Comparing measures of resilience based on cross-sectional and intensive longitudinal data

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Abstract

While resilience research has boomed, resilience has been conceptualized and operationalized in multiple ways. The aim of the present study is to compare a traditional measure of resilience, the Brief Resilient Coping Scale, with within-person process indicators from an experience sampling measures study (ESM). Method: In spring 2021, a sample of 186 teachers in southern Finland completed a startup session followed by an 8-day ESM period, with momentary reports on stressful events (workload, social interactions), and positive and negative affect completed twice a day. As expected, within-person variation in affect was predicted by stressful events. However, contrary to expectations, stress reactivity was not predicted by BRCS. The results are discussed in terms of resilience measurement, and in connection with Kahnemans theories on experiencing and remembering self.

150 words

Keywords: resilience, stress reactivity, experience sampling measures,

INTRODUCTION

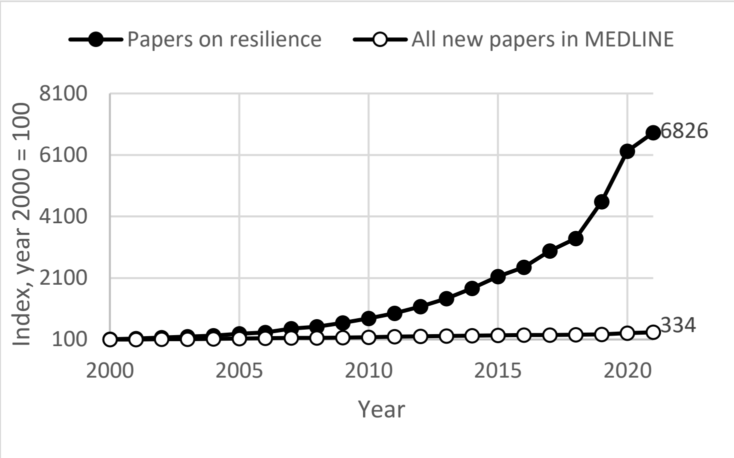
Resilience is a concept that has been defined and measured in numerous ways. According to Luthar et al. (Luthar et al., 2000), resilience refers to “a dynamic process encompassing positive adaptation within the context of significant adversity.” Two essential aspects of this definition are: 1) exposure to significant threat or adversity, and 2) positive adjustment despite major assaults on the developmental process (Luthar et al 2000). Historically, resilience has been studied from a developmental perspective, focusing on how severe adversities such as growing up in an abusive household affects different developmental trajectories, and how these trajectories are affected by risk and protective factors on an individual, community, and societal level. On the individual level, several instruments have been developed to measure individual differences in resilience, such as the Brief Resilient Coping Scale (Sinclair & Wallston, 2004). This retrospective self-report questionnaire asks the respondent to rate their tendency to cope with stressful situations in an adaptive and flexible way.

Recently, a growing number of scientists have directed interest toward resilience in relation to daily stressors rather than severe events that might affect development (Ong & Leger, 2022). The authors argue that since resilience refers to a dynamic system’s ability to adapt to stressful situations, measures of resilience should analyze the resilient process as it unfolds over time. Advances in technical and statistical methods allow for collection of intensive longitudinal data using for example smartphone applications, and analyses of the data using dynamic structural equation modelling (Hamaker et al., 2018; Hamaker & Wichers, 2017). The methods build on daily collected time series data on how stressful the respondent’s day has been and their affective state. Resilience is measured indirectly by analyzing how strongly stressful events alter affective state. In highly resilient respondents, it is expected that the affective state is stable, even in the face of stressful events. Conversely, respondents with lower resilience will display higher stress reactivity. A second aspect of resilience is the ability to rebound after stressful events. In respondents with low resilience, experiencing stressful events one day is expected to lead to increased negative affect not only the same day, but also the subsequent day. Proponents of these methods argue that they offer increased ecological validity, since questions are answered in the respondent’s natural environment, reduced recall bias, since respondents give their answers in real time, and reduced social desirability bias, since resilience is measured indirectly rather than as a direct self-evaluation.

