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Reflections on psychological resilience: a comparison of three conceptually different operationalizations in predicting mental health

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ABSTRACT

Background: Psychological resilience refers to the ability to maintain mental health or recover quickly after stress. Despite the popularity of resilience research, there is no consensus understanding or operationalization of resilience.

Objective: We plan to compare three indicators of resilience that each involve a different operationalization of the construct: a) General resilience or one's self-reported general ability to overcome adversities; b) Daily resilience as momentarily experienced ability to overcome adversities; and c) Recovery speed evident in the pattern of negative affect recovery after small adversities in daily life. These three indicators are constructed per person to investigate their cross-sectional associations, stability over time, and predictive validity regarding mental health.

Methods: Data will be derived from the prospective MIRORR study that comprises 96 individuals at different levels of psychosis risk and contains both single-time assessed questionnaires and 90-days intensive longitudinal data collection at baseline (T0) and three yearly follow-up waves (T1–T3). General resilience is assessed using the Brief Resilience Scale (BRS) at baseline. Daily resilience is measured by averaging daily resilience scores across 90 days. For recovery speed, vector-autoregressive models with consecutive impulse response simulations will be applied to diary data on negative affect and daily stressors to calculate pattern of affect recovery. These indicators will be correlated concurrently (at T0) to assess their overlap and prospectively (between T0 and T1) to estimate their stability. Their predictive potential will be assessed by regression analysis with mental health (SCL-90) as an outcome, resilience indicators as predictors, and stressful life events as a moderator.

Conclusion: The comparison of different conceptualizations of psychological resilience can increase our understanding of its multifaceted nature and, in future, help improve diagnostic, prevention and intervention strategies aimed at increasing psychological resilience.

HIGHLIGHTS
- We develop three different indicators of psychological resilience, each involving a different operationalization of the concept, using the data from the same sample.
- We will compare how these indicators relate to each other and how they predict future level of mental health.

Reflexiones sobre la resiliencia psicológica: una comparación de tres operacionalizaciones conceptualmente diferentes como predictores de salud mental

Antecedentes: La resiliencia psicológica se refiere a la habilidad de mantener la salud mental o recuperarse rápidamente después de estrés. A pesar de la popularidad de las investigaciones sobre resiliencia, no existe consenso respecto a la comprensión u operacionalización de la resiliencia.

Objetivos: Planificamos comparar tres indicadores de resiliencia en que cada uno involucra una operacionalización diferente del constructo: a) Resiliencia general o la habilidad general autoreportada para superar adversidades; b) Resiliencia diaria como la habilidad experimentada momentáneamente para superar adversidades; y c) Velocidad de recuperación evidente en el patrón de recuperación de afecto negativo tras pequeñas adversidades en la vida diaria. Estos tres indicadores son construidos por persona para investigar sus asociaciones transversales, estabilidad sobre el tiempo, y validez predictiva sobre la salud mental.

Métodos: Los datos serán derivados desde el estudio prospectivo MIRORR que comprende 96 individuos a diferentes riesgos de psicosis y contiene cuestionarios aplicados una sola vez y datos intensivos longitudinales colectados 90 días tras el punto de referencia (T0) y tres puntos de seguimiento anuales (T1–T3). La resiliencia general fue evaluada utilizando la Escala de Resiliencia Breve (BRS) al punto de referencia. La resiliencia diaria se mide promediando los puntajes de resiliencia diaria a lo largo de 90 días. Para la velocidad de recuperación, se aplicarán modelos vectoriales autorregresivos con simulaciones de respuestas de impulsos

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consecutivas a los datos diarios sobre afecto negativo y estresores diarios para calcular el patrón de recuperación afectiva. Estos indicadores se correlacionaran concurrentemente (en T0) para evaluar su superposición y prospectivamente (entre T0 y T1) para estimar su estabilidad. Su potencial predictivo se evaluara mediante un análisis de regresión con salud mental (SCL-90) como resultado, indicadores de resiliencia como predictores, y eventos vitales estresantes como moderador.

Conclusión: La comparación de diferentes conceptualizaciones de la resiliencia psicológica puede aumentar nuestra comprensión sobre su naturaleza multifacética y, en el futuro, ayudar a mejorar estrategias de diagnóstico, prevención e intervención enfocadas a aumentar la resiliencia psicológica.

对心理韧性的思考:预测心理健康的三种概念上不同操作化的比较

背景: 心理韧性是指在应激后保持心理健康或迅速恢复的能力。尽管韧性研究很受欢迎, 但对韧性的理解或操作化还未达成共识。

目的: 我们计划比较三个涉及构念不同操作化的心理韧性指标: a) 一般韧性或一个人自我报告克服逆境的一般能力; b) 日常韧性, 即暂时经历克服逆境的能力; c) 在日常生活中的小逆境后, 从负性情绪模式中恢复的明显恢复速度。这三个指标是为每个人构建的, 以考查其横断面关联, 随时间的稳定性以及对心理健康的预测有效性。

方法: 数据将来自前瞻性 MIRORR 研究, 包括 96 名不同精神病风险水平的个体, 包含单次评估问卷和基线 (T0)及3年追踪 (T1–T3) 的 90 天密集纵向数据。在基线时使用简要韧性量表 (BRS) 评估一般韧性。通过平均 90 天内每天的韧性分数来测量日常韧性。对于恢复速度, 具有连续脉冲响应模拟的向量自回归模型将应用于有关负性情绪和日常应激源的每日数据, 以计算情绪恢复模式。这些指标将被同时相关 (在 T0) 以评估其重叠, 并被前瞻性相关 (在 T0 和 T1 之间) 以估计它们的稳定性。其预测潜力将通过回归分析进行评估, 以心理健康 (SCL-90) 作为结果, 韧性指标作为预测指标, 应激现场事件作为调节因素。

