MILITARY PSYCHOLOGY
2024, VOL. 36, NO. 4, 393–402
https://doi.org/10.1080/08995605.2023.2188846

Longitudinal measurement invariance and growth curve modeling of psychological resilience across the deployment cycle

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ABSTRACT
The concept of resilience is embedded within military culture and professional identity. To date, temporal changes in individuals' perceptions of their own resilience have not been systematically assessed in highstakes occupational contexts, like the military. The current study examined change in selfreported resilience over time by: (1) examining the longitudinal measurement invariance of the Brief Resilience Scale (BRS); (2) assessing the longitudinal pattern of resilience across a combat deployment cycle; and (3) examining predictors of postdeployment resilience and change in resilience scores across time. U.S. Army soldiers assigned to a combat brigade completed a survey at four time points over the course of a deployment cycle: (a) prior to deployment to Afghanistan; (b) during deployment; (c) immediately following return to home station; and (d) approximately 2–3 months thereafter. The longitudinal measurement invariance of the BRS was established. Growth curve modeling indicated that, on average, self-reported resilience decreased across the deployment cycle, but there was considerable individual variation in the rate of change. Of note, loneliness, as measured during deployment, predicted the rate of change in self-reported resilience over time. Results have implications for the longitudinal analysis of resilience and for the development of interventions with military personnel.

ARTICLE HISTORY
Received 4 November 2022
Accepted 21 February 2023

KEYWORDS
Resilience; brief resilience scale; longitudinal measurement invariance; growth curve modeling; military

What is the public significance of this article?—The current study suggests that the Brief Resilience Scale is a valid questionnaire for measuring psychological resilience over time. Loneliness is an important predictor of changes in individuals' perceptions of their own resilience and should be a target for resilience interventions.

Researchers studying resilience have created a robust body of work implementing multiple approaches to conceptualizing (Britt et al., 2016; Kuntz et al., 2016), measuring (Cheng et al., 2020), and analyzing (Chopik, 2021; Flynn et al., 2021) the construct. Given the diversity of approaches, Britt et al. (2016) offers a useful framework for organizing the approaches for the study of resilience. Specifically, they differentiate between the "demonstration of resilience" and the "capacity for resilience" (p. 380). In the first approach, demonstrated resilience is viewed within the context of individuals' adaptation, such that resilient individuals are marked as those manifesting low scores on negative outcomes or negligible disruption in functioning following exposure to adversity (Bonnano, 2004; Britt et al., 2016; Cheng et al., 2020; Dickstein et al., 2010; Luthar et al., 2000). Resilience is thus a phenomenon that emerges, and is inseparable, from symptom scores or functional impairment indices.

In contrast, the second approach focuses on the capacity for resilience, whereby the construct is viewed and analyzed as a phenomenon separate from symptom variation. Within this approach, the resilience construct may generally be operationalized via multiple characteristics theorized to define resilience (e.g., hardiness, social support; Cheng et al., 2020; Sudom et al., 2014) or it may be operationalized via individuals' perceptions of their ability to adapt to stress (Cheng et al., 2020; Smith et al., 2008). This latter operationalization of resilience inspired the development of self-report instruments, such as the Brief Resilience Scale (BRS; Smith et al., 2008). The BRS has facilitated the examination of self-reported resilience as an explicit predictor of variation in constructs of interest, such as posttraumatic stress, depression, anxiety, and loneliness (Britt et al., 2021; Leys et al., 2021; van der Meulen et al., 2020; Vyas et al., 2016).

This focus on perceptions as a phenomenon distinct from symptomatology suggests that resilience is

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/08995605.2023.2188846

a process amenable to analysis in its own right (Smith et al., 2008). Using this approach, resilience has been deployed as a direct predictor, as a mediator, or as a moderator variable (Britt et al., 2021; Kuhn et al., 2022; Son et al., 2022; van der Meulen et al., 2020). Comparatively fewer studies have examined self-reported resilience capacity itself as the focal outcome (Chiang et al., 2021; Shahan et al., 2022).