As can be seen, the conceptualization and measurement of resilience can differ in significant ways with regards to e.g., adversity severity, focus on long-term development or in-the-moment reactivity, seeing resilience more as a personality trait or a dynamic reactivity at a certain point in time, and relying on retrospective cognitively reflected self-image or empirical data in the moment. Given that research on psychological resilience has proliferated during the last two decades (see Figure 1) (Su et al., 2023), it is imperative for the field to compare and contrast different operationalizations of the concept of resilience. For the current study, the main research question is as follows: how well are individual differences in reactivity to daily stressors captured by cross-sectional measures of resilience?

Figure 1

Relative increase in Number of Papers on Resilience and Total Number of Papers Indexed in MEDLINE yearly, during 2000-2021



Note. Data source for resilience trend: MEDLINE search, data source for all new papers: Alexandru Dan Corlan. Medline trend: automated yearly statistics of PubMed results for any query, 2004. Web resource at URL:http://dan.corlan.net/medline-trend.html. Accessed: 2023-03-08.

Aim and hypothesis

The aim of the current study was to directly compare two measures of resilience within a single sample, the first measure being a cross-sectional questionnaire, and the second a measure of within-person processes using dynamic structural equation modelling based on intensive longitudinal data. We hypothesized that the cross-sectional measure would explain a substantial part of variability in reactivity to stress.

METHODS

Sample and participants

In spring 2021, primary, middle, and secondary school teachers from 13 schools in three municipalities in southern Finland took part in a startup session followed by an 8-day momentary assessment period. Twenty-one cases that had less than two observations of daily stressors were removed due to requirements of the statistical procedures. In total, 186 teachers (79% women, 19% men, 1% other or missing; mean age 42 (range 23-66); 62% at primary school, 18% at middle school, and 30% at secondary school) completed a background survey and provided at least two momentary assessments. With an average compliance rate of 69% for momentary assessment sessions, and a total of 1710 measurement points.

Measures

For data collection, we used the app RealLifeExp by LifeData (https://www.lifedatacorp.com/). The app operates on both Android and iOS. Study participants first download the app, and then within the app uses a study-specific password to download a so called Lifepak. Once downloaded, users are informed in-app about study pupose and data management, and required to provide consent before moving on to the startup session. Once the startup session is completed, the Lifepak operates locally and sends notification-initiated sessions even without an ongoing online connection. The app provides opportunities for both registered and anonymous data collection. While registered participation would be convenient for a burst-wave design, our current study only aimed for one wave of data collection and thus prioritized an anonymous approach where participants were not required to create any user login. In line with this, the GPS feature of the app was disabled centrally upon creation of the Lifepak so that the project did not collect geographical data about participants.

To assess resilience in terms of a stable trait, the startup survey included the Brief Resilience Coping Scale (BRCS) by Sinclair and Wallston (2004). The scale consists of four items designed to capture tendencies to cope with stress in adaptive manners, such as "I look for creative ways to alter difficult situations", and participants were asked to reply to the statements on a 5-pont Likert scale (1=no, not at all, 5 = yes, absolutely)

To assess momentary negative affect (NA), the study used two items informed by the PANAS framework (see Watson, Clark, & Tellegen, 1988). Participants were asked twice a day to assess to what extent they felt stressed, and tired, on a 5-point Likert scale. The items were added together to form a sum score for analyses. Similarly, to assess positive affect (PA), participants were asked twice a day to report to what extent they currently felt that their work was enjoyable, meaningful, and manageable, and to what extent they felt appreciated. The four items were combined in a latent factor for analyses.

To assess stressors at work, a 6-point sum score was created based on four dichotomous items on workload, e.g. "In the last few hours, there have been unexpected tasks" or "In the last few hours, I've had time for breaks and recreation" (reversed), and two dichotomous items on social stress ("In the last few hours, I've been treated badly" / "In the last few hours, I've seen someone else being treated badly").