结论: 对心理韧性不同概念的比较可以提高我们对其多方面性质的理解, 并有助于在未来改进旨在提高心理韧性的诊断, 预防和干预策略。

1. Introduction

Most people will be exposed to risk factors for mental illness during their life (Bonanno, Westphal, & Mancini, 2011; Coyne, 1991; Vanaelst et al., 2012). Risk factors for mental health problems include childhood adversity, negative life events, trauma, and acute as well as chronic stress (Furber, Leach, Guy, & Segal, 2017; Trompetter et al., 2016). Traditionally, mental health research has mainly focused on identifying these risk factors and investigating how these may influence psychopathological development. More recently, attention has been turning towards factors that may protect people against developing new or more severe symptoms and mental disorders. Stable mental health and quick recovery in the context of adversities are referred to as 'psychological resilience' (Bonanno, 2004; Davydov, Stewart, Ritchie, & Chaudieu, 2010; Schultze-Lutter, Schimmelmann, & Schmidt, 2016) .

A better understanding of what protects people from developing psychopathology can enrich preventive and therapeutic clinical interventions and may, eventually, reduce the prevalence and burden of psychopathology (Bos, Snippe, De Jonge, & Jeronimus, 2016; Davydov et al., 2010; Jeste, Palmer, Rettew, & Boardman, 2015; Lee Duckworth, Steen, & Seligman, 2005). The idea of resilience originated in the observation of its outcome (Luthar, Cicchetti, & Becker, 2000): in the case of psychological resilience, this refers to people staying healthy (or recovering quickly) in the face of adversities (Luthar et al., 2000). For example, such as the ability to cope well with the death of a spouse over time

(Bonanno, 2004). Despite the common use of the term resilience there is no consensus definition (Aburn, Gott, & Hoare, 2016; Windle, Bennett, & Noyes, 2011); some approaches view resilience as the process or ability of bouncing back, others see it as stable health despite adversity (Kalisch et al., 2017). Additionally, some authors view resilience as a more or less stable trait (Connor & Davidson, 2003; Maltby, Day, & Hall, 2015), while others argue that resilience depends on a context- and time-dependent combination of factors (Bonanno, 2004; Bonanno et al., 2011). In the present paper, we follow Davydov and colleagues (Davydov et al., 2010) by adopting an integrative and unitary view on resilience as our 'mental immunity' that emerges from interactions within a complex multifaceted biopsychosocial systems (Luthar et al., 2000). The implication of this complex dynamic system is that resilience can change from moment to moment and between contexts, yet there are individual differences that depend less on the timing and context.

Psychological resilience has close connections to and partly overlaps with the concept of self-regulation. The two concepts are not identical. Self-regulation refers to processes by which people initiate, maintain, and control their own thoughts, behaviours, or emotions, with the intention of producing a desired outcome or avoiding an undesired outcome (Strauman, 2017; Wang & Saudino, 2011) and thus has an explicitly volitional nature. Although self-regulation can been seen as a predictor of resilience (Artuch-Garde et al., 2017), resilience captures

a broader mental health phenomenon that may be influenced by other factors as well. Furthermore, whereas self-regulation is defined as a general ability/process, the concept of resilience is used exclusively within the context of adversity, stress, and mental health.

The complexity and versatility of the phenomenon of resilience resulted in various theoretical perspectives and operationalizations in the literature. In this paper, we focus on three of these. The first approach is to see resilience as a general ability to successfully recover or bounce back from adversity. This declarative aspect of resilience can be measured by self-reported statements such as 'It does not take me long to recover from a stressful event' (an example item from the Brief Resilience Scale (Smith et al., 2008)). These measures are designed to tap into how someone understands their ability to cope with adversity in general (see Table 1) as part of their self-concept. This summary statement of one's characteristic response when facing adversity is conceptually similar to concepts such as ego-resiliency (Klohnen, 1996; Prince-Embury, 2013) or dispositional optimism and self-efficacy, which are known to protect against psychopathology (Conversano et al., 2010; Jenaabadi, Ahani, & Sabaghi, 2015; Schrank Brownell, Tylee, & Slade, 2014).

A second approach is to understand resilience as the naturalistic process of one's daily ability to cope with adversities in daily life, operationalized in intensive longitudinal data collection with items such as 'today I could handle what came my way' (Barta, Tennen, & Litt, 2012; Jaeggi, Buschkuehl, Perrig, & Meier, 2010; Myin-Germeys et al., 2009; Shiffman, Stone, & Hufford, 2008). Such items assess one's moment-to-moment perceived ability to recover from actual stressful events. Although conceptually such items may also partly overlap with self-regulation processes in daily life that play an important role in protecting from psychopathology (Strauman, 2017), self-regulation would particularly include the volitional aspect of experiences. Repeated measures over weeks or months can be used to derive an individual summary description of daily resilience that may overlap with the one-time assessment of

general resilience and/or prove to be more reliable (see Table 1). This more naturalistic measure reduces the retrospective bias associated with the former declarative approach, which can be influenced by individual differences and current emotional states (Myin-Germeys et al., 2009). Additionally, the 'daily resilience' approach increases ecological validity because it tracks the daily state of resilience within individuals, which cannot be revealed by group-level data (Fisher, Medaglia, & Jeronimus, 2018; Shiffman et al., 2008).

