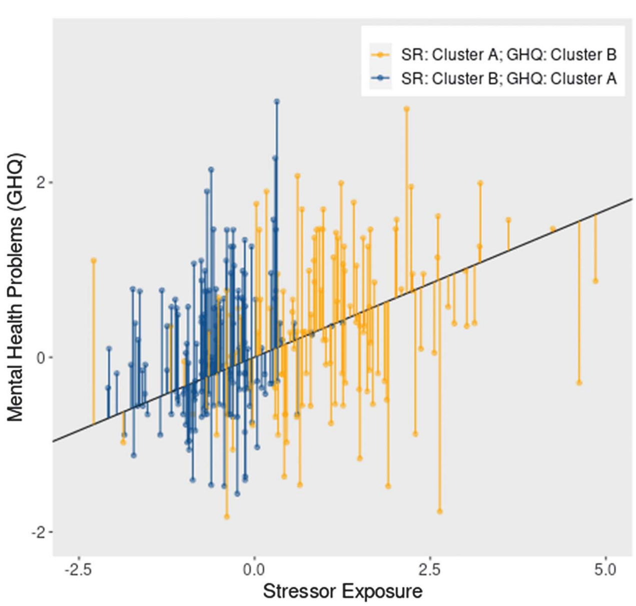
SR Versus Raw Scores of Mental Health Problems in Trajectory Modeling

Assessing background stressor exposure and integrating exposure information into trajectory modeling is only justifiable if SR-based clustering yields qualitatively different information than clustering based on raw mental health problem scores. Therefore, the trajectories were also calculated using GHQ data (see Supplemental Figure S3). This yielded notable differences in trajectory profiles (compare the SR-based three- and five-cluster separations in Figure 2).

Further, we discovered that cluster assignment in the GHQ-based modeling was affected by the participants' levels of stressor exposure. For simplicity, this is illustrated in Figure 4 only for the two-cluster separations. Depicted are the two groups of "switchers," meaning participants assigned to different clusters (A instead of B or vice versa) depending on the score used. Switchers assigned to the apparently nonresilient Cluster B in the GHQ-based separation but to the apparently resilient Cluster A in the SR-based separation (orange in Figure 4) also have significantly higher stressor exposure than opposite switchers (blue), $t(184.64) = 14.21$, $p < .001$, $d = 1.78$. Differences in mental health problems were much less pronounced ($d = 0.35$). This indicates that the GHQ-based separation can classify individuals as nonresilient mainly based on their exposure and does not consider that a highly exposed individual with a normative level of mental health problems is effectively more resilient than a much less exposed individual with the same but over-normative level of problems. By contrast, when using SR for modeling, participants with high stressor exposure but mental health problems within the norm (relative to the sample's normative mental health reaction) tend to be assigned into the resilient Cluster A.

Figure 4

Switchers Based on SR Versus Raw Scores of Mental Health Problems in Trajectory Modeling



Note. Differences in stressor reactivity for the two-cluster separations based on the outcome measure (SR vs. GHQ) are depicted for all four time points, showing only the switchers—individuals assigned to different clusters depending on the outcome measures. GHQ = General Health Questionnaire; SR = stressor reactivity. See the online article for the color version of this figure.

Discussion

Resilience to potentially traumatic or other adverse LEs can be operationalized by modeling distinct trajectories of mental health or functioning anchored to these events (Galatzer-Levy & Bonanno, 2012; Infurna & Luthar, 2018). These trajectories can then be used as dependent variables in analyses serving to identify predictors of the adaptive trajectories, that is, resilience factors (Infurna & Luthar, 2018; Kalisch et al., 2017). Although it is widely agreed that resilience is a good outcome despite adversity, trajectory modeling and resilience factor identification with the help of trajectory-based outcomes typically do not account for the presence of additional adversities ("background" stressors; Lowe et al., 2021) beyond the anchor event (Kalisch et al., 2021).

To address this issue, this article proposes a stressor reactivity framework (Kalisch et al., 2021) that incorporates the influence of background stressors present during a given observation time window on an individual's mental health. Specifically, stressor reactivity measures how much an individual's mental health response to the entirety of stressors reported during the observation window deviates from the sample's normal response, with positive stressor reactivity indicating a more pronounced reaction and negative stressor reactivity indicating a milder response. By using this framework, we can gain a more comprehensive understanding of an individual's resilience. Moreover, by extending the measurement of stressor reactivity across multiple time windows, we can obtain trajectories of responding that inherently control for stressor exposure, which may also change over time. We propose to use these exposure-controlled trajectories as outcomes in resilience factor identification analyses that additionally control for other stressors not captured in the stressor reactivity measures, such as past LEs. Factors identified with this method are considerably more likely to predict resilience in the proper sense of the term, rather than for instance a good mental health outcome that results merely from less exposure to stressors.