Within the military, in particular, resilience has been viewed as a malleable conduit by which personnel adjust to the unique demands of the military context. Indeed, it is this perspective that has driven the significant investment that the military has made into resilience research and training programs (Meredith et al., 2011). Thus, of particular interest here is the study by Shahan et al. (2022), one of the few to use the BRS as an outcome variable in understanding the resilience of individuals with a military background. The study was a cross-sectional examination of civilian emergency services workers, some of whom had experiences of war trauma and/or were military veterans. Results showed that prior exposure to war zone events was associated with *lower* resilience scores, but prior military service was associated with *higher* resilience. Such results are intriguing, but given that war zone events may be experienced by individuals as victims (e.g., refugees) or by individuals who were engaged in their occupational tasks (e.g., veterans), it is unclear what role combat events during a deployment may have on self-reported resilience in service members.

Moreover, there is little data on the longitudinal course of individuals' perceptions of their own resilience across a combat deployment cycle, or with regard to predictors of time-dependent changes in such perceptions. There is also little data on the longitudinal psychometric properties of the BRS. In a prior study, Cabrera et al. (2022) examined the factor structure of the BRS with a military sample, confirming its unidimensional structure, and establishing the cross-sectional measurement invariance across deployed and non-deployed samples. While this earlier study provides essential psychometric evidence for use of the BRS, there is still need to demonstrate the longitudinal stability of the BRS among military personnel.

Finally, there is also a need to identify factors that might predict self-reported resilience during periods of adversity. Previous studies have found key correlates of resilience in cross-sectional research (Leys et al., 2021; Vyas et al., 2016), or significant risk factors of adjustment among personnel serving in the military (Cabrera & Adler, 2021; Cacioppo et al., 2016; Hoge et al., 2004). These correlates and risk factors include psychological distress, loneliness, and occupational stressors (i.e., combat exposure).

Therefore, borrowing from the Britt et al. (2016) capacity-for-resilience approach, and Smith et al.'s (2008) operationalization of resilience via the BRS, the present study aims to advance the literature in three ways. First, we explore the longitudinal measurement invariance of the BRS. Second, we examine the average longitudinal change in individuals' perceptions of their own resilience across a combat deployment cycle, using an exploratory growth curve modeling approach (Chopik, 2021) leveraging the hierarchical linear modeling framework (Willett et al., 1998). Third, we examine how specific factors measured *during* a period of significant adversity (i.e., deployment to a combat zone) impact perceptions of resilience several months after this high-stress period, as well as the rate of change in resilience scores across time. Identifying predictors of resilience and rate of change over time can be used to develop potential intervention targets.

Method

Participants

Survey data were collected from U.S. soldiers serving in a combat brigade that deployed to Afghanistan in the 2013–2014 timeframe, over a period of approximately 11 months, as part of a larger longitudinal study of health and resilience across the deployment cycle (e.g., Adler et al., 2014; Adrian et al., 2018). With regards to survey administration, units were assembled in large meeting areas on post, and surveys were administered by study staff; individuals completed the survey and returned it to study staff the same day they received it. Soldiers were surveyed at four time points: (1) before deployment ("Time 1"); (2) during deployment ("Time 2," five months after Time 1); (3) at immediate re-integration following return to home station ("Time 3," approximately 9 months after Time 1); and (4) approximately 2–3 months after re-integration ("Time 4," approximately 11 months after Time 1). At Time 1, 2734 (89%) provided consent for the survey. Of these participants, 1222 subsequently deployed. These participants comprised the pre-deployment sample. At Time 2, all of these individuals completed a survey in Afghanistan. At Time 3, there were 785 participants (64% follow-up) and at Time 4, there were 538 participants (44% follow-up). Demographic characteristics of the analytic sample for each timepoint are presented in Table 1.

The study was conducted under a human-use protocol approved by the Institutional Review Board of the

Table 1. Demographics across the four measurement occasions.