A third operationalization of psychological resilience is the actual process of recovering from daily stressors, as opposed to the perception thereof that is captured in the 'daily resilience' operationalization. One way in which this recovery process is often operationalized is negative affect reactivity, which is usually defined as the contemporaneous association between stressors and negative affect (Cohen, Gunthert, Butler, O'Neill, & Tolpin, 2005). Many studies suggest that negative affect reactivity is often impaired in people with or at risk for psychopathological symptoms (Booij, Snippe, Jeronimus, Wichers, & Wigman, 2018; Cohen et al., 2005; Myin-Germeys et al., 2003; Myin-Germeys & Van Os, 2007; Vaessen et al., 2019; van Winkel et al., 2015). Building on these studies but taking a more inclusive approach to assess negative affect responses, we will investigate both the duration and amplitude of recovery of negative affect to baseline levels after daily stressors. Such operationalization of resilience as the recovery from stressors itself is closely tied to the dynamic systems framework (Scheffer et al., 2012; Veraart et al., 2012), in which a set of generic process indicators are thought to predict a complex system's liability to change (Dakos, Carpenter, van Nes, & Scheffer, 2015; Scheffer et al., 2009, 2018, 2012). Speed of recovery from minor perturbations is one of these general resilience indicators (Scheffer et al., 2018). Previous research from our group has shown that resilience, operationalized as the speed of negative affect recovery after daily life adversities based on time-series data, can predict trajectories of psychopathological symptoms (Kuranova et al., 2020).

Table 1. Comparison between three operationalizations of resilience in the current study.

Indicator	Definition	Hypothesized aspect of resilience phenomenon	Assessment
General resilience	Self-beliefs about general ability to successfully recover from adversity	Stable 'trait'-like aspects of resilience as a declarative set of self-schemata and beliefs about one's capacity to bounce back after adversity	Self-report questionnaire, assessed once each measurement wave
Daily resilience	Daily life experiences of ability to cope with adversity in everyday life	The moment-to-moment perceived ability to recover from actual stressful events.	90-days repeated assessments of self-perceived ability to deal with daily adversity
Recovery speed	Duration and amplitude of recovery of negative affect from daily unpleasant events	A direct measure of the process of overcoming small adversities in daily life	An application of the impulse response function to the vector-autoregressive model applied to 90-day repeated assessments of negative affect and daily adversity

The three operationalizations that we summarized in Table 1 may capture unique but complementary conceptualizations of psychological resilience and shared variance. Hitherto, no direct comparisons of these different operationalizations of resilience have been available, and it remains unclear whether, and to what extent, these conceptualizations overlap. Additionally, although being resilient leads to a better mental health outcome by definition (Jeste et al., 2015; Kalisch et al., 2017), we are unaware of a direct comparison of dynamic and general resilience indicators on their ability to predict mental health outcomes. When investigating this latter question, studying resilience requires the including the presence of psychological stressors because, by definition, resilience exists in the presence of adversity (Kalisch et al., 2017).

Given the high prevalence of mental disorders worldwide and the importance of resilience for good mental health (Jeste et al., 2015), it is of particular interest to study resilience in (sub)-clinical groups that have an increased risk for psychopathology. Even if they do not meet the criteria for clinical disorder, they are experiencing distress and may therefore benefit from resilience-enhancing interventions (Joyce et al., 2018; McGorry & Nelson, 2016). Moreover, individuals with sub-clinical psychotic symptoms provide a specifically good sample to study resilience, as many of these individuals stay in this subclinical phase long, and some may never make the transition to a psychotic episode, but still suffer from impaired functioning and reduced quality of life (Addington, Farris, Devoe, & Metzak, 2020; Gee & Cannon, 2011). These people who do not develop psychotic episode despite having symptoms may be considered relatively resilient, which is why we aim to assess the indicators of resilience in this population. However, it must be noted that, although the investigation of resilience is thus especially relevant in this population at increased risk for psychopathology in general and psychosis in particular, the specific nature of our sample should be kept in mind with regard to the generalizability of our findings.

The present paper is aimed to improve our understanding of psychological resilience by studying the three conceptualizations of psychological resilience in Table 1 in relationship to one another, prospectively, in the presence of adversity, and in a (sub)-clinical population. Specifically, we will investigate (i) how the above-mentioned three conceptualizations of resilience are associated with each other at the same time point; (ii) differences between the three measures in their stability over time and (iii) to what extent they buffer the effects of adversity on mental health outcome after one year (see Figure 1).

Although all three our operationalizations are aimed at assessing recovery from adversity, they all use different time frames over which resilience is assessed, as well as different conceptualizations of stressors. We argue that each indicator may tap into unique aspects of resilience, which may not be captured by the others. For example, despite needing a relatively long time to recover from negative affect, one may be overall satisfied with their way of handling things. Therefore, we refrain from formulating specific hypotheses for each comparison in all research questions. Our (limited) theoretical expectations are: With regard to research question one on the associations between the three indicators of resilience, we hypothesize that (i) General resilience will be associated stronger with Daily resilience than with Recovery speed and (ii) Recovery speed will be associated stronger with Daily resilience than with General resilience (see Table 2). This hypothesis was based on the notions that (i) content wise, the items assessing General resilience closely resemble the item assessing Daily resilience, and (ii) Daily resilience and Recovery speed are both based on dairy data (as opposed to General resilience). For research question two on stability of the resilience indicators, we expect General resilience to be more stable than Daily resilience and Recovery speed (see also Table 2). This expectation is based on the fact that commonly used general resilience questionnaires intend to measure more long-term tendencies in (perceived) ability to bounce back (using words such as 'usually', and 'tend to'), whereas Daily resilience and recovery speed indicators are by definition more changeable with time. For research question three on comparison how resilience indicators predict future mental health after adversity, we refrain from make any hypotheses as we feel there is too little empirical work to build solid expectations on.

