Comparative investigation of appraisal style measures in their predictive potential for stress resilience and implications for predictive modeling of resilience

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Abstract

Appraisal refers to the evaluation of stimuli or situations with respect to an individual's goals and needs. Stimuli or situations that are appraised as a threat to one' goals and needs ('stressors') induce stress responses ('stress'). Stressor appraisal occurs on various dimensions, of which the magnitude or cost of a potential adverse outcome, the probability of the outcome, and an individual's coping potential are the most important. Individuals show subjective biases on each of these dimensions, which can range from extremely unrealistically negative to extremely unrealistically positive. Positive appraisal style (PAS) is an integrative construct. Individuals with a PAS have an average tendency to appraise stressors in a realistic to mildly unrealistically positive fashion across the different stressor appraisal dimensions; hence, they typically avoid both negative and also delusionally positive appraisals. Positive appraisal style theory of resilience (PASTOR) posits that this global bias is key for stress resilience, as it enables individuals to generate stress responses when needed but also to avoid unnecessary and over-shooting stress responses that will exhaust one's resources and prevent resource replenishment during times of severe or lasting stressor exposure. We here use data from three prospective-longitudinal studies to compare recently validated self-report instruments for PAS with existing measures of appraisal biases in single dimensions in their relative predictive potential for resilience, using regularized regression methodology. We find that one PAS instrument, reflecting a tendency to produce general positive appraisal contents (PASS-content), and an optimism instrument, supposed to reflect a positive appraisal bias on the probability dimension, are consistent predictors of resilience over long time frames and superior in this quality to the other instruments (measures of positive appraisal processes, self-efficacy, and control). Generally, our results confirm the important role of appraisal biases in resilience. Item and nomological network analyses further indicate that the PASS-content instrument may more closely reflect individual differences in appraisal than the optimism instrument and thus be well suited for mechanistically interpretable prediction models based on well-defined psychological constructs. By contrast, the optimism instrument may reflect differences in life perspectives in addition to differences in appraisal. This makes the instrument less mechanistically interpretable; however, it may be better suited for clinical prediction models aiming at individual-level prognosis on the basis of maximized explained variance.

Introduction

Stress resilience is the maintenance or quick recovery of mental health during and after times of adversity, that is, a good long-term mental health outcome despite exposure to stressors (Kalisch et al., 2017). PASTOR claims that optimal stress response regulation is key for resilience (Kalisch et al., 2015). Individuals should be able to generate appropriate stress response when they are needed to protect the individual from harm; at the same time, they should not generate stress responses that are unnecessary, or unnecessarily strong or prolonged, since stress costs energy, time, and other (e.g., cognitive, social, financial) resources. By taxing resources and keeping the individual from rebuilding lost resources, massive and chronic stress responses can lead to resource depletion and eventual allostatic overload, resulting in damage to bodily and neural functions.

In PASTOR, the individual tendency to generate optimally tuned stress responses is a direct result of an individual's stressor appraisal tendencies. This derives from the claim of appraisal theory that emotional reactions to stimuli or situations are determined in quality and quantity by the appraisal of the stimulus/situation (Arnold, 1969; Frijda, 1993; Lazarus & Folkman, 1984; Scherer, 2001). Consequently, individuals should not underestimate threats (as otherwise they will fail to mount stress responses), but also not overestimate them (as otherwise they will consume too many resources). PASTOR claims that, across many occasions and over longer time frames, the optimal window of appraisal lies in the realistic to mildly unrealistically positive range ('positive appraisal style', PAS). A limited illusional bias towards slightly underestimating threats has the advantage that the individual is given relatively more time to replenish their resources, to explore opportunities, and to learn and build new coping strategies as compared to if they were in the constant alarm mode that an uncertain and dangerous environment would realistically require (Kalisch et al., 2015).

PASTOR recognizes that stressor appraisal takes into account the magnitude of the consequences (the costs) an adverse outcome would have, its probability, and one's ability to manage (to cope with, to control) the outcome in case it occurred. Literature contends that these appraisal dimensions can be at least partly differentiated, that is, are partly independent from each other, and has described different individual biases on each of them, namely catastrophizing vs. trivialization on the magnitude dimension (Reiss et al., 1986; Sullivan et al., 1995), pessimism vs. optimism on the probability dimension (Carver et al., 2010), and helplessness vs. over-confidence on the coping dimension (Bandura, 1977; Benight & Cieslak, 2011; Levenson, 1981). PAS integrates these specific tendencies by arguing that a resilient outcome over longer periods of adversity depends on an individual's average bias across appraisal dimensions. For instance, a habitual pessimist may still on average produce positive appraisals because they do not catastrophize and have high confidence in their coping abilities (Kalisch et al., 2015). As a consequence, PAS should be a better predictor of resilience than instruments assessing biases in single appraisal dimensions. While initial studies have found associations between PAS and resilience (Bögemann, Puhlmann, et al., 2023; Veer et al., 2021; Zerban et al., 2023), this specific claim remains untested. Alternatively, it could also be that a bias in a single dimension, or in just two dimensions, may be dominant in shaping resilience. Although such a potential finding of dimensional dominance, if systematically observed, would not invalidate the appraisal-theoretic account of resilience, it would require an adjustment of the theory in terms of a specification of the key posited appraisal dimension(s).

We here compare the relative predictive contributions of PAS and single appraisal dimensions in three prospective-longitudinal data sets that all feature questionnaire batteries and subsequent quantification of resilience outcomes: the Mainz Resilience Project (MARP) (Kampa et al., 2018, 2020), the Longitudinal Resilience Assessment (LORA) study (Chmitorz, Neumann, et al., 2020), and the observational study of the EU DynaMORE consortium (DynaM-OBS; (Wackerhagen et al., 2023)). In these studies, next to measurements of PAS, assessments of optimism (related to the probability dimension), general self-efficacy, and control (both related to the coping potential dimension) are available in different combinations. For the measurement of PAS, the studies include two different recently validated instruments (Petri-Romão et al., 2024). The Perceived Positive Appraisal Style Scale, process-focused (PASS-process) tries to index the mental operations people use to generate positive appraisals in difficult situations, including cognitive strategies such as positive reframing, distancing, or acceptance. The Perceived Positive Appraisal Style Scale, content-focused (PASS-content) tries to index the actual positive appraisals (appraisal contents, appraisal outcomes) that people generate in these situations. It is thus a more direct measure of the PAS construct, but it is not clear which of the two instruments provides better resilience prediction. By including both instruments in the comparison, we attempt to obtain a maximally holistic picture of how appraisal tendencies explain variance in resilience. For the analysis, we employ a regularized regression approach that has been developed to deal with collinear regressors (Hastie et al., 2015; Zou & Hastie, 2005).

We qualify our findings by discussing generalizability, the questionnaires' intercorrelation structure, their psychometric properties, and item content.

For further qualification, we investigate the nature of the relationship of the strongest identified predictor to resilience and its compatibility with PASTOR. Specifically, we ask whether the predictor-outcome relationship is mediated by a self-report measure of optimal stress response regulation. For this purpose, we use a battery questionnaire that assesses how easily individuals cope with, and recover from, stressful events (in short: 'good stress recovery') (Smith et al., 2008), which has already been confirmed as a mediator between PAS and resilience in the initial studies (Bögemann, Puhlmann, et al., 2023; Veer et al., 2021; Zerban et al., 2023).

These studies have also shown that PAS mediates the relationship between perceived social support and resilience. This particular test was based on the PASTOR claim that the effects of other resilience factors, including social support, on resilience can ultimately be explained by them shaping the way individuals appraise stressors. In the case of social support, individuals who perceive themselves as generally well supported by a strong social network should also generally perceive stressful challenges as less threatening. That is, PAS is understood in this framework as a mediating, proximal resilience factor (Kalisch et al., 2015). We therefore here want to know if the strongest predictor identified in the comparative analyses also mediates social support effects on resilience.

We conclude with a discussion of theoretical and practical implications, notably about how our results can be exploited for predictive resilience modelling and theory building.

Methods

Principles of study design and resilience quantification

MARP, LORA, and DynaM-OBS are longitudinal studies conducted in predominantly young adult samples. The MARP and LORA studies are ongoing, and data from on average 3.7 and 3 years, respectively, of data collection per participant have been released. DynaM-OBS is finished and has collected data over up to 9 months per participant.

All studies feature a questionnaire battery, part of a larger testing battery that also includes socio-demographic, behavioral, and biological measurements, which was administered at study baseline (B0) and repeated at least once (B1) at different post-baseline intervals, depending on the time frame of the study (planned: MARP: 1.75 years, LORA: 1.5 years, DynaM-OBS: 9 months, approximately). Next to PASS-content and PASS-process, the batteries comprise measures of optimism, general self-efficacy, internal locus of control, good stress recovery, and perceived social support. No measure of trivialization is available.

In addition to the battery, each study features a more frequent online monitoring component in which exposure to stressors (E) and mental health problems (P) are regularly assessed. In MARP and LORA, this is done every 3 months, in DynaM-OBS, this was done every 2 weeks over the first 6 months of data collection and every month thereafter. The online monitoring data used in this paper start with the first post-baseline assessment (T1) and include up include up to 16 additional monitoring time points in MARP (up until time point T17, corresponding to the time point of battery B2), up to 11 time points in LORA (until T12, also corresponding to B2), and up to 14 time points in DynaM-OBS (until study end).