	Time 1(n = 1222)	Time 2(n = 1222)	Time 3(n = 785)	Time 4(n = 538)
Age				
18–24	648 (53.0%)[a]	615 (50.4%)[b]	386 (49.2%)	250 (46.5%)
25–29	324 (26.6%)	333 (27.3%)	231 (29.5%)	158 (29.4%)
30–39	213 (17.4%)	231 (18.9%)	146 (18.6%)	111 (20.7%)
40 and Older	37 (3.0%)	41 (3.4%)	21 (2.7%)	18 (3.4%)
Gender				
Male	1159 (95.8%)	1154 (95.9%)	745 (95.2%)	520 (96.8%)
Female	51 (4.2%)	49 (4.1%)	38 (4.9%)	17 (3.2%)
Rank				
Jr Enlisted	688 (56.5%)	673 (55.5%)	415 (52.9%)	259 (48.3%)
NCO	381 (31.3%)	392 (32.3%)	284 (36.2%)	213 (39.7%)
Officer/Warrant O.	149 (12.2%)	148 (12.2%)	85 (10.8%)	64 (11.9%)

[a]Percentages are rounded up. Numbers may not sum to total sample size due to missing data.
[b]Changes in proportions for age and rank are normative or consistent with the military promotion tempo, and expected given the 11 months between the first and last assessments for these analyses.

Walter Reed Army Institute of Research (WRAIR). Participants provided informed consent prior to enrollment.

Measures

The outcome in this study was resilience, measured with the six-item Brief Resilience Scale (BRS; Smith et al., 2008). The BRS was designed to assess resilience, conceptualized as the ability to bounce back from stress or adversity. The items were: (1) "I tend to bounce quickly after hard times"; (2) "I have a hard time making it through stressful events"; (3) "It does not take me long to recover from a stressful event"; (4) "It is hard for me to snap back when something happens"; (5) "I usually come through difficult times with little trouble"; and (6) "I tend to take a long time to get over setbacks in my life." The second, fourth, and sixth items were reverse-coded, as they were worded negatively. Items were rated on a five-point scale (1 = *strongly disagree* to 5 = *strongly agree*). In this sample, the BRS demonstrated good reliability: .85 at Time 1; .87 at Time 2; .84 at Time 3; and .89 at Time 4.

Psychological distress was measured via the Patient Health Questionnaire Anxiety and Depression Scale (PHQ-ADS; Kroenke et al., 2016), a validated 16-item scale. Items were rated in terms of the past month on a four-point scale (0 = *not at all* to 3 = *nearly every day*), and summed to create the composite variable. The possible range was from 0 to 48. Measured during deployment, the PHQ-ADS yielded an alpha reliability index of .93.

Loneliness, measured during deployment, was assessed with items adapted from the UCLA 3-Item Loneliness Scale (Hughes et al., 2004). The three items were: "How often to do you feel that you lack companionship?"; "How often to do you feel left out?"; "How often do you feel isolated from others?" The original three-point response scale was modified to reflect four choices (1 = *Never* to 4 = *Always*). Cronbach's alpha for this scale was .84.

Combat exposure, measured during deployment, was comprised of a 22-item scale adapted from the WRAIR Combat Exposure Scale (Hoge et al., 2004; Wright et al., 2013). Sample items included: "Seeing dead bodies or human remains"; "Being wounded/injured"; "Being attacked or ambushed." On each question, the participant was asked the number of times they had experienced that event on combat deployments since 9/11 on a four-point scale (1 = *Never* to 4 = *Five or More Times*). Items were dichotomized (0 = *No* to 1 = *Yes*) and summed to create this predictor. Combat exposure items were considered formative, not reflective, so coefficient alpha for this measure was not calculated (Castro et al., 2012).

In addition, because the risk of cumulative combat exposure is likely to be correlated with age, we also controlled for age. For ease of interpretation, the age covariate was dichotomized into two groups: *18–24* vs. *25 and Older*.

