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Validity of Attention Bias Variability Indices for Posttraumatic Stress Disorder Research: Evidence From Patient Data

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Although initial findings indicated that threat-related attention bias variability (ABV), an index designed to capture dynamic shifts in threat-related attention over time, was positively correlated with the severity of posttraumatic stress disorder (PTSD) symptoms, a recent study relying on simulated data has raised questions regarding the validity and empirical utility of ABV. Specifically, the simulations suggested that core features of reaction time data distinct from threat-related attention bias, such as the reaction time standard deviation and mean, could explicate the reported elevated ABV among samples with PTSD. In the present study, we evaluated these suggestions in 95 PTSD-diagnosed participants. The results showed that ABV significantly and uniquely predicted PTSD symptom severity beyond the predictive value of core reaction time features, $\Delta R^2 = .05–.23$. Some of the predictions stemming from the simulated results were replicated, whereas others were not. Contrary to the conclusion drawn from the simulated data, the results from the current study suggest that ABV is a valid and replicable correlate of PTSD symptom severity.

Attention bias variability (ABV) is a novel reaction time–based index that attempts to capture dynamic fluctuations in threat-related attention bias (see Figure 1 for the ABV formula). ABV correlates with the severity of posttraumatic stress disorder (PTSD) symptoms (Naim et al., 2015) and is thought to reflect trauma-related dysfunction in threat monitoring (Shechner & Bar-haim, 2016). To date, five studies have reported that patients with PTSD exhibit elevated ABV compared to other clinical and healthy groups and that ABV positively correlates with PTSD symptom severity (Badura-Brack et al., 2015; Bardeen, Tull, Daniel, Evenden, & Stevens, 2016; Iacoviello et al., 2014; Naim et al., 2015; Swick & Ashley, 2017). These initial findings are of interest as the field has been struggling to establish valid and reliable behavioral markers for PTSD (Zoladz & Diamond, 2013). Specifically, whereas previous attempts to develop attentional bias indices have yielded measures possessing unacceptable reliability (Price et al., 2015), initial findings have indicated that the ABV index has somewhat improved psychometric properties (Naim et al., 2015).

To establish ABV as a valid behavioral marker of PTSD severity, it is important to verify that ABV predicts a unique portion of the variance in symptom severity not accounted for by other variables. Recently, concerns have been raised about the validity of the ABV index (Kruijt, Field, & Fox, 2016). Specifically, it has been suggested that the ABV index is contaminated by artifacts related to the distribution of reaction times (RTs) from which the index is calculated, which are independent of variability in threat-related attention bias as originally intended (Iacoviello et al., 2014). To evaluate this possibility, Kruijt et al. (2016) systematically manipulated the mean and standard deviation of simulated RT data, two measures presumed unrelated to fluctuations in threat-related attention bias. These simulations highlighted the possibility that a higher ABV could relate to either fluctuations in attention bias magnitude over time, even in the absence of a general attention bias, or to a larger standard deviation and smaller mean of trial RTs regardless of fluctuations in threat-related attention bias. These findings led the authors to conclude that ABV is "unsuitable for empirical research purposes" (Kruijt et al., 2016, p. 19). Such a conclusion would be bolstered considerably if it were replicated in data from real patients. Furthermore, to refute the validity of ABV, it would be important to show that ABV could not predict PTSD severity beyond the suggested artifacts, a feature that could not be validated using simulated data.

Simulations provide potent means to investigate complex phenomena by providing exact formulations and predictions (Lewandowsky, 1993). In the case of ABV, it seems that

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$$AB_i = \overline{RT}_{neutral_i} - \overline{RT}_{threat_i} \quad (1)$$

$$SD_{AB} = \frac{\sqrt{\sum_i (AB_i - \overline{AB})^2}}{n_{AB} - 1} \quad (2)$$

$$ABV = \frac{SD_{AB}}{\overline{RT}} \quad (3)$$

Figure 1. Attention bias variability (ABV) equations used in the current study. ABV was calculated according to equations (1)–(3), as per Naim et al. (2015). First, a trial-by-trial moving average algorithm computed mean reaction times for all successive 10 neutral trial blocks and all successive 10 threat trial blocks. Second, successive attention bias scores (indicated by AB in the equations) were calculated by subtracting the first threat block mean from the first neutral block mean, the second threat block mean from the second neutral block mean, and so on (block number is indicated by the index i in the equations), forming a series of consecutive attention bias scores (see equation 1). Third, the standard deviation of these successive bias scores, excluding the first bias score, was calculated, providing an index of variation in attention bias throughout the session (Equation 2). Finally, the standard deviation score was normalized by dividing it by the participant's mean overall reaction time (Equation 3).