These monitorings implement the Frequent Stressor and Mental Health Monitoring (FRESHMO) paradigm, which serves to determine participants' stressor reactivity as well as temporal changes therein (Kalisch et al., 2021). For this purpose, participants' average P scores are regressed upon their average E scores, to calculate the sample's norm mental health reactivity to stressors. Individual deviations from this normative E-P relationship (residuals on the regression line) constitute a continuous measure of the individual participant's stressor reactivity (SR score), where a positive residual signifies more and a negative residual signifies less reactivity than predicted based on the sample norm. Lasting under-normal reactivity is an operationalization of the definition of resilience as a good long-term mental health outcome despite adversity (Kalisch et al., 2017). By virtue of controlling for individual differences in stressor exposure, the SR score can be used to compare participants that differ in exposure (Kalisch et al., 2021).

These data structures allowed us to examine prospective associations of B0 questionnaires and, in the case of MARP and LORA, also B1 questionnaires with SR scores calculated over various intervals after the administration of a battery, as shown in Table 1. The SR scores calculated over ca. 3.7 (in MARP) and 3 (in LORA) years after B0 are the closest approximation of resilience, since they best reflect long-term outcomes.

Table 1. Predictors and outcomes used for prospective analyses in the three samples. BX, questionnaire battery time point; SR, stressor reactivity.

Study	Variable	Predictor time point / Outcome interval				
MARP	Predictors (battery questionnaires)	B0	B0	B0	B1	B1
	Outcome (SR score)	SR(B0-B2) (~3.7 yrs)	SR(B0-B1) (~1.9 yrs)	SR(B0-9 months) i.e., 3 monitorings post B0	SR(B1-B2) (~1.6 yrs)	SR(B1-9 months) i.e., 3 monitorings post B1
LORA	Predictors (battery questionnaires)	B0	B0	B0	B1	B1
	Outcome (SR score)	SR(B0-B2) (~3 yrs)	SR(B0-B1) (~1.5 yrs)	SR(B0-9 months) i.e., 3 monitorings post B0	SR(B1-B2) (~1.5 yrs)	SR(B1-9 months) i.e., 3 monitorings post B1
DynaM-OBS	Predictors (battery questionnaires)	B0	-	-	-	-
	Outcome (SR score)	SR(B0-9 months) i.e., entire study period	-	-	-	-

Studies

MARP (Mainz Resilience Project) is conducted by the University Medical Center of Johannes Gutenberg University and the Leibniz Institute for Resilience Research in

Mainz, Germany. At baseline (B0), MARP has included N=200 mentally healthy male and female participants between 18 and 21 years of age, recruited as a convenience sample. Inclusion criteria included the previous experience of stressful life events (a minimum of 3 before the age of 18). Exclusion criteria included current neurological or mental disorders, current psychoactive medication, and physical disorders with effects mental health. Participants gave their written informed consent. Ethical approval was obtained from the Medical Board of Rhineland-Palatinate, Mainz, Germany. Participants were reimbursed for their efforts. See (Kampa et al., 2018, 2020). A data freeze was performed November 11th 2022.

LORA (LOngitudinal Resilience Assessment) is conducted by the University Hospital of Goethe University in Frankfurt am Main, Germany, and the University Medical Center of Johannes Gutenberg University Mainz, Germany. At baseline (B0), LORA included N=1191 mentally healthy male and female participants between 18 to 50 years of age, recruited as a convenience sample on the basis of registration office data. Exclusion criteria included lifetime diagnoses of chronic mental disorders (e.g., schizophrenia, bipolar disorder), organic mental disorders, substance dependence syndromes, current severe axis I disorder, and current severe medical conditions. Participants gave written informed consent. Ethical approval was obtained from the Ethics Committee of the Department of Medicine at the Goethe University Frankfurt and the Medical Board of Rhineland-Palatinate, Mainz. See (Chmitorz, Neumann, et al., 2020). A data freeze was performed in April 2022.

DynaM-OBS (DynaMORE observational study) has been conducted by the EU Horizon 2020 project DynaMORE (Dynamic MOdelling of REsilience; www.dynamore-project.eu) at: Department of Psychiatry and Psychotherapy, Charité–Universitätsmedizin Berlin, Germany; Neuroimaging Center (NIC), Johannes Gutenberg University Medical Center Mainz, Germany; Donders Centre for Cognitive Neuroimaging (DCCN), Nijmegen, The Netherlands; Sagol Brain Institute, Tel Aviv University (TAU) and Tel Aviv Soursaky Medical Center, Tel Aviv, Israel; and Faculty of Psychology, University of Warsaw, Poland. Study conduct was done in each site's official language. At baseline (B0), DynaM-OBS included N=258 mentally healthy male or female participants between 18 and 25 years of age (except Israel: 18-27 years), recruited as a convenience sample. Inclusion criteria included the previous experience of stressful life events (a minimum of 3) and a score of >20 on the General Health Questionnaire-28 (GHQ-28; (Goldberg & Hillier, 1979)), indicating the presence of mental distress. Exclusion criteria included lifetime diagnosis of any severe mental or organic disorder that affects neurodevelopment, diagnosis within 9 months before inclusion of any mental disorder other than a mild depressive episode. Ethical approval was obtained from each site's ethics committee. See (Wackerhagen et al., 2023).

Battery measures

Self-report questionnaires administered as part of the testing batteries (B0, B1, ...) in the three studies include:

- Perceived Positive Appraisal Scale Style, content-focused (PASS-content), a 14-item instrument that assesses the frequency of positive appraisals in difficult or stressful situations (e.g., “I think that I can deal successfully even with the worst situation”, “I tend to see things rather optimistically”, “I think that you shouldn’t make mountains out of molehills”). Sum scores range from 14 to 56, higher scores denoting a more positive appraisal tendency (Petri-Romão et al., 2024).
- Perceived Positive Appraisal Style Scale, process-focused (PASS-process), a 10-item instrument that assesses the frequency of mental operations (cognitive strategies and tactics) that people use in stressful situations to generate positive appraisals (e.g., “I try to look at the situation from an objective perspective”, “I think that I can become a stronger person as a result of what has happened”). Sum scores range from 10 to 50, higher scores denoting a more frequent use of such positive appraisal and reappraisal processes (Petri-Romão et al., 2024).
- Life Orientation Test-Revised (LOT-R), a 10-item instrument of which three items assess dispositional optimism (OPT). Sum scores range from 0 to 24, higher scores denoting a more optimistic disposition (Chiesi et al., 2013).
- General Self-Efficacy Scale (GSE), a 10-item instrument that assesses the perceived ability to cope with various demands and challenges. Sum scores range from 10 to 40, higher scores denoting a more optimistic disposition (Scholz et al., 2002).
- Two Locus of Control (LOC) scales were used. In MARP and LORA, LOC was measured with a 28-item instrument of which four items assess the degree individuals perceive outcomes to be determined by their own actions (Rotter, 1966). Sum scores for these questions range from 0 to 23, higher scores denoting a higher internal locus of control (iLOC). In DynaM-OBS, a dedicated 4-item version was used, with scores ranging from 4 to 20 (Kovaleva et al., 2014).
- Brief Resilience Scale (BRS), a 6-item instrument that assesses the ability to cope with and recover from stress. Sum scores divided by item number range from 1 to 5, higher scores denoting better stress recovery (Smith et al., 2008).
- Two scales for perceived social support were used. In MARP and DynaM-OBS, the construct was measured with the Oslo 3 Social Support Scale (OSSS-3), a 3-item instrument. Sum scores range from 1 to 14, higher scores denoting higher support (Kocalevent et al., 2018). In LORA, the construct was measured with the Fragebogen zur Sozialen Unterstützung (F-SozU), a 14-item instrument. Mean scores range from 1 to 5, higher scores denoting higher support (Fydrich et al., 1999).
- Subjective social status scale, an instrument requiring participants to place themselves on ladders representing different parts of society, where people at the top are the “best off” and people at the bottom are the “worst off”. A mean score of a

participant's placement height is created from 3 subscales (professional life, community, wider society), higher scores denoting higher perceived social status (Adler et al., 2000).

The B0 batteries also included a socio-demographic assessment.

Online monitoring measures

Self-report questionnaires administered as part of the regular online monitoring (T0, T1, T2, ...) include:

- General Health Questionnaire (GHQ-28), a 28-item instrument that assesses internalizing (anxiety- and depression-related) mental health problems over the past weeks. Sum scores range from 0 to 84, higher scores denoting more mental health problems (Goldberg & Hillier, 1979).
- Mainz Inventory of Microstressor (MIMIS), a 58-item list of commonly occurring daily hassles. Respondents indicate on how many days out of the past seven a list item occurred. If an item occurred, respondents also indicate its burdensomeness (Chmitorz, Kurth, et al., 2020). Exposure to daily hassles is quantified as the sum count of the number of days indicated across all items (Kalisch et al., 2021). In DynaM-OBS, 23 additional stressors were included in the assessment, covering events related to the COVID-19 pandemic (Wackerhagen et al., 2023).
- Adapted version of the Life Experience Questionnaire (Canli et al., 2006), a 27-item list of life events. Respondents indicate each item that occurred over the past three months and subsequently rate an item's burdensomeness. Exposure to life events is quantified as sum count of all reported items (Kalisch et al., 2021). Administration of the list in DynaM-OBS was restricted to time points 3, 6, and 9 months after baseline. Data are not considered due to the rare occurrence of life events in this short-duration study.