Clustering Based on SR Scores

With the present study, we have shown that, by using SR scores to cluster individuals in response to specific anchor LEs, several plausible separations are obtained, with fit indices pointing toward the two- and five-cluster separations. Whereas the two-cluster separation is quite sparse, the five-cluster separation describes the variety of corresponding individual time courses very well (cf. Figure 3). Notably, the separations include both one frequent nonreactive trajectory with stably low SR levels and one rare reactive trajectory with high SR levels that resemble well-described extreme trajectories in the previous literature (Galatzer-Levy et al., 2018).

Comparison of Clustering Approaches: KML Versus GMM

The comparison between GMM and KML revealed that GMM identifies a distinct three-class separation (cf. Supplemental Figure S2), which exhibits less overlap with individual trajectories compared to the five-cluster separation favored by KML (cf. Figure 3). As GMM requires a priori assumptions about the shape of the trajectory (linear, quadratic), which were not available for our initial exploratory use of the SR score for trajectory building, we favored KML. KML is strongly data-driven, easy to implement, and computationally less complex than the conventional methods and does not require any normality or parametric assumptions within clusters (Verboon & Pat-El, 2022), which appeared appropriate given there is no prior experience with SR-based trajectories. While our analysis did not show a clear superiority of one method over the other, with both approaches extracting valid classes/clusters, future research may indicate a clearly preferable method to be used for SR trajectories.

SR Versus Raw Scores of Mental Health Problems in Trajectory Modeling

The comparison between trajectory modeling based on SR and based on raw mental health scores revealed divergences in trajectories in the three- and the five-cluster/class solutions (cf. Figure 2 and Supplemental Figure S3). This indicates that SR-based modeling is not simply a more expensive form of the traditional modeling approach but can yield qualitatively different results. Further supporting this argument, we found in a comparison of the respective two-cluster/class solutions that some participants with a substantial degree of stressor exposure are categorized within the resilient Cluster A with the SR method and within the maladaptive Cluster B with the raw mental health score method (cf. Figure 4). This demonstrates method-dependent differences in classification and, moreover, highlights that the raw mental health score method fails to account for individual differences in stressor exposure.

Validity of SR Clusters

Our logistic regression analyses showed that the two- and five-cluster separations, obtained from KML and based on SR scores, are meaningfully predicted by a well-validated resilience factor, SOC (Antonovsky, 1979; Eriksson & Lindström, 2006; Grevenstein et al., 2018), such that individuals in clusters with high SR (Cluster D, gray, and Cluster E, red, in Figure 2) before and in response to the occurrence of an LE had low SOC values at baseline. By contrast, perceiving the world as understandable, manageable, and meaningful seems to contribute to low SR (Cluster A, green) both before and in response to the LE. This analysis also corrected for other stressors not captured by the SR-based modeling (lifetime LE exposure, number of LEs between T0 and preanchor, and SR at preanchor). To identify resilience factors in future studies as well, we explicitly recommend controlling for such additional stressors, as the SR-based clustering itself cannot and should not take these stressors into account. Predictability by SOC lends construct validity (Cahill et al., 2022) to the identified separations.

We also found an association between cluster membership and the development of mental health conditions over the course of the study, in the sense of a pronounced distinction between the extreme trajectories. This held for the five-cluster separation, but not for the two-cluster separation, in an analysis that controlled for the level of stressor reactivity at trajectory baseline. This could suggest that the five-cluster separation contains information about the dynamics of individual change that is not contained in the two-cluster separation, where individuals are essentially grouped according to their starting SR values. Prospective association with a different type of mental health outcome indicates predictive validity for these two separations (Cahill et al., 2022). On this basis, the five-cluster separation in particular appears justified, as it is both, plausible and clearly survives the construct and the predictive validity tests.

We conclude that our exposure-controlled trajectory approach can generate solutions that are suitable for the identification of resilience factors, although a more substantive interpretation will require further experiences with this method and analysis of other data sets, including from independent cohorts and/or from longer term observations. At this point, a clear distinction must be made between the classification with the primary aim of capturing resilience to identify resilience factors and the identification of people who need support.