2. Methods

2.1. Study design and sample

The data will be taken from the Mapping Individual Routes of Risk and Resilience (MIRORR) study (Booij et al., 2018). This observational study follows young adults with different levels of risk for psychosis for three years and thus consists of four assessment waves with follow-ups after one, two and three years after baseline. Questionnaires and interviews about mental health, factors of risk, protection and resilience were assessed at all waves. In addition, the first two waves contained a three-month period of intensive longitudinal data collection using daily diaries. These diary assessments consisted of 90 consecutive daily reports on psychopathological symptoms, emotions, functioning and stress. In the current work, questionnaire and diary data from the first two waves will be used to answer the first and second research question. To answer research question three, a repeated measures
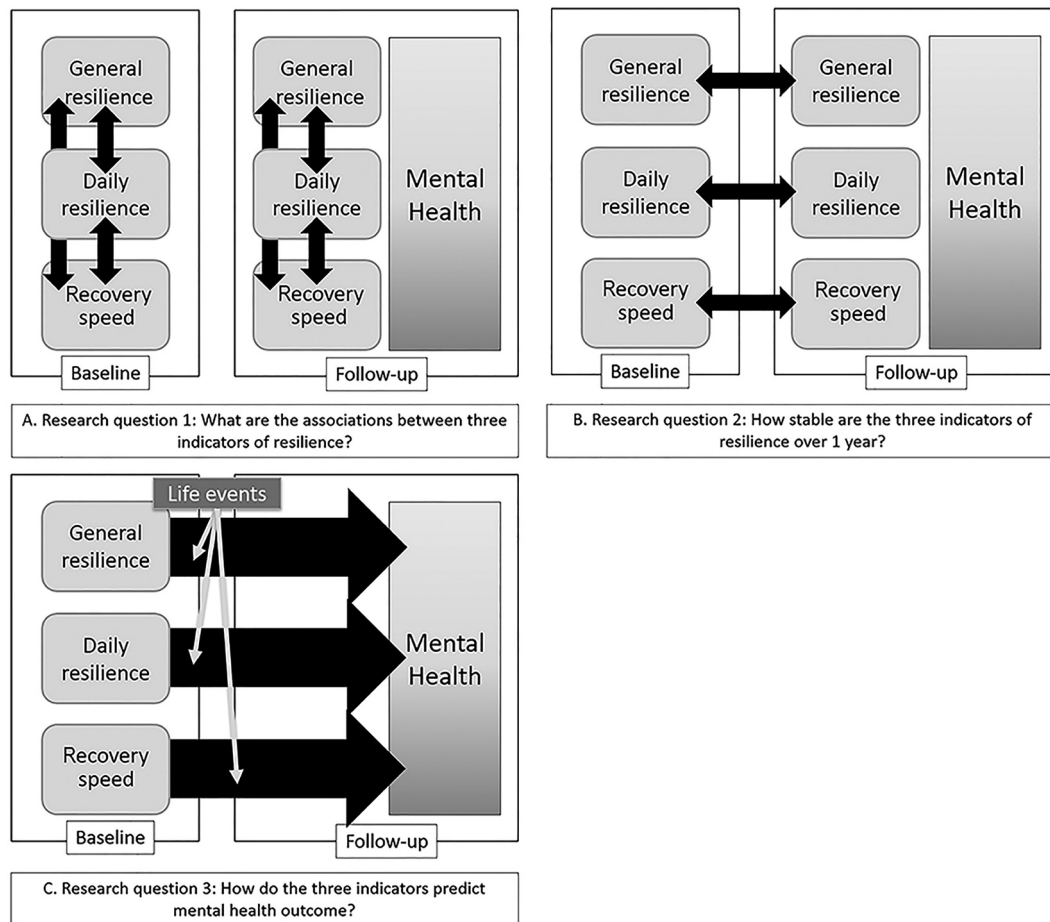
Figure 1. Schematic representation of research questions. In this figure, parts (a), (b), (c) depict research questions 1, 2, and 3 respectively. 'General resilience', 'Daily resilience' and 'Recovery speed' refer to the three operationalizations of resilience. 'Mental health' refers to mental health outcomes measured after one- and two-years follow-up (only one measurement wave is depicted for parsimony and readability), and 'Life events' refer to possible negative life events happening between the measurement waves. Arrows represent the various associations that will be investigated with each research question.

design will be used, including available diary data from the first two waves and questionnaire data from the first three waves.

Recruitment for the study started in September 2015. The study comprises four subgroups. Subgroup 1 comprised participants from the general population with a relatively high level of subclinical psychotic experiences, not seeking mental healthcare For this subgroup, we recruited 100 individuals from the general population who completed the Community Assessment of Psychic Experience (CAPE) questionnaire (Konings, Bak, Hanssen, Van Os, & Krabbendam, 2006). The 25 individuals with the highest scores were invited to participate in the main study. Subgroup 2–4 comprised people who were receiving mental healthcare a broad range of psychopathological problems. Allocation to subgroup 2, 3 or 4 was based on the level of psychotic experiences, which served as an indicator of risk for developing psychosis. Subgroup allocation was based on early detection practices in which all newly referred mental health care patients are screened for psychotic symptomatology, regardless of the type of symptoms they are referred for (Wigman et al., 2020). After screening by the Prodromal

Questionnaire (PQ)-16 (Ising et al., 2012), participants with a score of <6 (meaning mild, non-psychotic psychopathology) were allocated to subgroup 2. Individuals with a score of ≥6 points of PQ-16 were further screened by the Comprehensive Assessment of At Risk Mental State (CAARMS) (Yung et al., 2005), which assesses the presence of an ultra-high risk (UHR) for psychosis. Of these, individuals without UHR status for psychosis were assigned to group 3, and individuals with UHR status for psychosis were assigned to group 4. Thus, each subgroup represented a higher risk for developing psychosis (see the study protocol for detail (Booij et al., 2018). Please note that subgroup allocation will not be used in the current study and is presented here for reference.