Data cleaning and final samples for analysis

Required minimum numbers of completed online monitorings per outcome interval (cf. Table 1) in MARP and LORA were four for B0-B2, three for both B0-B1 and B1-B2, and two for the nine months after a battery. In DynaM-OBS, where monitoring was more frequent (see above) and restricted to nine months post battery, no minimum required number was fixed. This resulted in N=169 analyzable participants in MARP (mean age: 19.1 years (sd=0.8), n=94 (55.95%) female, n=112 (66.67%) university students), N=1034 analyzable participants in LORA (mean age: 28.8 years (sd=8.0), n=686 (66.34%) female, n=576 (52.42%) university students, n=466 (45.07%) with university education, n=463 (44.78%) in employment), and N=218 analyzable participants in DynaMORE (mean age: 22.1 years (sd=2.3), n=128 (58.71%) female, all studying or in vocational training).

Calculation of stressor reactivity (SR)

For each monitoring time point in MARP and LORA, a total stressor exposure (E) score combining exposure to daily hassles and life events was computed as the mean of the z-scored daily hassles and life events counts, as prescribed (Kalisch et al., 2021). For DynaM-OBS, the daily hassles count at each monitoring time point was used. Mental health problems (P) were expressed as the GHQ-28 total score.

In MARP and LORA, the sample's normative stressor reactivity (E-P relationship) was calculated by regressing participants' average P scores of the first nine months (monitoring time points T1, T2, T3) onto their average E score of the same period. We only used this early study period for normation because both studies are still ongoing, and we want to avoid changes in normation with every new data release before the final release after study end (Kalisch et al., 2021). By contrast, in DynaM-OBS, where data collection is finished, all available monitoring time points could be used to establish the normative E-P line (Wackerhagen et al., 2023). In MARP, the relationship was linear and was not improved by adding a quadratic term. In LORA, the relationship was also predominantly linear. Only in DynaM-OBS, the model fit was markedly improved by adding a quadratic term, such that the norm E-P relationship was built including this term.

Next, for each outcome interval of interest (e.g., B0 to B1; cf. Table 1), a participant's average E and P scores in that interval were used to calculate the participant's residual onto the normative E-P line, a lower residual denoting a relatively lower stressor reactivity (SR).

Data analysis

In agreement with previous work (Bögemann, Puhlmann, et al., 2023; Veer et al., 2021; Zerban et al., 2023) and to prepare all prediction analyses, the associations between the socio-demographic covariates and the main SR outcome in each sample (MARP and LORA: SR(B0-B2), DynaM-OBS: SR(B0-9 months); cf. Table 1) was tested in separate univariate regressions, to retain all covariates surviving a likelihood ratio test at $p<0.2$ for further analyses (Supplementary Tables S1-S3). For comparison of appraisal-related questionnaires in their predictive potential for the SR outcomes defined in Table 1, regularized regression using two penalty terms of equal weighting ($\alpha=0.5$), combining elements of ridge and lasso regression (elastic net regression) (Hastie et al., 2015), was performed for each outcome in each sample. The λ parameter was set to minimise cross-validation error (MSE) as the minimum lambda. Separate predictive testing of the single resulting best predictor across samples and outcomes was done using multivariate linear regression.

Mediation analyses were performed using a regression-based approach (Hayes, 2013). The directed paths a (x to mediator) and b (mediator to outcome) were tested separately in linear regressions. The indirect effect (ab) was estimated by bootstrapping the regression model.

Code

The code is available on https://osf.io/zvkpu/.

Results

Psychometric properties of the appraisal-related questionnaires

The baseline (B0) questionnaire batteries were repeated after approximately 1.9 years in MARP, 1.5 years in LORA, and 9 months in DynaM-OBS (see Table 1). Internal reliabilities (Cronbach's α, Guttman's λ, McDonald's ω) at these time points are reported in Table 2. All instruments showed sufficient reliability, but PASS-process and iLOC – especially the shorter version of the iLOC instrument used in DynaM-OBS - were somewhat inferior to the other instruments. Test-retest reliabilities (intra-class correlation coefficients, ICCs) are reported in Table 3. PASS-content, OPT, and GSE showed good to very good test-retest reliability, while again PASS-process and iLOC performed less well.

Table 2. Internal reliabilities of appraisal-related questionnaires at B0 and B1 batteries. OPT, optimism; GSE, general self-efficacy; iLOC, internal locus of control.

Questionnaire	**Study**	**Predictor time point**					
		B0	B1	B0	B1	B0	B1
		Cronbach's α		**Guttman's λ 6**		**McDonald's ω**	
PASS-content	MARP	0.85	.84	0.86	0.86	0.86	0.85
	LORA	0.86	0.88	0.87	0.88	0.86	0.88
	DynaM-OBS	0.77	0.84	0.79	0.86	0.77	0.84
PASS-process	MARP	0.72	0.69	0.79	0.78	0.73	0.69
	LORA	0.56	0.52	0.61	0.61	0.57	0.55
	DynaM-OBS	0.77	0.79	0.81	0.85	0.78	0.8
OPT	MARP	0.75	0.78	0.74	0.78	0.75	0.79
	LORA	0.75	0.8	0.73	0.79	0.77	0.8
	DynaM-OBS	0.77	0.82	0.76	0.82	0.78	0.83
GSE	MARP	0.85	0.87	0.85	0.88	0.85	0.87
	LORA	0.84	0.87	0.84	0.87	0.85	0.87
	DynaM-OBS	0.84	0.86	0.84	0.86	0.84	0.86
iLOC	MARP	0.68	0.7	0.72	0.76	0.68	0.71
	LORA	0.72	0.74	0.73	0.76	0.72	0.74
	DynaM-OBS	0.45	0.53	0.4	0.5	0.49	0.6

Table 3. Test-retest reliabilities of appraisal-related questionnaires between B0 and B1 batteries.

Questionnaire	Study	ICC
PASS-content	MARP	0.72
	LORA	0.72
	DynaM-OBS	0.63
PASS-process	MARP	0.58
	LORA	0.55
	DynaM-OBS	0.53
OPT	MARP	0.69
	LORA	0.70
	DynaM-OBS	0.70
GSE	MARP	0.69
	LORA	0.70
	DynaM-OBS	0.72
iLOC	MARP	0.47
	LORA	0.67
	DynaM-OBS	0.60

Questionnaire intercorrelations (nomological network analysis I)

Questionnaire intercorrelations in the three samples at the baseline time point (B0) are given in Table 4. Intercorrelations were in the small to moderate range. PASS-content was generally more highly correlated with the other questionnaires than PASS-process. This may be related to the poorer reliabilities of the PASS-process instrument. It may also indicate a better reflection of appraisal tendencies by PASS-content, in line with it targeting appraisal contents more directly than the PASS-process instrument, which tries to assess the cognitive positive appraisal and reappraisal processes that may eventually lead to positive appraisal contents. GSE and OPT were correlated slightly less to each other than PASS-content was to them, presumably expressing that they are thought to target single and separate appraisal dimensions rather than integrate several dimensions, as is intended by PASS-content. Nevertheless, the numerical difference of their intercorrelations to the correlations with PASS-content were not strong, suggesting either that they do not fully succeed in separating the probability from the coping potential dimension or that PASS-content does not succeed in integrating several dimensions. iLOC was separable from the other questionnaires by being generally less related.

Table 4. Intercorrelations of appraisal-related questionnaires at baseline (B0). Values: Pearson's R.

		PASS-content	PASS-process	OPT	GSE	iLOC
PASS-content	MARP	1	0.56	0.55	0.59	0.19
	LORA	1	0.54	0.56	0.58	0.29
	DynaM-OBS	1	0.58	0.56	0.62	0.36
PASS-process	MARP	0.56	1	0.18	0.42	0.14
	LORA	0.54	1	0.29	0.42	0.18
	DynaM-OBS	0.58	1	0.31	0.43	0.19
OPT	MARP	0.55	0.18	1	0.52	0.26
	LORA	0.56	0.29	1	0.49	0.29
	DynaM-OBS	0.56	0.31	1	0.53	0.46
GSE	MARP	0.59	0.42	0.52	1	0.31
	LORA	0.58	0.42	0.49	1	0.31
	DynaM-OBS	0.62	0.43	0.53	1	0.41
iLOC	MARP	0.19	0.14	0.26	0.31	1
	LORA	0.29	0.18	0.29	0.31	1
	DynaM-OBS	0.36	0.19	0.46	0.41	1

Comparative elastic net analyses

Figures 1 to 3 show the results of the elastic net analyses with covariates in MARP, LORA, and DynaM-OBS, respectively. Results of analyses without covariates were not markedly different and are given in Supplementary Figures S1 to S3. Restricting the analysis in LORA to the 66% of participants with the highest stressor exposure E between B0 and B2 also did not markedly change the results (Supplementary Figure S4). All appraisal-related questionnaires were negatively associated with SR, in line with the operationalization of resilience as relatively lower stressor reactivity.