Limitations

Several qualifications are necessary. First, we build relatively short trajectories with only two monitoring time points (postanchor 3M, postanchor 6M) after the time point at which the anchor LE is reported. It is possible that longer observation windows would have led to other, or additional, trajectories or to a different evaluation of the obtained separations. In particular, we cannot be sure based on our short trajectories that the endpoint levels of SR at postanchor 6M are stable. Second, one aim was to comprehensively capture the LEs experienced by each participant, given the pivotal role of objective stressor exposure in calculating the SR score. Therefore, we only included trajectories of participants who had data capturing 1 year without missings on LEs. To ensure we did not systemically exclude a significantly different group of individuals through the approach, we conducted a comparative analysis between the study sample and the excluded sample. While demographic variables were comparable, a significant difference in stressor exposure emerged, indicating a violation of the missing completely at random assumption. It is likely that people with increased strain will drop out of studies. This is a general problem in longitudinal resilience research and underscores the need for consideration in future study designs. Recognizing this limitation, we advocate for the justifiable and necessary practice of imputing missing measurement points. Methods such as those described in Enders (2011) can be employed for imputing missings in latent growth curve analyses. However, the extent to which objective stressor exposure can be imputed remains an important question for future research. Third, for the calculation of SR scores, we use a mental health instrument (GHQ) that mainly assesses internalizing symptoms. It is possible that other mental health outcomes (e.g., externalizing symptoms) or non-symptom-related outcomes (e.g., life satisfaction or psychosocial functioning) would have resulted in different trajectories. Fourth, while capturing a comprehensive list of potential stressors with 58 DHs and 27 LEs, it is still possible that some relevant stressors are not included in the lists. Given the related nature of stressors (frequently causing or exacerbating each other), the already very extensive stressor assessment is, however, likely to exhibit considerable redundancy and therefore to capture the most relevant within- and between variance in exposure, even if single stressors may have been missed. Fifth, the occurrence of some stressors may be forgotten during retrospective recall. Ideally, direct assessment of stressors using ecological momentary assessment be the preferred approach. However, the participant burden over the duration of our study makes such methods impractical. It should also be noted that we only requested participants to recall their DHs, which may be less memorable than LEs, over the past 7 days at each monitoring time point, instead of 3 months, as for the LEs. Sixth, our stressor assessment provides no information about whether a stressor or its absence is caused by the participant. Some participants may develop fewer mental health problems following an LE because they are more effective in reducing or avoiding additional exposure (e.g., participants with higher problem-solving skills). These participants' resilience might be underestimated with our exposure control approach. Future research on this methodology should therefore assess potential links between individual coping behaviors and exposure and correct for such potential influences. Last, it is possible that we would have obtained different separations in other populations. We only analyze one specific cohort (the LORA sample), which is relatively young and educated, and therefore not representative of the general population.

It is therefore important to note that we do not claim to have detected definitive response patterns that will generalize across trajectory durations, outcomes, and populations. Our objective is not to identify general response types or to make statements about their relative frequencies but to obtain normative solutions (Galatzer-Levy et al., 2018). Instead, we aim to provide proof of principle that an exposure-controlled trajectory approach is a suitable way to identify resilience factors. Resilience factor identification is a relevant aim as resilience factors are potential targets for the development of new preventions and interventions (Infurna & Luthar, 2018). Our conclusion that resilience factor identification is feasible with the exposure-based trajectory approach is preliminary and warrants confirmation in other samples.

Limitations of Clustering Approaches: KML Versus GMM

It may be considered a limitation that the commonly employed growth mixture models identified different separations, especially in the separations with more classes (whereas the resulting two-cluster/class separations showed similar trajectories). At this moment in the development process of exposure-based trajectory modeling, there cannot be a definitive recommendation either for or against a specific method. It may nevertheless be helpful already at this stage to consider some of the key pros and cons of the two approaches. First, KML does not require any assumptions regarding the shape of the resulting trajectories and is independent of time-scaling (Genolini & Falissard, 2010). The downside of this flexible method is the assumption that the within-cluster variance is equal across clusters (Teuling et al., 2021). Additionally, the approach is sensitive toward outliers and participants being close to the cluster boundary in between clusters (Teuling et al., 2021). This limitation motivated us to exclude two extreme outliers from our data set. Compared to KML, GMM is significantly slower in computing. On the other hand, GMM is more robust to nonnormal groups and group outliers (Genolini & Falissard, 2010; Teuling et al., 2021) and can account for within-cluster variability (Verboon & Pat-El, 2022). However, GMM needs information about the expected slope of the trajectory. Moreover, GMMs often show label-switching problems, as the class ordering can change freely during sampling (Teuling et al., 2021).

With these differences in mind, recent comparative evaluations of clustering methods (Teuling et al., 2021; Verboon & Pat-El, 2022) have concluded that the different methods (including GMM and KML) yield similar results and that KML can even outperform other methods when the number of repeated measures is low. Others have argued that GMM should be preferred over KML (Martin & von Oertzen, 2015; Twisk & Hoekstra, 2012). For the moment, we conclude that it is possible to use the SR score as a basis for describing the reaction to LEs in combination with different classification algorithms. Further studies are needed to critically evaluate the influence of the modeling method, which was, however, beyond the scope of this proof-of-principle study.

Conclusion

We provide proof of principle that it is possible to detect plausible temporal profiles of responding to a major LE based on stressor reactivity, rather than pure mental health, scores. These profiles exhibit construct and predictive validity and can be used as outcomes in analyses serving to identify resilience factors. We also show that controlling for additional stressors in these analyses is feasible. We propose to evaluate this novel approach to resilience factor identification in future studies.

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Received March 1, 2023
Revision received December 12, 2023
Accepted December 21, 2023 ■