All participants included in the current work were aged 18 or older and provided written informed consent for participation (for details see study protocol (Booij et al., 2018)). The study was conducted in accordance with the Declaration of Helsinki, and was approved by the medical ethical committee of the University Medical Center Groningen (NL52974.042.15). The study protocol trial registration number is NL6058 (www.trialregister.nl).

Table 2. Research questions, hypothesis, analysis plan and interpretation given to different outcomes.

Question	Hypothesis (if any)	Analysis Plan	Interpretation given to different outcomes
(1) What are the associations between three indicators of resilience?	General resilience will be associated more strongly with Daily resilience than with Recovery speed. Recovery speed will be associated more strongly with Daily resilience than with General resilience.	To estimate cross-correlations between the three resilience indicators at each assessment wave. To compare differences in estimated correlations	The correlation coefficients and differences between them will be interpreted as to what extent three indicators measure the same aspect of resilience, also in comparison to each other.
(1) How stable are the three indicators of resilience over 1 year?	General resilience will be more stable over the course of one year compared to Daily resilience and Recovery speed.	To estimate correlation between baseline and follow-up assessments of each indicator. To compare differences in estimated correlations	The correlation coefficients and differences between them will indicate how stable resilience indicators are, also in comparison to each other.
(1) How do the three indicators predict mental health outcome in the presence of adversity?	No expectations.	To specify a series of multilevel linear regression models with and without interaction effects of resilience indicators with adversity. To compare differences in regression coefficients.	The regression coefficient and the differences between them will indicate to what extent a change in the level of resilience indicator is associated with the change in the mental health on the next measurement wave, also in comparison to each other.

2.2. Sample characteristics

For the first follow-up one year later, data from 89 people, of whom 68 have also completed diary data, are available and for second follow-up years later questionnaire data from at least 78 participants are available (number available at 23 December 2020, the data for the second follow-up will be fully collected at May 2021). At baseline, participants were on average 24.7 (SD 4.2) years old, mostly female (76%) and had mostly completed upper secondary education (54.2%). Baseline level of severity of psychopathological symptoms, as measured with the Symptom Check List-90 (SCL-90) questionnaire (Derogatis & Unger, 2010) (see *Instruments*), was on average 186.7 (SD 59.4) which roughly corresponds to 'high' and 'very high' categories for the general population based on Arrindell et al. (2003). The average number of past negative events (in the year prior to baseline assessment) recorded with the Brugha List of Threatening Experiences (Bebbington & Hurry, 1985) (see *Instruments*) was 1.5 (SD 2.0)

2.3. Instruments

2.3.1. Daily diary procedure

The time-series data were collected with 90 daily questionnaires administered every evening on a smartphone. These diary items covered a broad range of feelings and experiences and comprised both retrospective ('Over the past day, I felt . . . ') and momentary items ('At this moment, I feel . . . '). In the current study, only retrospective items will be used, as the resilience indicators will be constructed based on the information about the whole past day. The specific diary items used for the resilience indicators are described below.

2.3.1.1. Mental health. The severity of psychopathological symptoms was assessed with the Symptom Check List-90 (SCL-90) questionnaire (Derogatis & Unger, 2010). The SLC-90 comprises 90 items assessing severity of psychopathological symptoms in the past 7 days with a 5-point Likert scale ranging from 1 ('Not at All') to 5 ('Extremely'). We will use a sum score of all 90 items, as previous research suggests that all items load with high reliability on one underlying latent construct of psychological distress. Lower sum scores are indicative of better mental health.

2.3.1.2. Adverse life events. The number of adverse life events in the past year was recorded with the Brugha List of Threatening Experiences (Bebbington & Hurry, 1985) (LTE). The LTE comprises of 12 major categories of stressful life events measured as 'yes/no' questions that were selected because of their established long-term consequences (see Table 3 for the

Table 3. Twelve major categories of stressful life events from Brugha List of threatening experiences (Bebbington & Hurry, 1985).

Serious illness or injury to subject
Serious illness or injury to a close relative
Death of first-degree relative including child or spouse
Death of close family friend or second-degree relative
Separation due to marital difficulties
Broke off a steady relationship
Serious problem with a close friend, neighbour or relative
Unemployed/seeking work for more than one month
Subject sacked from job
Major financial crisis
Problems with police and court appearance
Something valuable lost or stolen

list). For the current study, the number of negative events that happened between the measurement waves will be added as the index of adversity for research question three on how the three indicators predict mental health outcomes in the presence of adversity.

2.4. Resilience indicators

For this study, three different resilience indicators will be estimated, both at baseline and at the one-year follow-up assessment;

(1) **General Resilience**: For this indicator, the mean score of the Brief Resilience Scale (BRS; (Smith et al., 2008) will be used. The BRS consists of six items scored on a 5-point Likert scale (1 = 'strongly disagree', 5 = 'strongly agree').

(2) **Daily Resilience**: for this indicator, the individual mean level of the daily resilience item over 90 days is calculated ('Today I could handle what came my way', scores ranging from 0 ('Not at all') to 100 ('Very much')).

(3) **Recovery Speed**: Recovery speed will be calculated as the duration and amplitude of the pattern of negative affect recovery to its mean level after experiencing a negatively appraised event (see below for a detailed description), using the 90 diary assessments.

2.5. Analysis plan

Prior to answering the research questions, the dynamic indicator of resilience needs to be constructed. To do this, we will use measures of (i) daily negative affect and (ii) negatively appraised events.