Within the MARP and the LORA cohorts, who both provided five different outcome intervals for SR score prediction from altogether two different predictor time points (B0 and B1, cf. Tabe 1), there was substantial variability in the strengths and ranking of predictors between analyses. This indicates that the elastic net methodology applied to a set of collinear regressors may be sensitive to even subtle changes in cohort composition and outcome interval definition. Prediction results also varied between cohorts. For example, sex/gender was a comparatively highly ranked covariate in MARP and especially LORA, but not in DynaM-OBS; similarly, PASS-content was usually ranked highly in MARP and LORA, but not in DynaM-OBS. DynaM-OBS, which unlike the German studies MARP and LORA is a transnational study in five countries and also only provides one short-term SR outcome (SR(B0-9months)), generally stood apart. This observation suggests that generalizability of elastic net results should not be assumed, unless a pattern can be reliably identified across multiple and differently composed cohorts. Note that study site in DynaM-OBS was not selected as a covariate by our covariate selection procedure (see Methods) and that calculating the analysis for this sample without the participants from the Tel Aviv site, which differed in age and stressor exposure from the other sites, did not change the results (not shown).

On this background, a remarkable finding is that, among the appraisal-related questionnaires (excluding covariates), OPT emerged as the strongest predictor in seven out of eleven analyses. PASS-content was the strongest predictor in two analyses and the second strongest in five analyses. Results for these two instruments were different compared to the other instruments. GSE was the strongest predictor in only one analysis and the second strongest predictor in only two analyses. iLOC substantially contributed to variance explanation in only one analysis. PASS-process generally performed poorly, and poorer than PASS-content, with the exception of DynaM-OBS, where it was the second strongest predictor and better than PASS-process.

An interim conclusion is that the optimism and positive appraisal style constructs are relevant appraisal-related constructs for resilience prediction.

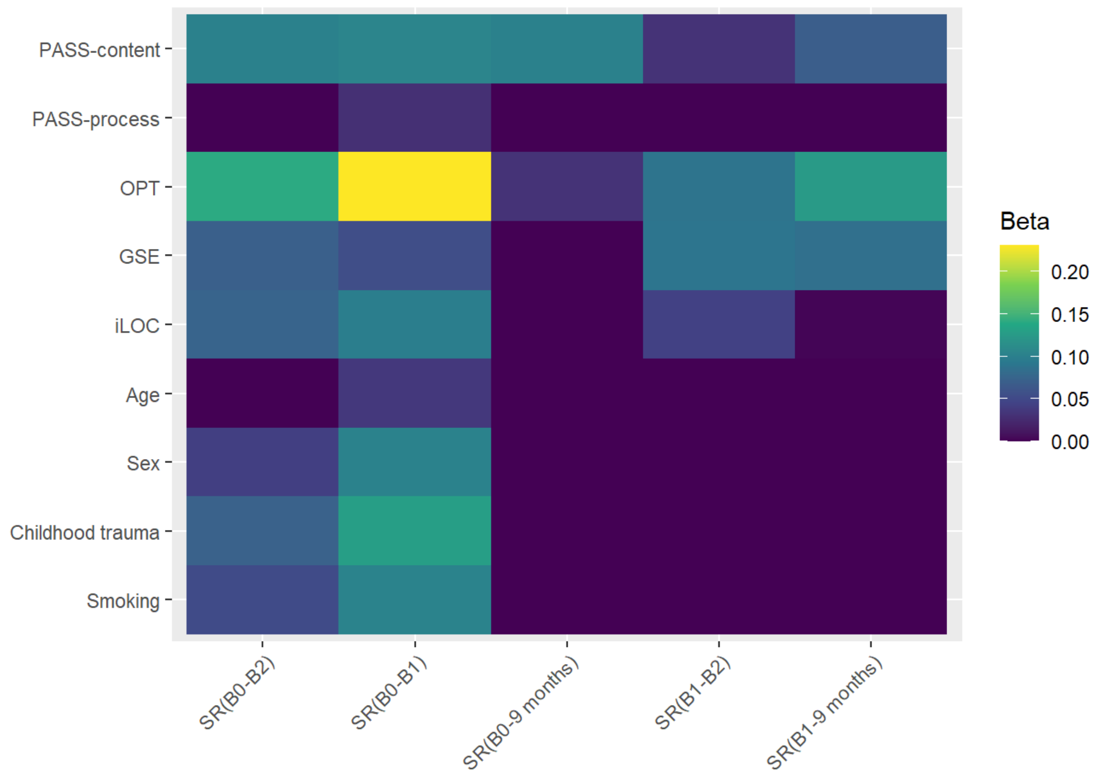

Figure 1. MARP: Results of comparative elastic net analyses. Color code shows the size of the standardized absolute beta. All values reflect prospective associations with SR. The direction of the association is negative for the case of all appraisal-related questionnaires (not shown).

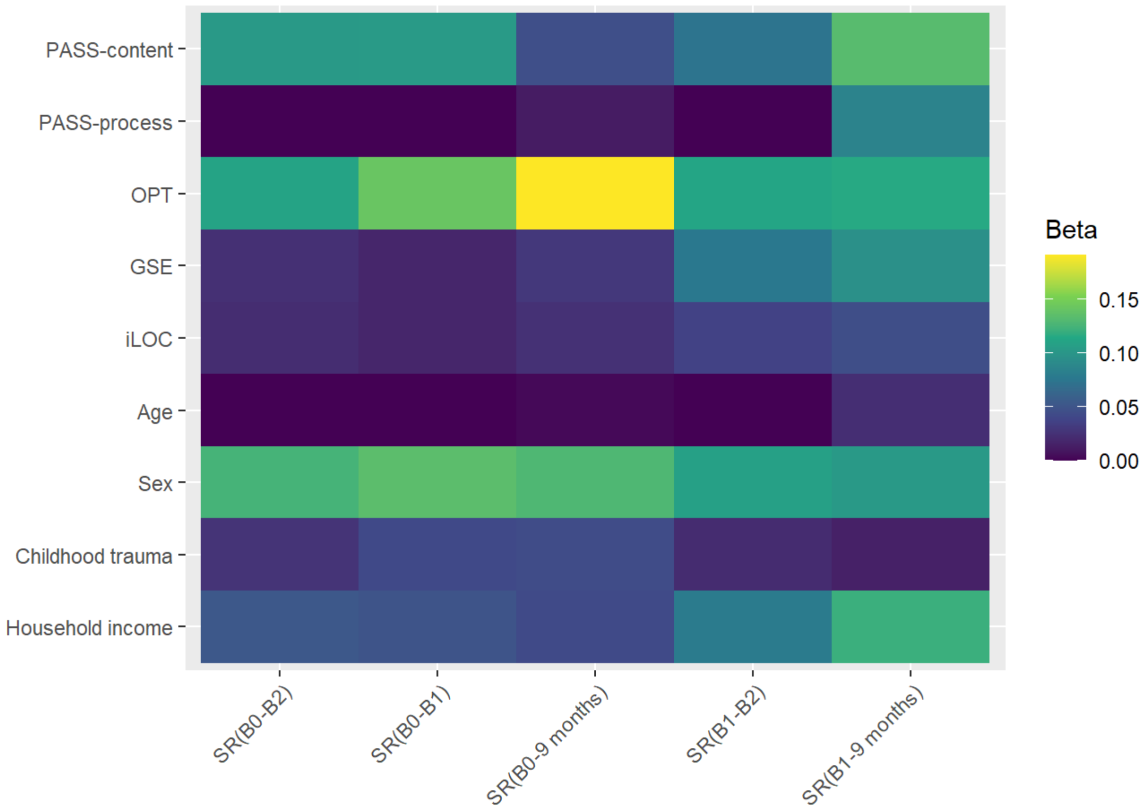

Figure 2. LORA: Results of comparative elastic net analyses. Color code shows the size of the standardized absolute beta. All values reflect prospective associations with SR. The direction of the association is negative for the case of all appraisal-related questionnaires (not shown).

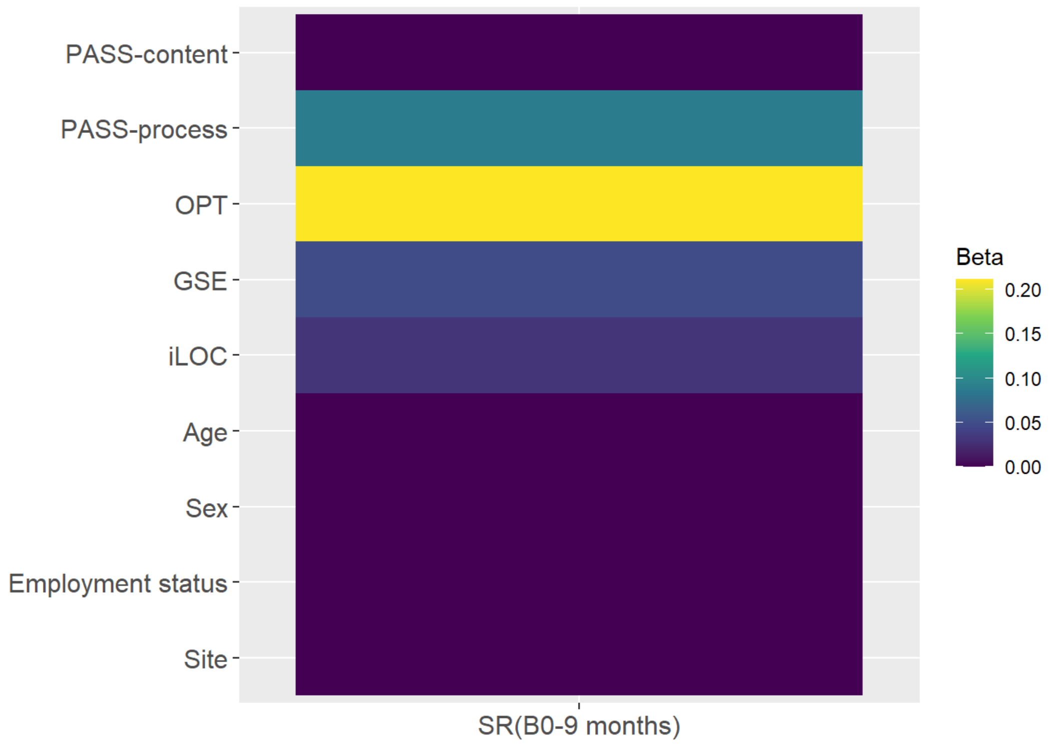

Figure 3. DynaM-OBS: Results of comparative elastic net analyses. Color code shows the size of the standardized absolute beta. All values reflect prospective associations with SR. The direction of the association is negative for the case of all appraisal-related questionnaires (not shown).