computer simulations could potentially shed light on the contribution of various relevant and irrelevant factors to the value of the index and, thus, better delineate the potential relation between the ABV index to its constituting elements. Nevertheless, simulations hinge on the parameters entered by the experimenter (Lewandowsky, 1993), which do not always conform to those in the real world. A basic assumption in the simulations performed by Kruijt et al. (2016) is that RTs are drawn from a normal distribution, thus permitting independent manipulation of mean RT and standard deviation values. However, manual RT distributions are typically positively skewed (McCormack & Wright, 1964; Ratcliff, 1993; Rouder, Lu, Speckman, Sun, & Jiang, 2005; Swick & Ashley, 2017). Hence, the standard deviation and mean RT are expected to positively correlate. Assuming independence between the standard deviation and mean RT, Kruijt et al. (2016) predicted that increases in mean RT would be associated with decreases in ABV given that mean RT appears only in the denominator of the ABV formula (see Figure 1). In addition, the simulations have also shown that increased standard deviation is positively correlated with the ABV index. However, if the standard deviation and mean RT are positively correlated, then it is not clear whether the pattern of results observed in the simulations would be replicable in real empirical data.

The simulations also suggest that ABV might be increased by both fluctuations in threat-related bias and by basic properties of RTs, which could lead distinct constructs to generate the same ABV patterns. This could render ABV a measure related only to these artifacts or other features unrelated to attentional fluctuations. In the present study, we evaluated this possibility by examining whether ABV predicts PTSD severity beyond the basic properties of RTs, using real data. Specifically, we explored whether ABV could predict PTSD severity beyond mean RT and standard deviations of RTs (i.e., the RT properties suggested by Kruijt et al., 2016). To rule out the possibility that ABV captures other important parameters of the RT distribution except for mean RT and standard deviation, we further examined its prediction beyond other measures that better capture the entire RT distribution rather than a single element of it. First, we calculated a "dummy ABV" index. The formula of the dummy ABV index is identical to that used for the original ABV index. Critically, however, after the data of each participant were recorded, his or her RTs were randomly reassigned for the "threat trials" and "neutral trials" conditions. Then, bias scores were calculated by subtracting trials newly assigned as "neutral" (which could be originally either threat or neutral trials with an equal probability) from trials that were newly assigned as "threat" (which could be originally either threat or neutral trials with an equal probability; see Equation 1 in Figure 1). Thus, the attention bias scores entered into the formula no longer represented threat-related attention bias but rather general characteristics of the RT distribution. We postulated that if ABV merely captures the distribution of RTs, then the original ABV would not have a predictive contribution to PTSD symptom severity beyond the dummy ABV index, which has been derived from the very same RT data used in the original ABV. Second, we examined whether ABV succeeds in predicting PTSD symptom severity beyond the parameters of the ex-Gaussian distribution (Swick & Ashley, 2017). The ex-Gaussian distribution consists of two elements: the Gaussian distribution and an exponential element that represents the rightward tail usually observed in RT distributions. As RT distributions tend to be positively skewed (McCormack & Wright, 1964; Ratcliff, 1993; Rouder et al., 2005; Swick & Ashley, 2017), the estimated parameters of the ex-Gaussian distribution may better delineate the shape of the entire RT distribution. These parameters include mu (the average of the Gauss), sigma (the variance of the Gauss), and tau (the average and variance of the exponential tail).

The purpose of the current study was to examine the validity of the ABV index and its relation to PTSD symptom severity, given recent concerns with the measure. Specifically, we evaluated (a) whether ABV relates to basic RT properties (i.e., if it positively correlates with RT standard deviation and negatively correlates with mean RT) and (b) whether ABV uniquely predicts PTSD symptoms beyond the basic properties of the RT distribution (i.e., RT standard deviation, mean RT, dummy ABV, and the ex-Gaussian parameters mu, sigma, and tau).