Analytic plan

All analyses were performed in MPlus (v8.6; Muthen & Muthen, 1998–2017) and *R* Statistical Software (v4.1.3; R Core Team, 2022). First, the longitudinal measurement invariance of the BRS scale was assessed. For measurement invariance testing, full-information maximum likelihood, with a robust estimator ("MLR"), was used. The Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Standardized Root Mean Square Residual (SRMR), and Root Mean Square Error of Approximation (RMSEA) were reported. Hu and Bentler (1999) criteria were used to assess model fit.

Table 2. Means, standard deviations, and correlations.

	Mean	SD	Psychological Distress	Loneliness	Combat Exposure	Age	Resilience (T1)	Resilience (T2)	Resilience (T3)	Resilience (T4)
Psychological Distress	6.80	8.14	–							
Loneliness	6.13	2.50	.47***	–						
Combat Exposure	5.84	6.36	.20***	.04	–					
Age	N/A	N/A	.06	.04	.44***	–				
Resilience (T1)	23.90	4.34	−.23***	−.23***	.11**	.10**	–			
Resilience (T2)	23.31	4.34	−.28***	−.35***	.11**	.14***	.53***	–		
Resilience (T3)	23.10	4.29	−.17***	−.27***	.19***	.17***	.46***	.50***	–	
Resilience (T4)	22.75	4.58	−.19***	−.26***	.17**	.13***	.44***	.46***	.64***	–

Note: Coefficients are rounded up. $^{***}p < .001$ $^{**}p < .01$ $^{*}p < .05$.

We also followed recommendations in Putnick and Bornstein (2016) and Vandenberg and Lance (2000).

Second, growth curve modeling, using the *R* package *nlme* (Pinheiro et al., 2022) and restricted maximum likelihood ("REML") estimation, was employed to examine the base longitudinal pattern of resilience across the deployment cycle. We followed recommendations in Willett et al. (1998) and Bliese and Ployhart (2002). In addition, predictors assessed during deployment were included in the growth curve model, to determine which factors were predictive of post-deployment resilience scores and resilience scores across time. To clarify, resilience was measured at the four timepoints. Psychological distress, loneliness, combat exposure, and age were measured at one timepoint (during deployment, Time 2), so these variables represented time-invariant covariates.

As reported earlier, there were missing data. However, we noted no differences on resilience at baseline between completers and non-completers. Specifically, those individuals who dropped out at Time 3 did not differ from those individuals who remained in the study with regards to baseline resilience (t = .46, p = .64); likewise, those individuals who dropped out at Time 4 did not differ from those who remained in the study in terms of baseline resilience (t = .85, p = .40). In addition, we conducted a test of missingness (Little's MCAR Test; Little, 1988) for the dataset. This test did not reject the null hypothesis that data were missing completely at random, $\chi2(303) = 334.47$, $p = .10$.[1] Correlations, means, and standard deviations are presented in Table 2.

Results

Longitudinal measurement invariance

For longitudinal measurement invariance, we selected the bifactor solution identified by Sanchez et al. (2021) in a civilian sample, and replicated by Cabrera et al. (2022) in a military sample. This solution has been shown to provide adequate reliability and across-sample stability in cross-sectional analyses, and is thus the best option for longitudinal tests within a confirmatory framework. The bifactor model was defined with a global resilience factor aligned to all six items, a "positive" factor aligned to the positively-worded items in the scale, and a "negative" factor aligned to the negatively-worded items in the scale. These last two factors were deemed "nuisance factors" (DeMars, 2013; Rodriguez et al., 2016), representing variation tied to item wording that functionally obscured the measurement of the core construct and were not of substantive conceptual interest.