Single regression analysis models with OPT

Given the dominant role of OPT in the comparative analyses, we calculated separate covariate-controlled multivariate linear regression models for each predictor-outcome combination, using OPT as single predictor. All models were significant; OPT was always a significant negative predictor of SR (Tables 5 to 7). Variance explained (adjusted R^2) ranged from around 10 to 20 %. Restricting the analysis in LORA to the 66% of participants with the highest stressor exposure E between B0 and B2 also did not change the results (Supplementary Table S4). This suggests OPT is a strong candidate for resilience prediction on the basis of appraisal theory.

Table 5. MARP: multivariate linear regression model results for OPT.

Predictor time point (battery)	B0	B0	B0	B1	B1
Outcome interval (SR score)	B0-B2 (~3.7 yrs)	B0-B1 (~1.9 yrs)	B0-9months (~9 m)	B1-B2 (~1.6 yrs)	B1-9 months (~9 m)
OPT	**-0.314***** (0.078)	**-0.355***** (0.082)	**-0.204**** (0.086)	**-0.363***** (0.112)	**-0.381***** (0.105)
Age	-0.122 (0.096)	-0.142 (0.099)	-0.062 (0.110)	-0.096 (0.134)	-0.070 (0.123)
Sex	**0.414**** (0.160)	**0.418**** (0.166)	**0.326*** (0.176)	**0.401*** (0.220)	0.312 (0.197)
Childhood trauma	0.281 (0.234)	0.255 (0.238)	0.119 (0.288)	0.280 (0.304)	0.322 (0.277)
Smoking	0.048 (0.041)	0.041 (0.041)	0.040 (0.044)	0.024 (0.050)	0.018 (0.046)
Number of assessments	**-0.114*** (0.065)	**-0.128*** (0.066)	-0.070 (0.066)	0.050 (0.096)	0.024 (0.085)
Constant	2.707 (2.108)	3.286 (2.163)	1.367 (2.414)	0.219 (3.046)	0.131 (2.792)
Observations	133	128	114	85	87
R^2	0.235	0.245	0.104	0.172	0.194
Adjusted R^2	0.199	0.207	0.054	0.109	0.133
Residual Std. Error	0.891 (df = 126)	0.901 (df = 121)	0.914 (df = 107)	0.976 (df = 78)	0.899 (df = 80)
F Statistic	**6.462***** (df = 6; 126)	**6.542***** (df = 6; 121)	**2.074*** (df = 6; 107)	**2.707**** (df = 6; 78)	**3.205***** (df = 6; 80)

$^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 6. LORA: multivariate linear regression model results for OPT.

Predictor time point (battery)	B0	B0	B0	B1	B1
Outcome interval (SR score)	B0-B2 (~3 yrs)	B0-B1 (~1.5yrs)	B0-9 months (~9 m)	B1-B2 (~1.5 yrs)	B1-9 months (~9 m)
OPT	**-0.209***** (0.023)	**-0.232***** (0.024)	**-0.248***** (0.029)	**-0.241***** (0.032)	**-0.240***** (0.033)
Age	0.002 (0.003)	-0.0002 (0.003)	0.0003 (0.004)	0.004 (0.004)	0.003 (0.004)
Sex	**0.304***** (0.048)	**0.329***** (0.050)	**0.299***** (0.061)	**0.254***** (0.066)	**0.247***** (0.069)
Childhood trauma	0.002 (0.002)	0.003 (0.002)	0.005 (0.003)	0.0005 (0.003)	0.002 (0.004)
Household income	**-0.024*** (0.013)	-0.020 (0.013)	-0.023 (0.016)	**-0.046***** (0.018)	**-0.058***** (0.019)
Constant	**-0.522***** (0.138)	**-0.578***** (0.146)	**-0.564***** (0.175)	**-0.356*** (0.193)	-0.319 (0.205)
Observations	1,038	1,038	932	764	712
R^2	0.123	0.133	0.113	0.105	0.113
Adjusted R^2	0.119	0.128	0.108	0.099	0.107
Residual Std. Error	0.722 (df = 1032)	0.766 (df = 1032)	0.867 (df = 926)	0.850 (df = 758)	0.854 (df = 706)
F Statistic	**28.924***** (df = 5; 1032)	**31.566***** (df = 5; 1032)	**23.631***** (df = 5; 926)	**17.710***** (df = 5; 758)	**18.046***** (df = 5; 706)

***p<0.05; **p<0.01; ***p<0.001**

Table 7. DynaM-OBS: multivariate linear regression model results for OPT.

Predictor time point (battery)	B0
Outcome interval (SR score)	SR(B0-9 months)
OPT	**-0.316***** (0.043)
Age	-0.011 (0.019)
Gender	-0.079 (0.081)
Employment status	0.008 (0.011)
Site	0.016 (0.030)
Constant	0.253 (0.430)
Observations	218
R^2	0.238
Adjusted R^2	0.220
Residual Std. Error	0.607 (df = 212)
F Statistic	**13.208***** (df = 5; 212)

***p<0.05; **p<0.01; ***p<0.001**

Interim discussion

The psychometric properties (Table 2) and intercorrelations (Table 3) did not sufficiently distinguish OPT from PASS-content and OPT and PASS-content from the other appraisal-related questionnaires, especially GSE, to explain the described pattern of findings based on purely methodological considerations. The general finding of a dominant role for OPT could indicate that PASTOR is wrong in claiming that an integration of biases across multiple stressor appraisal dimensions is key for resilience (Kalisch et al., 2015) and that, instead, an optimistic bias on the probability dimension is the single most important factor.

Comparison of the questionnaire instructions and items of the LOT-R instrument (used for OPT) and the PASS-content instrument suggests a possible alternative explanation. The LOT-R invites respondents to judge their attitude independent from any stressful or challenging situation ("Please answer the following questions about yourself"), whereas the PASS-content explicitly asks respondents to mentally place themselves in such situations before answering the questions ("Please think about how you usually act in difficult, uncertain, burdening, stressful or critical situations and what you usually feel and think"). Accordingly, the LOT-R items used for the calculation of the optimism score ("In uncertain times, I usually expect the best"; "I'm always optimistic about my future"; "Overall, I expect more good things to happen to me than bad.") majoritarily refer to general future expectations, such that a person with an overall positive life outlook is likely to score high. Life perspectives may be partly influenced by respondents' objective current life situation and also the realistic estimates the current situation allows them about their future. By contrast, the PASS-content items (e.g., "I think that every difficult situation will end eventually", "I think that there is a solution for every problem", "I think that you should not make mountains out of molehills") majoritarily refer to the appraisal of stress situations. The PASS-content instrument may therefore more closely target stressor appraisal biases.

Relationship of OPT and PASS-content with socio-economic status (nomological network analysis II)

The conclusion that OPT scores might partly reflect life perspectives, in addition to more narrowly reflecting an appraisal bias on the probability dimension, is not contradictory to the original formulation of the construct (Carver & Scheier, 2014). To further investigate this, we calculated correlations with indicators of socio-economic status as likely partial determinants of life outlook. See Table 8. Household income was significantly positively correlated with OPT in LORA and was always numerically more highly correlated with OPT than with PASS-content, across samples. The difference in LORA was statistically significant ($z=2.36$, $p=0.02$, Fisher's test). PASS-content even showed a marginally significant negative correlation with household income in DynaM-OBS. Perceived social status was significantly correlated with both instruments in MARP and DynaM-OBS, with a numerically pronounced, but non-significant higher correlation for OPT than PASS-content in DynaM-OBS.

Overall, these results indicate that life perspective may play some role in shaping responses on the OPT instrument and that this effect may be more pronounced than in the case of the PASS-content instrument.

Table 8. Correlations of OPT and PASS-content with indicators of socio-economic status.