The negative affect variable will be constructed as the mean score per day of the following six negative items from the circumplex model of affect, including unpleasant quadrants with low and high activation level (Yik, Russell, & Steiger, 2011): 'I felt apathetic today', 'I felt tired today', 'I felt down today', 'I felt anxious today', 'I felt restless today', 'I felt irritable today'. Scores range between 0 ('Not at all') and 100 ('Very much').

The negatively appraised events variable will be represented by the item asking about the most unpleasant daily event. This is assessed with the questions 'think about the most important negative event of today' followed by 'how unpleasant was this event?' The level of unpleasantness is measured from 0 ('Very unpleasant') to 100 ('Neutral').

2.6. Vector autoregressive (VAR) analyses

For each individual, a model of the association between the unpleasantness of negative events and the level of negative affect at consecutive time points will be estimated, using vector autoregressive (VAR) analyses (Zivot & Wang, 2006). After that, the results of this VAR model will serve as input for an impulse response function (IRF) analysis (Lütkepohl, 2010), which will be used to estimate negative affect recovery after an unpleasant event. The area under the response curve of the IRF will be calculated, and this area under the curve (AUC) score will be used as a dynamic resilience indicator, with a higher AUC representing longer time and higher amplitude of recovery and thus lower resilience. We now explain this procedure in more detail.

First, the lagged associations between the unpleasantness of negative events and negative affect score will be estimated using vector-autoregressive modelling. The VAR model will consist of a set of multivariate regression equations of the system of two variables, where each variable is regressed on the time-lagged values of itself and the other variable. That is, levels of negative affect at time t will be predicted by negative affect scores at measurement occasion t_{-1}; t_{-2}; ... t_{-p} and by the unpleasantness of the negative event at measurement occasion t_{-1}; t_{-2}; ... t_{-p}. The time lag between t-1 and t is one day in this study, between t-2 and t two days, and so on.

This model will be fitted for each individual separately. All analyses will be performed in the latest available version of R, using the 'vars' package for the VAR modelling (Pfaff & Stigler, 2015). As 'vars' does not allow for missing data in time series, we will impute potential-missing data with the optimal approach for the current dataset, which will be decided

by comparing six imputation strategies: two multiple-imputation strategies (MICE; (van Buuren & Oudshoorn, 2007) and Amelia (Honaker, King, & Blackwell, 1998)) and four single imputation strategies (mean imputation, Kalman smoothing (Welch & Bishop, 2001), Exponential moving average, Linear moving average (Pratama, Permanasari, Ardiyanto, & Indrayani, 2017)). The number of estimated lags will depend on the AIC criterion for each individual, with a maximum of three. Three lags were chosen as we deem it unlikely that unpleasant daily events four days ago explain current negative affect above and beyond negative affect and other unpleasant events over the past three days. However, if the AIC criterion will favour more than three lags for more than 20% of the individuals under study, we will increase the maximum number of lags for all individuals. All models will be tested for three assumptions. The stationarity assumption means that the mean, variance and auto-correlation structure of the residuals do not change over time. The homoscedasticity assumption states that residuals are similar across different values of independent variables. The white noise assumption holds that residuals are not correlated. When these assumptions are violated, an exogenous variable (e.g. time trend or day of the week) and/or dummy variable indicating outliers at more than two standard deviations (SDs) from the mean will be added. In case none of the above-mentioned or alternative solutions will solve the unmet assumption, the individual will be omitted from the analysis.

2.7. The impulse-response function and AUC

Impulse response function (IRF) analysis (Lütkepohl, 2010) allows us to model how a system reacts to a shock. One variable is given an instantaneous impulse, and we then examine how this shock propagates through the system and impacts on the other variables over time. In relation to our research questions, IRF is ideally suited to simulate the pattern of affect recovery after negative events, because this function allows us to simulate a shock of one SD of level of unpleasantness of the events, as well as modelling the pattern of recovery of negative affect over several lags.

Since we are interested in effects of an increase in negative (unpleasant) events on negative affect, both on the same day as well as on the next days, the orthogonalized impulse response function (OIRF) will be used (Lütkepohl, 2005). A limitation of the OIRF is its sensitivity to the order of the same day (lag 0) variables in the VAR model; therefore, it is not possible to disentangle the directionality of the lag 0 effects. In this study, we choose the following order; negative event at lag 0 leading to lag 0 negative affect. This consideration will be covered in more detail in the limitations paragraph of the Discussion section.

After the IRF will be modelled, the area under the function curve with respect to baseline (AUCb) will be calculated with the formula proposed by Pruessner and colleagues (Pruessner, Kirschbaum, Meinlschmid, & Hellhammer, 2003). The resulted AUCb will be used as dynamic resilience indicator for this individual.

Research question 1: What are the associations between three indicators of resilience?

Cross-correlations between the three resilience indicators will be estimated at each assessment wave (i.e. between General and Daily resilience, General resilience and Recovery speed, and between Daily resilience and Recovery speed). Before the analysis, we will check the linearity of the indicators' distribution and presence of outliers. In the case these statistical assumptions are met, Pearson correlation coefficients will be calculated. If these assumptions are not met, Spearman rank correlation coefficients will be calculated instead, as this measure is more robust against non-linearity and outliers. Next, correlation coefficients will be transformed using Fisher's Z-transformation and the differences between them compared based on procedure by Meng and colleagues (Meng, Rosenthal, & Rubin, 1992).

Research question 2: How stable are the three indicators of resilience over 1 year?

The correlations between the two assessments of each indicator will be estimated (e.g. between General indicator at baseline and General indicator at follow-up). Before the analysis, the assumptions will be checked and corrected, and correlations compared similar to the analysis for Research question 1.

Research question 3: How do the three indicators predict mental health outcome in the presence of adversity?