Cross-sectionally, the covariance between the global factor and each of the nuisance factors was set to zero, and the covariance between the nuisance factors was likewise set to zero, consistent with the standard definition of these types of structures (DeMars, 2013; Koch et al., 2017). Longitudinally, the global resilience factors were allowed to covary freely with each other. For the nuisance factors, adjacent time points were allowed to covary. That is, the positive factor at Time 1 was allowed to covary with the positive factor at Time 2; the positive factor at Time 2 was allowed to covary with the positive factor at Time 3; and so on. The same process was applied to longitudinal covariation of the negative factors. The means and variances of the nuisance factors were constrained at all measurement occasions at zero and one, respectively. Covariation indices of residuals for like items over time (e.g., item 1 at Time 1 with item 1 at Time 2) were freely estimated. Collectively, these steps were explicitly taken to: (1) ensure model identification; (2) focus measurement invariance analysis on the factor of interest (i.e., the global resilience factor); and (3) avoid model convergence issues.

Table 3 provides fit measures for longitudinal measurement invariance analyses. The process began by testing a "configural" model, which served as the baseline model for subsequent analyses and which tested the stability of the factor structure across time. Here, we constrained the means and variances of the global resilience factor to zero and one, respectively, for model identification. A poor fit

Table 3. Longitudinal measurement invariance tests of the brief resilience scale.

	χ^2	χ^2 sig	df	χ^2 Diff[a]	χ^2 Diff. Sig.	CFI	TLI	SRMR	RMSEA	RMSEA (90%) CI		RMSEA *p*-val
Config.	294.840	< .001	180	–	–	.985	.977	.028	.023	.018	.027	> .99
Metric	304.370	< .001	195	8.25	.91	.985	.979	.031	.021	.017	.026	> .99
Scalar	326.934	< .001	210	22.40	.10	.984	.980	.032	.021	.017	.026	> .99

[a]Analyses utilized robust maximum likelihood ("MLR"); chi-square difference tests used an adjusted formula.

here would have yielded a hard stop for any subsequent testing. However, as shown on Table 3, the configural model yielded adequate fit to the data. In the next step in this process (i.e., the "metric" model), the factor loadings across time were constrained to be equal, while the variances of the global resilience factor at Time 2, Time 3, and Time 4 were freed for estimation. We then tested whether the metric model showed significant decrement in model fit relative to the configural model. A chi-square difference test between the configural and metric models was found to be non-significant ($\chi^2(15) = 8.25$, $p = .91$), indicating that factor loadings could be relied upon to provide a stable index of the relationship between the items and the resilience construct, thereby establishing metric invariance. Finally, the last step measured a scalar model, wherein the metric model was modified to constrain the item intercepts to be equal across time, while freeing the means of the global resilience factor at Time 2, Time 3, and Time 4. Failure to establish equivalence would have suggested that longitudinal mean change comparisons could not be made, as the item intercepts would have contaminated results (i.e., confusing true change in the factor and item-level random change). Fortunately, a chi-square difference test between the scalar and metric models yielded a non-significant result ($\chi^2(15) = 22.40$, $p = .10$), establishing scalar invariance of the construct across time.

The interfactor correlations across time for the global resilience factor were relatively consistent. The correlations of Time 1 with each subsequent time point were as follows: Time 1 with Time 2 (.71); Time 1 with Time 3 (.69); and Time 1 with Time 4 (.62). The correlation between Time 2 and Time 3 was .68, while the correlation between Time 2 and Time 4 was .61. The correlation between Time 3 and Time 4 was .89, which was likely due to the short time between these two measurement occasions. All correlations were significant at $p < .001$.[2]

These findings, therefore, support the longitudinal measurement invariance of the BRS in this sample.

Unconditional growth curve model

For unconditional analyses, we initially regressed resilience scores on a null model (i.e., with no predictors) to extract the intraclass correlation coefficient (ICC) for resilience. In this case, the ICC value of .49 indicated substantial individual-level variation in resilience and provided justification for the inclusion of a random intercept in the model. Thus, in the first step, the model was defined via a fixed intercept and a random intercept.