In addition to subject-level variables from the startup session and momentary assessment response variables, the data set also included automatically generated design-related variables (subject ID and GDPR consent) and time-related variables such as day number, session number within days, response lapse (time from session notification to response initiation) and response time (time from session initiation to completion).

Procedure

The study was conducted in collaboration between the Faculty of Education and Welfare Studies at Åbo Akademi University, the Swedish Teachers Union in Finland, and the municipalities Helsinki, Turku and Raasepori. The study was conducted in accordance with the guidelines of the Finnish National Board on Research Integrity (TENK, 2019). Prior to data collection, the project was discussed with heads of education and school principals at 13 Swedish speaking schools, who in turn decided on which weeks to conduct the ESM-study and helped to organize online startup sessions during staff meetings at participating schools. Teachers were informed about the purpose and design of the study in brief by email and more fully at staff meetings, including assessment scheduling, time window, and that assessments would continue regardless of whether the previous assessment was completed or not. Following a Q&A, those that opted to participate downloaded the RealLifeExp app, provided in-app consent for data collection in accordance with GDRP standards, and completed a 10-15-minute startup survey.

Within a week of the startup session the momentary assessment period began. To keep the participant burden low and the ecological validity high, data collection was scheduled for 8 working days (i.e., from Wednesday to the following Friday, with the weekend free). The study used a time-contingent sampling scheme with four assessment sessions each day: once in the morning (at 7:15), twice during school hours (at 10:15 and 13:00), and once in the evening (at 17:00). Workload, social interaction and affect items were identical over school hour sessions, with other questions (not explored in this study) at the morning and evening sessions. Each session was initiated by a push notification from RealLifeExp, with a response window of 90 minutes to ensure that teachers would have at least one break between classes during which they would be able to respond.

As noted by Esiele et al. (2020), participants tend to perceive longer sessions to be more burdensome than the number of sessions, and research should therefore ensure that individual sessions are kept short. Median response lapse from notification to initiated reply in our study was 18 minutes, and median response time for sessions was 49 seconds. To further balance the involvement required, each participant received monetary compensation in the form of a gift card of 20€. Participants could also opt to take part in a post-study interview on their user experiences, and 15 teachers chose to do so. In these interviews, the participants highlighted how the momentary assessments were comparatively easy and felt more meaningful to respond to than traditional surveys, but also noted that despite the typical response time being less than a minute, they sometimes did not have time for the assessments during busy school days (for more details on the interviews see blogs2.abo.fi/reboot).

After the data collection was completed, all data were downloaded, pseudonymized and stored in password-locked servers at ÅÅU, with an offline external backup securely stored at the PIs office.

Statistical analyses

In preparation for the analysis, startup and momentary assessment data was combined, and ordered in long format, so that each row of data corresponded to a particular assessment moment for a given subject yet also contain all variables from the startup session. Design- and time-related variables were screened for missing data (none was found), and based on day and session variables, a time variable was computed so that each day was divided into eight 3-hour blocks (for a total of 80 blocks), and each session attached to a specific block.

To check whether the data required a multilevel approach, intraclass correlation coefficients (ICC) were calculated for dependent and independent variables by dividing between-person variance by the overall variance of each variable (between- plus within-person variance). Furthermore, individual panel plots were created in SPSS by means of syntax provided by Laurencau and Bolger (2021) and visually inspected to ensure that there were no out-of-range values or other data anomalies.

The main analyses were conducted within the dynamic structural equation modelling framework (Hamaker et al., 2018). Model parameters were estimated by Bayesian estimators to allow for estimation of random slopes and to limit model convergence issues. At this stage we have relied on non-informative priors, 10 00 iterations.