To estimate how well the resilience measures at one assessment wave predict mental health outcomes one year later (in the presence of adversity), a series of multilevel linear regressions will be specified. To assess the predictive value of the resilience indicators in the presence of adversity, interaction effects of resilience indicators with adversity will be assessed, because resilience indicators should protect against mental health deterioration, particularly in the context of adversity. Adversity will be assessed by the number of negative events between the measurement waves, with people reporting zero events also included in the analysis. However, as the data will come from (sub)-clinical sample, thus participants already being in the context of adversity, we are going to interpret both main effects of resilience indicators and interaction

effect with adversity, adding therefore interaction effects as second step to the model. For each resilience indicator separately, a multilevel model will be fitted with the SCL-90 sum score as the outcome variable, and the following variables as predictors: i) a lagged (i.e. measured at the previous time point) resilience indicator score, ii) the number of negative events that happened between the assessment waves, iii) the interaction between lagged resilience score and the number of negative events between assessment waves, iv) the lagged SCL-90 score. Because the data describe the same people at two assessment points, random intercepts (for individuals) will be added to account for the shared variance (Pinheiro & Bates, 2000).

To compare how the three resilience indicators predict future mental health outcome in the presence of adversity, the differences between the resilience indicators, both in their main effects and their interactions with the two adversity indices, will be assessed by comparing the Beta coefficients from the models using a Z-score test. The assumptions of the linear mixed models (linearity, homogeneity of variance and normality of residuals) will be tested, and in case of their violations, data transformation will be performed.

2.8. Multiple comparison correction

The comparison between resilience indicators will be conducted on the between-person level. We will assess three related but separate research questions. Because of the differences in the analytical methods, predictors, and outcomes, the research questions 1 and 2 will be considered as one family of tests, and research question 3 as another. Because of the study's exploratory nature, within each family of tests, False Discovery Rate correction following the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995) will be applied with an alpha level set at 0.05.

2.9. Power analysis

Data for the current paper have already been collected, and it is not possible to increase the sample further. Thus, we estimated the power that can be achieved with the given sample size and proposed analyses. Although, we plan to use the False Discovery Rate correction following the Benjamini–Hochberg procedure (Benjamini & Hochberg, 1995), for the following power analysis the alpha-level for the tests within the family of tests were calculated based on Bonferroni correction principle, as it is not possible to apply the Benjamini–Hochberg procedure before the results are known. Consequently, the power analysis is more conservative than necessary. All power analyses were conducted with the 'pwr' (Champely et al., 2018) package.

The power analysis for the Recovery Speed index is based on the power of the VAR models. Because the purpose of VAR models in the current work is to create a personalized dynamic resilience measure, the generalizability of the associations between the unpleasantness of events and negative affect beyond the period of dairy data collection (as represented by the *p*-values for the B-coefficients) is irrelevant for our research questions. Moreover, exact power estimation for individual VAR models is not straightforward, as it is not possible to estimate the expected effect size, direction of causality, and exact number of lagged influences and presence of bidirectional and feedback effect. Based on previous work, 60 to 90 measurements are recommended to identify reciprocal associations between multiple variables (Bos, Hoenders, & De Jonge, 2012; Lütkepohl, 2005; Rosmalen, Wenting, Roest, de Jonge, & Bos, 2012; Van Gils et al., 2014).

For research questions 1 and 2 on the cross-sectional and temporal associations between resilience indicators, we will use correlation analyses. The effect sizes are expected to range from moderate to large given that the resilience indicators are expected to reflect different parts of the same theoretical construct. Therefore, the expected effect size of the correlation analysis is set at 0.40, based on the conventional effect magnitude by Cohen (Cohen, 1988). For these research questions, there will be nine comparisons in total, and therefore the overall alpha for the family of tests will be 0.05/9 that is about 0.0056. Additionally, the sample size differs between baseline (95) and first follow-up wave due to the second diary study being optional and drop-out from the study (on first follow-up 89 filled in questionnaire data from whom 68 also filled in diary data). Taking this information into account, the power for the correlation analyses between different predictors at baseline is estimated at 0.90 and 0.75 on follow-up, and between same predictors over time as 0.88 for the General resilience predictor and 0.75 for Daily resilience and Recovery speed predictors (see Appendix A for the R-script).

For research question 3 on the predictive value of the three resilience indicators for mental health one year later, multilevel regression analysis will be used. For reasons of parsimony, we performed a power analysis separately for the unilevel model for individuals at first follow-up and the unilevel model for people at both first and second follow-ups (ignoring the fact that the same people were assessed twice), because the power for the actual multilevel model will lie between these two calculations.

Overall, there will be three comparisons using alpha 0.016 (0.05/3). In these models, based on the F-test for linear regression, the degrees of freedom are represented as u, the numerator degrees of freedom, that is, the number of coefficients in the model, and v, the denominator degrees of

freedom, so that n (sample size) = v + u + 1. Therefore, in these models, u will be four (resilience predictor, the baseline levels of mental symptoms, the number of adverse life (LTE) events between assessments, and the interaction between the LTE and resilience predictor) and the v for first follow-up will be 84 (89-4-1) for the General indicator and 63 (68-4-1) for Daily resilience and Recovery speed, and 162 for both follow-ups (89 + 78-4-1) for General indicator and 120 (68 + 57-4-1) for Daily resilience and Recovery speed. We do not have theoretical expectations about the effect size (f^2), and therefore we have built power curves for both models (see Figure 2):

In sum, for the General resilience indicator, effect sizes between ~0.07 and ~0.14 (small effects) and higher can be detected with power ≥60%; and for Daily resilience and Recovery speed only effect sizes between ~0.1 and ~0.18 (medium effects) and higher can be detected, which is a major limitation, and therefore the results for this research question will be considered as preliminary evidence.