In the second step, Time was included as the sole predictor of resilience. The definition of this model allowed for two things: (1) it indicated the fixed or average pattern of change over time; and (2) it provided an opportunity to assess individual-level variation in the rate of growth over time. That is, we identified the average trajectory of change, and assessed how much individuals varied around that common trajectory. Consistent with the third objective of this study, codes for the Time term were defined such that the intercept was set at the last measurement occasion (Biesanz et al., 2004). In addition, the coding for the Time variable was defined to reflect the unequal spacing of measurement occasions.[3] Thus, the model yielded a significant effect for the fixed Time slope, $t(2389) = -7.12$, $p < .001$.[4] This result indicated that individuals' average self-reported resilience decreased significantly over time. Moreover, analyses indicated that inclusion of random slopes for Time improved model prediction significantly, $\chi^2(2) = 24.75$, $p < .001$. This finding suggested that while individuals, on average, declined in their self-reported resilience, the rate of change differed across individuals. Consequently, we re-defined the model to add a fixed slope for Time and a random slope for Time.

In the third step, we examined the longitudinal correlation structure of resilience. The most flexible approach is a general-unstructured correlation structure. This correlation structure does not make *a priori* assumptions about temporal relationships (e.g., that they are equal); it freely estimates the correlations from the data; and it allows greater model flexibility. Fitting a general-unstructured structure yielded significant improvement in model fit, $\chi^2(6) = 15.00$, $p = .02$. With this result, we incorporated this correlation structure into our model.

In the last step defining the level-1 model, we examined changes in the variance of resilience across time. A cursory examination showed relatively little change in the time-dependent variance of resilience. Various formal tests that accounted for heteroscedasticity did not yield significant improvement in model fit.

Therefore, the final unconditional model was defined with a fixed intercept, a random intercept, a fixed term for Time, a random term for Time, and a general-unstructured correlation structure. With completion of these steps, we proceeded to the level-2 conditional model.

Conditional growth curve model

The conditional model added our within-deployment (Time 2) predictors of interest: psychological distress, loneliness, combat exposure, and age.[5]

As noted earlier, the model intercept was set at the last measurement occasion (i.e., the second post-deployment session, or Time 4). As a result, conditional model main effects reflected the predictive value of the selected covariates, measured during deployment, on self-reported resilience, as measured approximately 2–3 months after respondents returned to home station. Results yielded main effects for all covariates.

In exploratory analyses, we examined a series of cross-level interactions (e.g., combat-by-Time, distress-by-Time) and level-2 interactions (e.g., combat-by-distress, loneliness-by-age). There was one significant cross-level interaction, between loneliness and Time, such that individuals reporting higher loneliness during deployment also reported steeper declines in resilience across the deployment cycle. This finding is illustrated in Figure 1. There were no significant level-2 interactions. Results of significant model effects for the conditional growth curve model are presented in Table 4.

To frame the impact of these findings, we leveraged the *EMAtools* package (Kleiman, 2021) in *R* to derive Cohen's *d* estimates for each of our significant effects. Cohen's *d* for psychological distress was −.21; for loneliness, it was −.47; for combat exposure, it was .23; and for age, it was .20. For the main effects, Cohen's d ranged from small to medium. For the cross-level interaction, the effect size was −.09, which denoted a small effect, which was not surprising given the difficulties with detecting interaction effects in field research (McClelland & Judd, 1993).

Discussion

The three objectives for this study were to: (1) assess the longitudinal measurement invariance of the Brief Resilience Scale (BRS); (2) chart the longitudinal course of individuals' self-perceived resilience across a combat deployment cycle; and (3) examine the value of constructs measured *during* deployment in predicting resilience at the last post-deployment measurement occasion and across the full deployment cycle.