		Household income	Perceived social status
OPT	MARP	0.08 (p=0.3101)	**0.20** (p=0.0078)
	LORA	**0.15** (p<0.0000)	-
	DynaM-OBS	-0.12 (p=0.1101)	**0.35** (p<0.0000)
PASS-content	MARP	**-0.01** (p=0.8815)	**0.23** (p=0.0020)
	LORA	0.05 (p=0.1169)	-
	DynaM-OBS	**-0.15** (p=0.0499)	**0.22** (p=0.0005)

Mediation analyses with OPT

PASTOR claims that positive appraisal biases promote resilience because they contribute to optimal stress response regulation (Kalisch et al., 2015). To further qualify OPT as resilience predictor, we asked whether the association between OPT at baseline (OPT(B0)) and the largest SR outcome interval available in each cohort (MARP: SR(B0-B2): 3.7 years; LORA: SR(B0-B2): 3 years; DynaM-OBS: SR(B0-9 months): 9 months) is mediated by good stress recovery, as assessed with the BRS questionnaire, at B0. Mediation was significant in each case. See Figure 4A-C.

PASTOR further claims that appraisal biases are proximal in their effect on resilience and therefore mediate the effects of other resilience factors (Kalisch et al., 2015). Figure 4D-E shows that OPT mediated the negative effects of perceived social support on SR in all three cohorts.

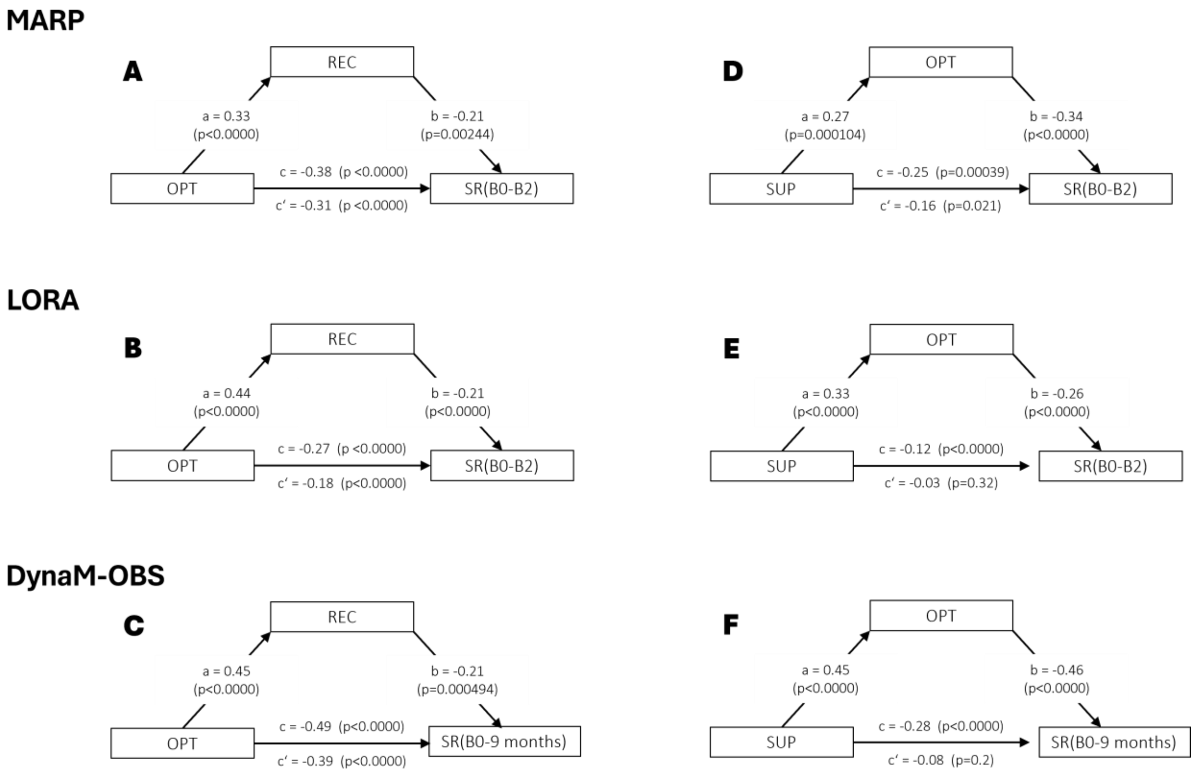

Figure 4. Results of mediation analyses with OPT. The negative effect of OPT(B0) on SR was mediated by good stress recovery (REC) at B0 in (A) MARP (SR outcome interval: B0-B2) (mean bootstrapped indirect effect ab: -0.07, 95% CI [-0.14,-0.01]), (B) LORA (SR outcome interval: B0-B2) (ab: -0.09, 95% CI [-0.13,-0.06]), and (C) DynaM-OBS (SR outcome interval: 3 monitorings post B0) (ab: -0.09, 95% CI [-0.15,-0.04]). OPT(B0) mediated the negative effect of perceived social support (SUP) at B0 on SR in (D) MARP (ab: -0.09, 95% CI [-0.17,0.03]), (E) LORA (ab: -0.09, 95% CI [-0.17,-0.03]), and (F) DynaM-OBS (ab: -0.2, 95% CI [-0.29,-0.12]). a, effect of predictor on mediator; b, effect of mediator on outcome; c, total effect of predictor on outcome; c’, direct effect of predictor on outcome removing the mediator.

Discussion

In this paper, we operationalize outcome-based resilience as relatively lower individual stressor reactivity (SR), that is, as lower observed mental health problems relative to what would be expected based on a participant's stressor exposure. Less-than-predicted reactivity of a person's mental health over longer time frames can be considered an approximation of resilience as good long-term mental health despite adversity (Kalisch et al., 2021).

Our comparative prediction analyses show that, over three samples and different SR outcome intervals, OPT is nearly always a stronger negative predictor than other appraisal-related questionnaires. OPT was also a significant negative predictor in single regression analyses, typically explaining >10% of the variance in SR. Further, across samples, the negative prospective associations of OPT with SR were mediated by good stress recovery, an index of optimal stress response regulation, and OPT mediated the negative prospective association of perceived social support, an established resilience factor (Bonanno et al., 2015; Schäfer et al., 2022), with SR.

PASS-content ranked second as negative SR predictor in the comparative analyses. GSE and iLOC did not contribute substantial independent prediction. Both the OPT and PASS-content instruments showed good psychometric properties and were temporally stable (Tables 2 and 3).

Generally, these findings confirm a role for appraisal biases in resilience, as postulated by PASTOR (Kalisch et al., 2015). Moreover, they are relevant for predictive modeling of resilience.

Implications for predictive modeling

Predictive modeling can have two distinct purposes, clinical and mechanistic. Clinical prediction models try to achieve maximum predictive accuracy, in order to afford individual-level prognosis. Individual prognosis can be relevant for clinical decision-making, in the case of resilience modeling in particular for the planning and adaptation of preventive interventions. Clinical models usually sacrifice explainability for explained variance, by including all available predictors that contribute to variance explanation independent of whether their contribution can be mechanistically interpreted. Predictors also often come from different measurement modalities (e.g., (Schultebraucks et al., 2021). An important requirement for clinical models is generalizability, such that they can be applied to other populations or to the same population at later time points. Our results indicate that a self-report measure of optimism, such as the LOT-R, should be part of any clinical model, as it is likely to explain substantial variance in diverse populations. The PASS-content instrument may be added. The PASS-process, GSE, and iLOC instruments are unlikely to be relevant.

Mechanistic models, by contrast, try to generate insights into the mechanisms that produce the predicted outcome. They sacrifice predictive accuracy for explainability, by focusing on predictors that index a defined construct, such that one can interpret findings in mechanistic terms. Generalizability, too, is a relevant criterion for mechanistic models, to exclude that a result has been obtained by chance or by overfitting to a given sample. On the basis of these considerations, we propose that the PASS-content instrument is a relevant candidate for mechanistic resilience models. It can be well interpreted as reflecting positive appraisal biases across different stressor appraisal dimensions, and it exhibits some generalizability across the various cohorts analyzed in this paper. The latter statement is moderated by absence of effects in the DynaM-OBS sample (cf. Figure 3). We note that this sample only provides a single and relatively short SR outcome interval (nine months after baseline), unlike five intervals – including a very long-term interval of 3+ years - in MARP and LORA. Insofar as resilience is defined as good long-term mental health despite exposure, the long-term predictions in MARP and LORA should be given strongest weight in the interpretation of findings. Here, PASS-content performed well (cf. Figures 1 and 2).

OPT as operationalized by the LOT-R may be a less suitable candidate for mechanistic modeling, due to its item content and association with indices of socio-economic status (Table 8), which indicate that LOT-R scores might be conceptually less circumscribed as a construct and impacted by respondents' life perspectives. That is, in addition to indexing an appraisal bias on the probability dimension, the LOT-R may also index a person's general expectations about their future (Carver & Scheier, 2014). These reservations do not apply to the GSE and iLOC constructs, but the respective instruments were also globally clearly less successful in predicting resilience in our analyses. The latter might be seen as support for the PASTOR claim that average bias across the various stressor appraisal dimension is a more important factor than single biases on single dimensions (Kalisch et al., 2015).

PASS-process performed generally considerably less well than PASS-content, except in the case of DynaM-OBS, where it was superior. Again, based on above reasoning, we give the DynaM-OBS results less weight than the long-term MARP and LORA results in our conclusions. We therefore classify PASS-content as the better of the two predictors. Its superiority over PASS-process may lie in its better psychometric properties and also in its more direct indexing of appraisal contents; that is, employing mental operations or cognitive strategies to generate positive appraisals in stressful situations (PASS-process) may not necessarily be successful and, hence, less directly benefit mental health (Petri-Romão et al., 2024).