2.10. Methodological issues

Our proposed study has methodological issues that will affect how our results can be compared to other studies of psychological resilience. The first issue relates to the sampling strategy and generalizability. The majority of our study population has psychopathological symptoms, which can be considered as stressors, also at baseline, before the adversity, which is not always the case for the general population. Nevertheless, even in the general population, a substantial proportion of the people will have mild psychopathological symptoms (even though not diagnosed or in clinical care), so although the results are not fully generalizable to general population, they are also not restricted only to people who undergo medical treatment. The next methodological issue relates to the proposed way of assessing adversity, namely the number of negative life events as assessed with the Brugha List of Threatening Experiences (Bebbington & Hurry, 1985). One drawback of this assessment is that it does not take into account the severity of the experienced stress. Additionally, we could not assess
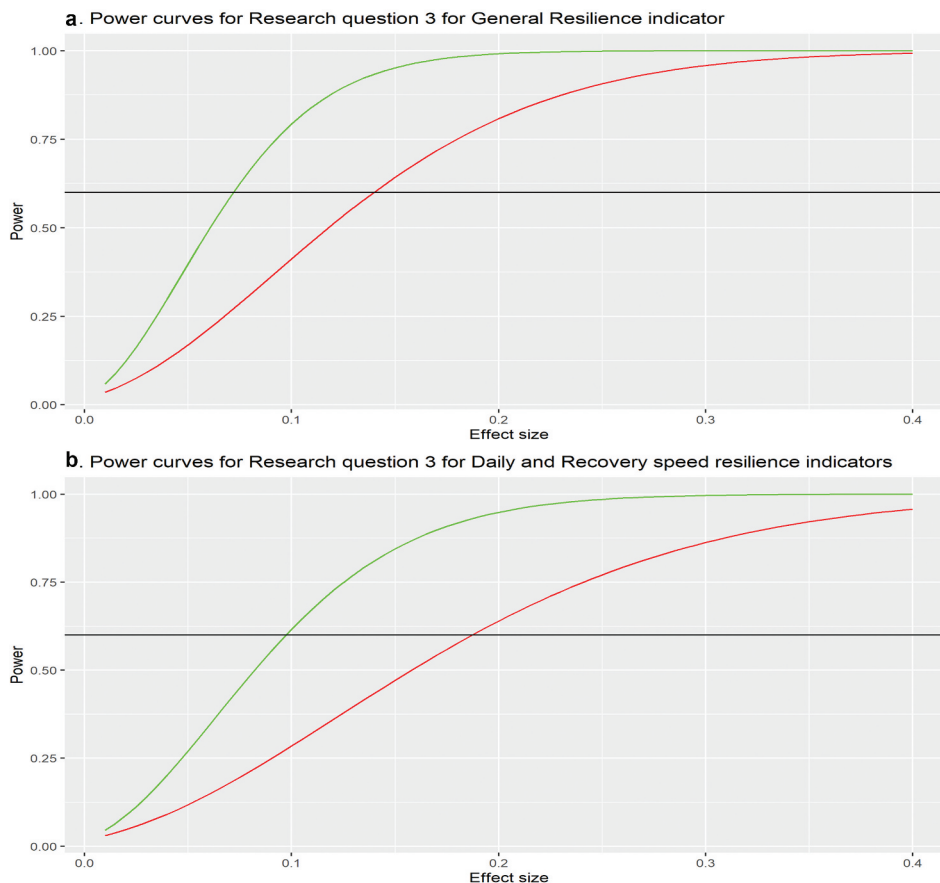

Figure 2. Power curves for General resilience indicator (a) and Daily and Recovery speed resilience indicators (b). In these figures, the x-axis describes the level of power for the test and the y-axis the effect size. The upper green line depicts the power curve for unilevel model for data from both follow-ups, whereas the lower red line depicts the power curve for unilevel models for the data from the first follow-up only. The black vertical line corresponds to 60% power.

the exact moment the adversity happened between two assessment waves, and therefore participants could be at different stages of recovery. However, given the time scale (1 year) between the assessment waves, and the fact that all items included in Brugha List of Threatening Experiences have been established as having long-term consequences for mental health (Bebbington & Hurry, 1985; Hobson et al., 1998), we believe that this way of assessing adversity can provide useful information. Finally, the power analysis shows that the proposed analysis for specifically the third research question does not have sufficient power to detect small effect sizes. This lack of power will lead to an increased chance of false-positive findings, and therefore, all results for this research question should be considered preliminary, although potentially suggesting interesting directions for the future research.

Acknowledgments

Authors' contributions

All authors were involved in the formulation of the research hypotheses, questions and analytical approaches. JW and SB participated in data collection, study design, and data management. JW, SB, BJ, and AK managed literature searches and power analyses and wrote the first version of the manuscript. AK, JW, SB, BJ, and AO participated in editing and finalizing the manuscript. All authors have contributed to and have approved the final manuscript.

Code availability

All code files are publically available at Open Science Framework with DOI 10.17605/OSF.IO/CQV7Y

Data availability statement

As there is a possibility to identify participants based on their clinical and intensive longitudinal diary data, the datasets generated and/or analyzed during the current study cannot be made publicly available based on European law.

Disclosure statement

Ethics approval and consent to participate

All participants included in the current work were aged 18 or older and provided written informed consent for participation (for details see study protocol (Booij et al., 2018)). The study was conducted in accordance with the Declaration of Helsinki, and was approved by the medical ethical committee of the University Medical Center Groningen (NL52974.042.15). The study protocol trial registration number is NL6058 (www.trialregister.nl).

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