Concerning the longitudinal measurement invariance of the BRS, we successfully documented the time-dependent invariance of this measure during a period of time in which there was potential for measurement instability because a significant occupational event had transpired (i.e., a combat deployment). It is clear that the BRS yields construct stability across time. Such stability facilitates future work using this instrument to chart temporal changes in individuals' perceptions of their own resilience (i.e., resilience as an outcome) or to assess temporal covariation of this construct with other constructs of interest (e.g., resilience as a time-varying covariate of combat-related post-traumatic stress). Taken together with cross-sectional results reported in Cabrera et al. (2022), these findings support treating the BRS as invariant in a high-risk occupational context like the military.

To our knowledge, this study is also the first to examine time-dependent changes in soldiers' perceptions of their own resilience across a full combat deployment cycle. Unconditional modeling showed that these

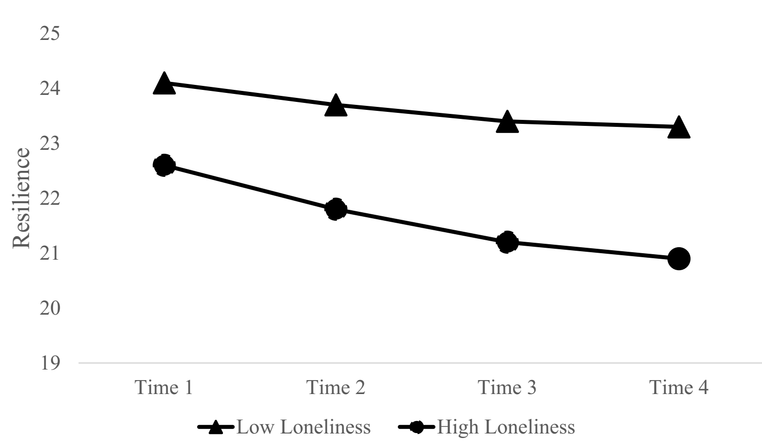

Figure 1. Cross-level interaction between loneliness and time in predicting temporal change in brief resilience scores.

Table 4. Fixed and random parameter estimates for conditional model predicting brief resilience scale scores.

	Estimate	Standard Error	*p*-Value
Fixed Effects			
Intercept	22.77	.15	< .001
Loneliness	−.48	.06	< .001
Psychological Distress	−.07	.02	< .001
Combat Exposure	.10	.03	< .001
Age	1.03	.31	.001
Time	−1.02	.16	< .001
Time x Loneliness	−.16	.07	.03
Variance Estimates for Random Effects			
Intercept	10.64		
Time	6.50		
Correlation (Intercept with Time)	.45		
σ^2	7.20		

Non-significant estimates have been omitted for brevity.

perceptions, on average, weakened significantly over time. This finding suggests that in response to a combat deployment, individuals tend to decrease in their self-reported resilience over time. It is unclear whether this shift is due to: (1) an enhanced awareness of the limits of resilience, given the extreme stress associated with combat; (2) a declining confidence in their own resilience; or (3) a depletion of their actual capacity for resilience.

We also identified several significant predictors of resilience. In terms of rate of change, there was a cross-level interaction between loneliness and time, which showed that individuals who felt more isolated and disconnected during deployment experienced greater declines in resilience across the full deployment cycle. Although the interaction effect was small, this finding was consistent with results reported by Britt et al. (2021), which demonstrated the links among pre-deployment resilience, social connection at post-deployment, and subsequent mental health. In addition, psychological distress predicted resilience 2–3 months after return to home station. It may be that both loneliness and psychological distress undermined or depleted an individual's sense that they can withstand stress and bounce back from adversity.

While there was a decrease in resilience overall, for those individuals most exposed to extreme stress (those reporting higher levels of combat), resilience scores were relatively *higher* 2–3 months following deployment. This novel finding needs to be understood in the context of previous work. Generally, combat exposure has been a risk factor for mental health (Hoge et al., 2004; Thomas et al., 2010; Wright et al., 2013) and, in their study of personnel in emergency services, Shahan et al. (2022) showed that prior war exposure was associated with lower resilience. However, some longitudinal studies have found that combat exposure is not always a significant predictor of deleterious outcomes (Cabrera & Adler, 2021; Russell & Russell, 2019). One possible explanation for finding that combat exposure predicts higher resilience 2–3 months after deployment is the unique context of the military, where deployment to a combat zone is an integral and valued aspect of military life. Viewed through this occupational lens, it may be that individuals with greater combat exposure feel increased confidence in their ability to handle stress. Nevertheless, the general trend over time is for resilience scores to decrease.