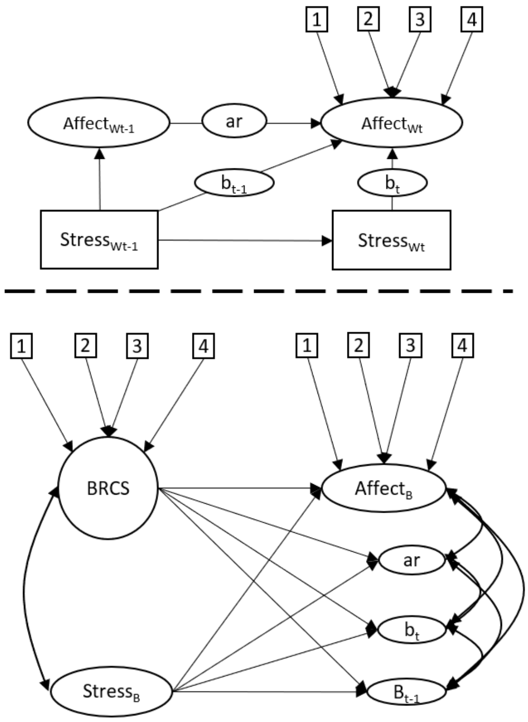


Figure 2 depicts a dynamic structural equation model that can be used to analyze how much of variance in stress reactivity is explained by the BRCS questionnaire. Above the dashed line is the within level of the model. Square boxes represent items from daily diaries, where the subscript *t* denotes time, and *t-1* denotes the previous time point. Arrows represent regressions and factor loadings. Affect is measured by four indicators, and is regressed on affective state at the previous time point, and stressful events the same time point. By combining data over time from all measurement points, the strength of the connection between experiences of stressful events and negative affect the same and the subsequent day can be estimated. Circles on the regression arrows indicate that it is a random parameter (i.e., parameters are allowed to vary in strength for different respondents).

On the between level, Negative affect^B represents the means of negative affect across time. Regressing this variable on organizational factors is interpreted in the same way as ordinary between-person analyses (e.g. based on cross-sectional data). A strength of dynamic structural equation modelling is that it allows intricate cross-level interactions. The circles on the between level represent the distribution of parameter estimates of the individuals. For example, regressing the latent variable β_t on a measure of some communication variable, tells us how the different ways of communicating in the organization is associated with the stress reactivity (i.e., resilience) of the people in the organization.

RESULTS

Confirmatory factor analysis of the BRCS measure

To evaluate the statistical properties of the BRCS measure, we analyzed it using confirmatory factor analysis. The model had acceptable fit: $X^2(2) = 3.6$, $p = .165$, n = 175-177; Root Mean Square Error of Approximation (RMSEA) = 0.018; Comparative Fit Index (CFI) = .973; Standardized Root Mean Square Residual (SRMR) = .030.

Table 1.

Confirmatory factor analysis of the Brief Resilient Coping Scale

Item	Loading	S.E.	Est./S.E.	*p*
1[a]	1.000	0.000	-	-
2	1.203	0.361	3.338	0.001
3	1.107	0.335	3.306	0.001
4	0.911	0.213	4.283	<.001

Note. [a]first item fixed for scaling.

Momentary assessment data

The ICCs for stress (.29), negative affect (.51) and positive affect (.43), all showed that a noticeably part of each variable varied within persons and thus suggested a multilevel framework.