On the basis of these considerations, we retain PASS-content as prime candidate among the appraisal-related instruments for future mechanistic modeling.

An interesting question from a mechanistic perspective is raised by the high temporal stability of PASS-content (Table 3). PASTOR has constructed PAS as a relatively stable but also malleable style that may change as a result of life experiences. For instance, it is hypothesized that individuals may change the way they appraise challenges towards the positive when they make experiences of mastery, receive helpful inspiration, or undergo successful therapy. Experiences of failure or overburdening or negative socio-cultural influences may have the opposite effect (Kalisch et al., 2015). Future research should therefore investigate more precisely how stable PAS is over time and which types of influences may modify it. The MARP and LORA data sets provide an opportunity for modeling temporal change, due to its repeated PAS assessments in the testing batteries. Change modeling was, however, beyond the scope of the current investigation. Other opportunities for examining temporal effects may be provided by intervention studies with repeated PAS measurements (e.g., (Bögemann, Riepenhausen, et al., 2023; Mediavilla et al., 2022).

Limitations

This study has several limitations and short-comings. First, all our measurement instruments rely on self-report and may therefore be subject to reporting and memory biases. Next to the predictor instruments, this also applies to the instruments used here to assess stressor exposure and mental health and employed in the calculation of the SR score. Second, because they are self-report instruments, our appraisal-related questionnaires cannot inform about appraisals that occur non-consciously and non-verbally. We may thus have missed important aspects of appraisal (Robinson, 1998). Third, we did not have at our disposal an instrument for the assessment of positive bias on the appraisal dimension of magnitude, or cost. The existing instruments for this dimension that we are aware of have been developed in a clinical context for the purpose of detecting negative bias, that is, catastrophizing (e.g., (Reiss et al., 1986; Sullivan et al., 1995). Developing an instrument sensitive for the opposite, that is, trivialization, may be a worthwhile endeavour. Finally, we believe that more studies with more diverse samples in terms of socio-demographics, type and extent of stressor exposure, and other mental health outcomes are necessary to further substantiate our conclusions.

Conclusions

We recommend that clinical prediction models of resilience for the purpose of individual-level prognosis should employ an optimism instrument, in particular the LOT-R, and, if feasible, a positive appraisal style instrument, in particular the PASS-content. Mechanistic prediction models should employ the PASS-content.

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Conflict of interest

The authors declare no conflict of interest.

Data availability and code

Data will be made available at the time of peer-reviewed publication. Code is available on https://osf.io/zvkpu/

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Supplementary Materials

Table S1. MARP: Covariates

Variable	p value	<0.2
age in years	0.456	No
sex	0.0101	Yes
relationship status	0.395	No
employment status	0.292	No
education	0.242	No
student status	0.368	No
mental illnesses in the family	0.652	No
monthly income	0.992	No
monthly household income	0.804	No
smoking[1]	0.0906	Yes
weed[2]	-2.42e-1	No
life events score[3]	0.570	No
childhood trauma[4]	0.0251	Yes
number of assessments[5]	0.00203	Yes

Note: [1] number of cigarettes per day/month; [2] times per month; [3] summary of life events score; [4] childhood trauma questionnaire (CTQ); [5] number of assessments between the respective baselines

Table S2. LORA: Covariates

Variable	p value	<0.2
age in years	2.49e- 1	No
sex	2.07e-10	Yes
relationship status	3.76e- 1	No
employment status	8.01e- 1	No
education	9.66e- 1	No
persons household income[1]	2.84e- 1	No
household income[2]	9.38e- 4	Yes
smoking	NA	NA
life events score[3]	2.83e- 1	No
childhood trauma[4]	4.17e- 4	Yes
alcohol use[5]	3.19e- 1	No

Note: [1] number of persons contributing to your household income; [2] average monthly net income of your household; [3] summary of life events score before baseline; [4] childhood trauma questionnaire (CTQ); [5] alcohol use disorder identification test (AUDIT)

Table S3. DynaM-OBS: Covariates

Variable	p value	<0.2
age	0.995	No
gender	0.730	No
education[1]	0.367	No
alcohol consumption (amount)	0.970	No
alcohol consumption (frequency)	0.378	No
household income[2]	0.327	No
personal income[2]	0.306	No
relationship status	0.532	No
employment status	0.107	Yes

Note: [1] highest degree optained; [2] converted into EUR as a total amount

Table S4. LORA: multivariate linear regression model results for OPT in the 66% of participants with highest stressor exposure (E) from B0 to B2.

Predictor time point (battery)	B0	B0	B0	B1	B1
Outcome interval (SR score)	B0-B2 (~3 yrs)	B0-B1 (~1.5yrs)	B0-9 months (~9 m)	B1-B2 (~1.5 yrs)	B1-9 months (~9 m)
Optimism	**-0.224*****	**-0.243*****	**-0.242*****	**-0.260*****	**-0.243*****
	(0.031)	(0.032)	(0.039)	(0.042)	(0.043)
Age	0.002	-0.001	0.002	0.006	0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Sex	**0.371*****	**0.384*****	**0.351*****	**0.323*****	**0.309*****
	(0.063)	(0.066)	(0.080)	(0.087)	(0.091)
Childhood trauma	-0.001	0.001	0.004	-0.002	0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Household income	**-0.038****	**-0.032***	**-0.038***	**-0.066*****	**-0.071*****
	(0.017)	(0.018)	(0.022)	(0.024)	(0.025)
Constant	**-0.498*****	**-0.547*****	**-0.597*****	-0.349	-0.360
	(0.179)	(0.189)	(0.226)	(0.251)	(0.269)
Observations	688	688	618	500	461
R^2	0.133	0.138	0.106	0.119	0.122
Adjusted R^2	0.127	0.131	0.099	0.110	0.112
Residual Std. Error	0.774 (df = 682)	0.816 (df = 682)	0.932 (df = 612)	0.907 (df = 494)	0.908 (df = 455)
F Statistic	**20.941***** (df = 5; 682)	**21.774***** (df = 5; 682)	**14.563***** (df = 5; 612)	**13.373***** (df = 5; 494)	**12.655***** (df = 5; 455)

***p<0.05; **p<0.01; ***p<0.001**

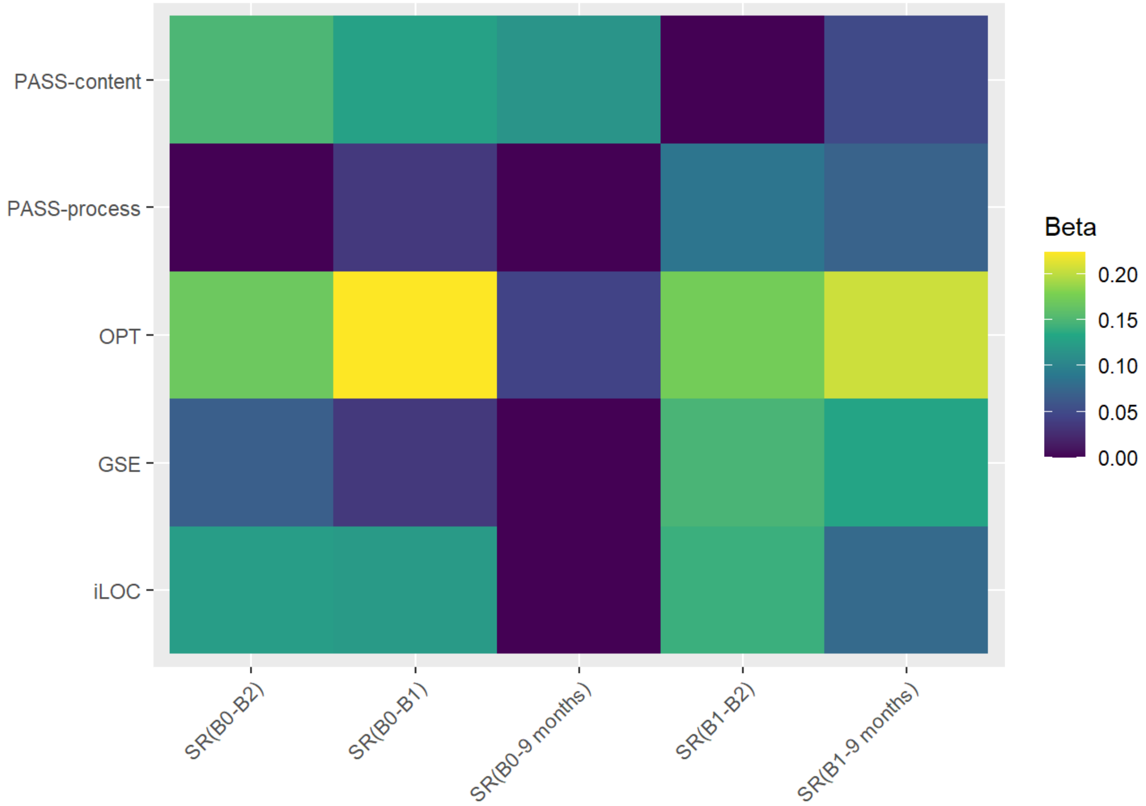

Figure S1. MARP: elastic net analysis without covariates.