Limitations and future research

There are limitations to the present study that warrant mention. First, the list of covariates, while targeting key concepts such as mental distress and loneliness, is based on what was available in the existing survey. Other covariates such as coping styles, previous traumatic exposure, and personality might be useful predictors to examine in future work. In addition, covariates in this study were measured at only one timepoint (during deployment), which did not allow for more complex analyses of change. Second, there were not enough individuals in the sample to stratify by gender. Future studies should examine this variable, and how it relates to resilience. Third, this study only followed participants up to 2–3 months after returning from their deployment. Thus, our ability to observe changes in resilience following deployment was constrained. Additional measurement occasions may reveal the inflection point at which resilience levels recover.

Future research should clarify whether time-varying covariates and alternative longitudinal approaches (e.g., parallel process latent growth modeling) elucidates the process underlying decreases in resilience across the deployment cycle. It may also be useful to assess longitudinal invariance and time-dependent changes in resilience in other groups experiencing significant occupational events, such as emergency personnel operating during a major disaster, expatriate employees relocating to a new culture, or athletes performing in high-stakes competitions. By examining a range of contexts, the construct of resilience may gain value as a tool for researchers and practitioners.

Conclusions and implications

This study extends the resilience literature by establishing the longitudinal measurement invariance of the BRS and focusing on the time-dependent variation of resilience across a period of heightened occupational demand (i.e., deployment to a combat zone). These results demonstrate that deployment to a combat zone may degrade resilience over time. These results also confirm the importance of targeting loneliness as an upstream risk factor influencing changes in resilience. Such targeting could involve training individuals, teams, and leaders in the need to facilitate social connectedness. This approach can leverage the context of high-risk occupations where individuals operate within teams, and leaders are a powerful component of the occupational culture. As a dynamic process, resilience hinges on the strengths and internal resources that individuals *believe* they possess: beliefs that can be measured, that can change across time, and that may empower or hinder individuals as they adjust to adversity. Thus, examining the capacity for resilience as a direct outcome, including its longitudinal characteristics, can be useful for streamlined assessment, self-awareness, and studies testing resilience-building interventions.

Notes

1. For additional information on the treatment of missing data, please refer to the Supplementary Materials.
2. Factor loadings and item intercepts derived from the configural model are provided in the Supplementary Materials.
3. The length of the study was approximately 11 months, from Time 1 to Time 4. With the intercept set at Time 4 (=0), 11 months became the base unit of time measurement of this study and each time code was defined relative to this length of time. Time 1 took place 11 months prior to Time 4, so the Time 1 code was set to −1. Time 3 took place two months prior to Time 4, so this became a fractional quantity of 11 months and its time code was set to −0.18. Time 2 took place 6 months prior to Time 4, so this also became a fractional quantity and its time code was set to −0.55.
4. A test for a second-order, or "curvilinear" slope, did not yield a significant estimate, $t(2388) = .746$, $p = .46$.
5. We assessed the potential for collinearity among the four predictors. Results did not show problematic collinearity using thresholds provided by Kutner et al. (2004) and Shrestha (2020).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

All authors are employees of the U.S. Government. Manuscript preparation was conducted as part of routine assigned duties.

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Data availability statement

Data are not available due to legal restrictions. Authors do not possess legal authority from the U.S. Government to release supporting data to the public.

Disclaimer

The opinions and assertions expressed herein are those of the author(s) and do not reflect the official policy or position of the Uniformed Services University of the Health Sciences, the Walter Reed Army Institute of Research, or the Department of Defense. The investigators have adhered to the policies for protection of human subjects as prescribed in AR 70–25.

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