Main analyses

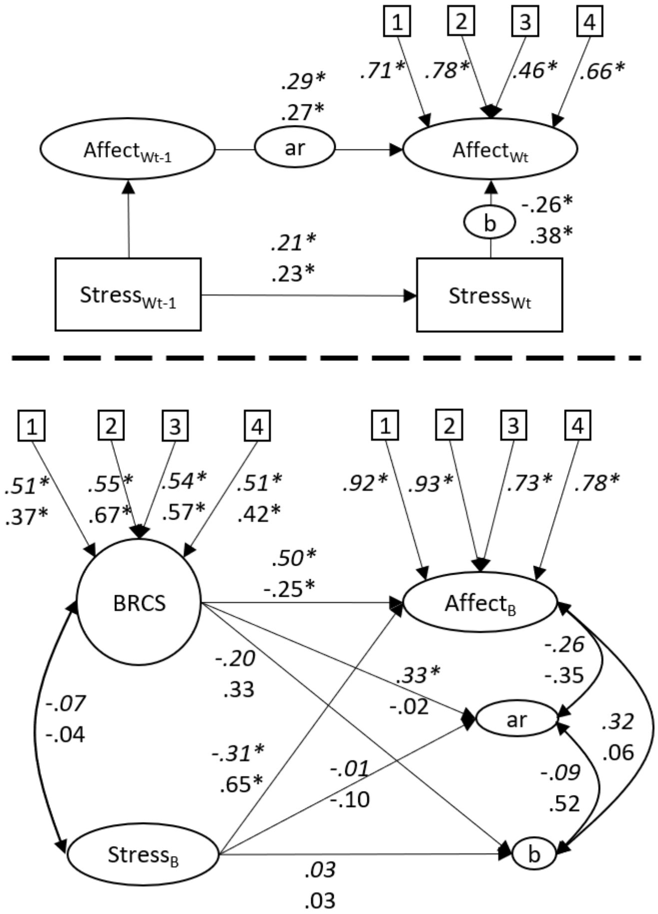
When including the parameter b_{t-1} between affect at timepoint *t* and stress at time *t-1,* the models either did not converge, or displayed unstable trace plots. Additionally, PSR values were not reliably low, but fluctuated around 1.2. Consequently, this parameter was left out of the models.

Results from the main analyses are depicted in Figure 2. As expected, on the within level, stressful events during the last few hours predicted current affect in the expected direction (*i.e.*, stressful events reduced positive affect and increased negative affect).

On the between-level, contrary to our hypothesis, stress reactivity was not significantly predicted by the BRCS measure. This means that the participants' responses to the BRCS questionnaire did not explain how strongly their affective state was affected by stressful daily events. The BRCS did, however, predict the respondents' mean levels of positive and negative affect, so that respondents who score higher on BRCS in general report higher levels of positive affect and lower levels of negative affect. In a similar way, level of stressful daily events did not predict stress reactivity, but did predict mean levels of affect, so that higher mean levels of stressful events predicted lower levels of positive affect and higher levels of negative affect. There was no statistically significant correlation between mean level of affect and stress reactivity. Parameter estimates are presented in Tables 2 and 3.

Figure 2

Dynamic Structural Equation Models of Resilience as Measured by Stress Reactivity and by BRCS



Note. Cursive numbers (above) depict parameter estimates from the model of positive affect, non-cursive numbers (below) depict parameter estimates from the model of negative affect. Positive affect is a latent factor measured by four indicators, while negative affect is a sum score of two items. BRCS is a latent variable measured by four indicators.

Table 2

Parameter estimates for model of positive affect

				95% CI	
Parameter	Standardized estimate	Posterior S.D.	p	LL	UL
			Within-level		
Affect by *work feels meaningful* (1)	.709*	.016	.000	.671	.734
Affect by *work feels fun* (2)	.775*	.014	.000	.747	.803
Affect by *work feels manageable* (3)	.460*	.025	.000	.412	.511
Affect by *I feel appreciated* (4)	.662*	.019	.000	.624	.693
Auto-regression (ar)	.293*	.035	.000	.224	.355
Affect on stress (b_t)	-.257*	.029	.000	-.306	-.187
Stress auto-regression	.214*	.040	.000	.128	.289
			Between-level		
Affect by *work feels meaningful* (1)	.916*	.028	.000	.853	.961

Affect by *work feels fun* (2)	.931*	.026	.000	.873	.973
Affect by *work feels manageable* (3)	.729*	.050	.000	.619	.814
Affect by *I feel appreciated* (4)	.775*	.043	.000	.678	.847
BRCS by item 1	.505*	.093	.000	.290	.663
BRCS by item 2	.546*	.082	.000	.372	.694
BRCS by item 3	.539*	.081	.000	.366	.684
BRCS by item 4	.509*	.081	.000	.337	.653
Affect on BRCS	.500*	.095	.000	.308	.679
ar on BRCS	.334*	.162	.024	.003	.632
b on BRCS	-.201	.158	.101	-.512	.109
Affect on stress	-.311*	.086	.000	-.485	-.139
ar on stress	-.009	.148	.476	-.306	.272
b on stress	.026	.152	.432	-.269	.323
Affect with ar	-.259	.214	.124	-.661	.161
Affect with b	.320	.191	.044	-.041	.703
ar with b	-.089	.263	.360	-.655	.374
BRCS with stress	-.074	.112	.254	-.291	.147