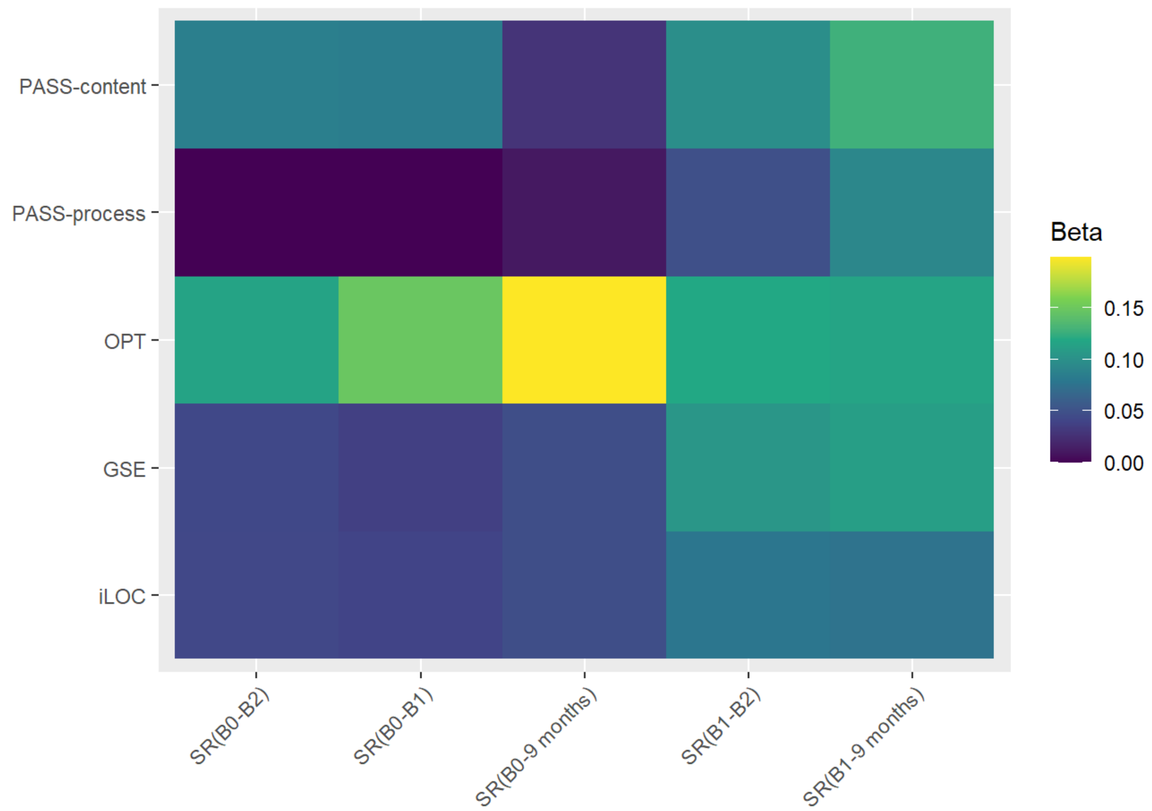

Figure S2. LORA: elastic net analysis without covariates.

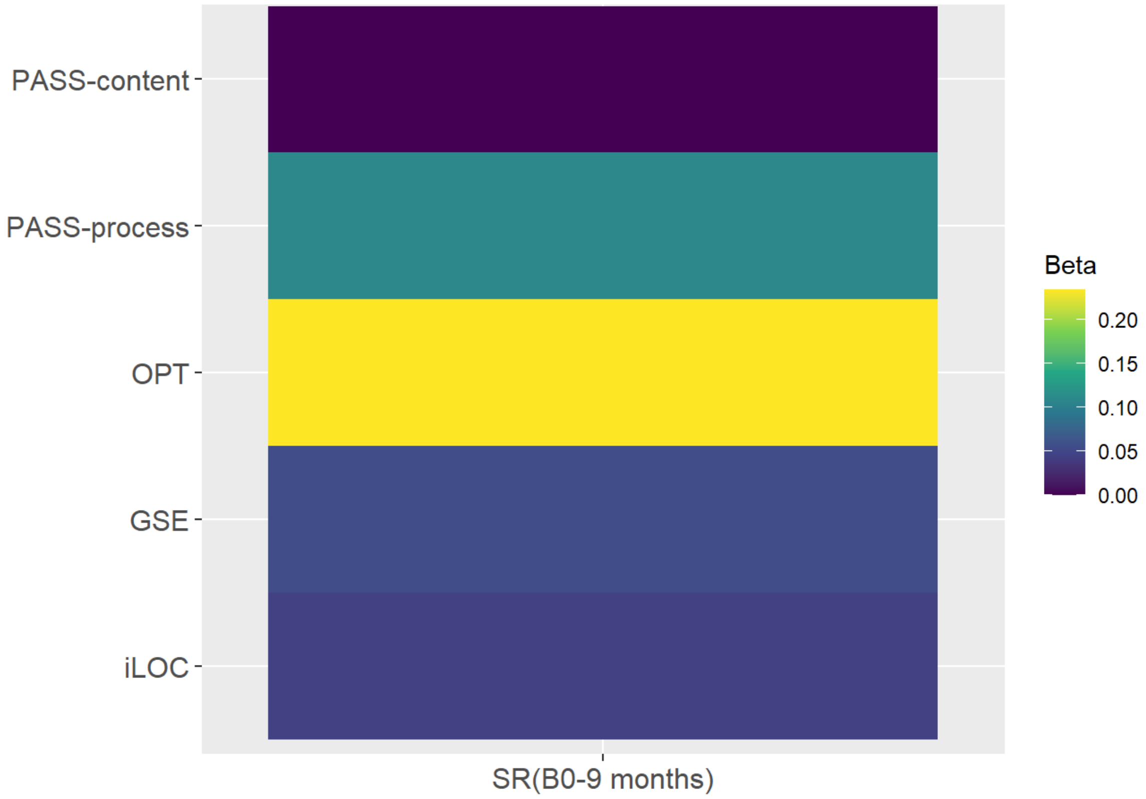

Figure S3. DynaM-OBS: elastic net analysis without covariates.

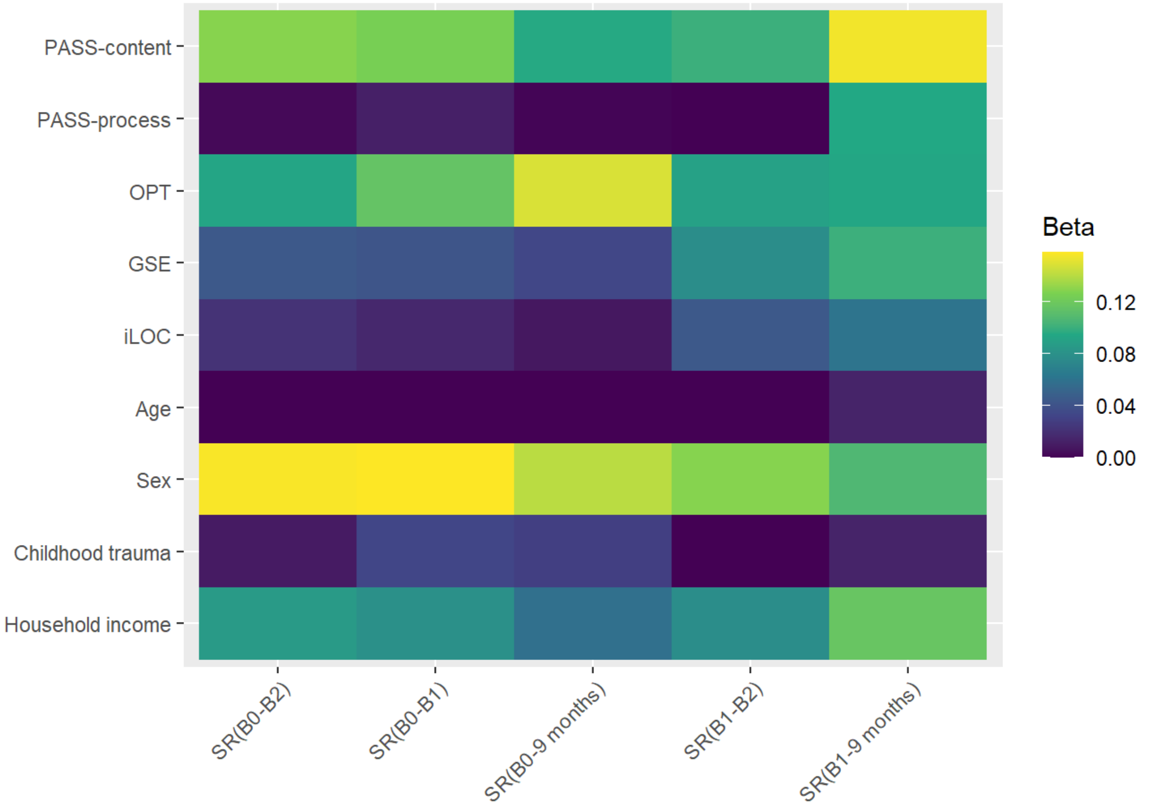

Figure S4. LORA: elastic net analysis with covariates in the 66% of participants with highest stressor exposure (E) from B0 to B2.