Table 3

Parameter estimates for model with negative affect

				95% CI	
Parameter	Standardized estimate	Posterior S.D.	p	LL	UL
			Within-level		
Auto-regression (ar)	.265*	.035	.000	.207	.338
Affect on stress (b)	.384*	.021	.000	.344	.424
Stress auto-regression	.227*	.033	.000	.163	.297
			Between-level		
BRCS by item 1	.368*	.127	.000	.075	.569
BRCS by item 2	.662*	.090	.000	.483	.837
BRCS by item 3	.568*	.084	.000	.394	.724
BRCS by item 4	.417*	.090	.000	.232	.585
Affect on BRCS	-.253*	.080	.001	-.407	-.093
ar on BRCS	-.019	.206	.465	-.405	.398
b on BRCS	.332	.194	.050	-.068	.685
Affect on stress	.650*	.058	.000	.526	.753
ar on stress	-.103	.178	.276	-.441	.268
b on stress	.028	.192	.441	-.339	.412
Affect with ar	-.354	.206	.050	-.748	.065
Affect with b	.059	.217	.396	-.334	.503
ar with b	.520	.298	.073	-.217	.941
BRCS with stress	.044	.113	.351	-.264	.179

Evaluation of models

To evaluate robustness of the results we more than doubled the number of iterations. On inspection of the trace plots for all parameters, they were found to be satisfactory. To evaluate the sensitivity of the models, we ran models using only single daily measures and models based on sum scores of the BRCS-scale and positive affect (rather than latent variables). The interpretation of the main results were the same in this analyses, leading us to conclude that the models are stable.

DISCUSSION

This was the first study to look at resilience in two ways. Contrary to our expectations, traits did not explain variance in daily process. Further, the two measures displayed different relations to positive and negative affective state. The results of the present study indicate that resilience operationalized in terms of stable traits (such as the BRCS) and as stress reactivity measure different things. Consequently, our findings suggest that researchers planning studies on resilience need to decide on whether they want to study the process of positive adjustment, and, if so, should not measure resilience by means of a between-person level questionnaire. Further research is needed to clarify the time scales by which resilience operates and is operationalized.

A plausible explanation for lacking findings is that the BRCS measures personality traits. Previous studies have shown that personality traits are rarely predictive of day-to-day behaviors or reactions.

Our results may to some extent also be due to different wording and focus: the BRCS has a more cognitive, problem-solving approach to resilience, whereas the DSEM only indirectly assess resilience by looking at strength of association between experienced stress and affective state. However, the creators of the questionnaires and many of those who use it explicitly state that they assume the measure is a proxy for intraindividual process. This might indicate that at least some of those previous results should be interpreted differently, that is, previous findings based on the BRCS might not indicate differences between people in terms of how they are affected by stress, but maybe some other difference between people such as general self-efficacy.

Yet to be done:

- add comparisons to previous findings regarding strength of b. Look at Ong for references.
- Look up Kahneman and Riis (2005): experiencing self and remembering self? Or something along those lines, he has studied this in other contexts and concluded that they are not the same (i.e., same as we showed).

As noted by Kahneman (e.g., Kahneman & Riis, 2005) everyday experiences reported by means of immediate introspection and long-term evaluations of experiences are not necessarily in perfect correspondence.

Suggestions for further research: Baseline functioning (e.g. ability to do your work) and emotional experience…

[limitations]

There are several limitations that need to be considered

- Generalizability with regards to how resilience was measured (the stressors and affect, in a work context in schools). Self-report BRCS – reflect how views oneself
- Sample: western industrialized society with well-educated adult sample

In conclusion...

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