Method

Participants and Procedure

The sample comprised 95 participants ($n = 15$ female) with a mean age of 34.92 years ($SD = 11.95$, range: 21–64); it reflected consecutive cases of treatment-seeking patients who contacted our university-based clinic for either research or treatment

purposes between March 2011 and May 2013 and were diagnosed with PTSD based on the Clinician-Administered PTSD Scale (CAPS; Blake et al., 1995). The sample reflected participants who were included in other studies (Naim et al., 2014; Naim et al., 2015) as well as those who did not meet the inclusion criteria for these specific studies but did meet the diagnostic criteria for the current study. All participants provided written informed consent. The Tel Aviv University institutional review board approved the study.

Participants contacted our lab to participate in clinical research on PTSD treatment. After a brief telephone screen, individuals who were potentially eligible were invited to an in-person interview during which PTSD was diagnosed using the CAPS. In addition, participants filled out the self-report PTSD Checklist (PCL; Blanchard, Jones-Alexander, Buckley, & Forneris, 1996) and completed the dot-probe task.

Measures

PTSD. In addition to its diagnostic purposes, the CAPS was also used to evaluate the severity of PTSD symptoms according to criteria in the fourth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-IV*; Blake et al., 1995). The CAPS is used to measure the frequency and intensity of PTSD symptoms using a scale of 0–4, with total scores ranging from 0–136 and higher scores reflecting worse symptom severity. In the current sample, the mean score was 74.97 ($SD = 17.96$). The CAPS has demonstrated strong psychometric properties (Weathers, Ruscio, & Keane, 1999). In the current sample, the Cronbach's alpha value was .95.

The PCL (Blanchard et al., 1996) is a self-report questionnaire composed of 17 items that assess PTSD symptom severity according to *DSM-IV* criteria and are rated on a scale of 1 (*not at all*) to 5 (*extremely*). Total PCL scores range from 17–85, with higher scores reflecting worse symptom severity. The PCL has demonstrated strong psychometric properties (Blanchard et al., 1996). In the current sample, Cronbach's alpha value was .92, and the total PCL mean score was 52.16 ($SD = 12.99$), which is above the accepted clinical cutoff of 43–44 (Blanchard et al., 1996; Freedy et al., 2010).

Dot-probe task. The dot-probe task is commonly used to assess threat-related attention bias (e.g., Wald et al., 2011). In the current study, each trial started with a fixation cross (500 ms), followed by a pair of words (500 ms), one of which was neutral (e.g., line) and one which was threat-related (e.g., dead). The number of letters and frequency of use were matched between the words of each pair. Then a probe (either $<$ or $>$) was displayed until response. The probes appeared with equal probability at either the location of the neutral word (neutral trials) or at the location of the threat word (threat trials). Participants had to discriminate probe type as fast as possible without compromising accuracy. Each participant performed 160 trials.

In analyses, we excluded trials with incorrect response (4.0% of all trials), responses faster than 200 ms ($<$0.1% of all trials), responses slower than 2000 ms (1.8% of all trials), threat trials deviating more than 2.5 standard deviations from a participant's mean RT for threat trials (2.4% of all trials), and neutral trials deviating more than 2.5 standard deviations from a participant's mean RT for neutral trials (4.4% of all trials). Similar trial exclusion procedures have been applied in previous ABV studies (e.g., Naim et al., 2015).

For each participant, we calculated the mean RT and the standard deviation of RTs for neutral trials, threat trials, and across all trials (see Table 1). The traditional attention bias score was calculated for each participant by subtracting the average RT for neutral trials from the average RT for threat trials (e.g., Iacoviello et al., 2014). The split-half internal consistency for the attention bias scores did not reach significance, $r(94) = .05$, $p = .632$. The ABV index, per Naim et al. (2015; Figure 1) was calculated. Briefly, a trial-by-trial moving algorithm calculated successive attention bias scores defined as the difference in RTs between neutral trials and threat trials. The variance of attention bias scores was calculated and then divided by the participant's mean overall RT. The split-half internal consistency for the ABV index in the current sample was significant, $r(94) = .31$, $p = .003$, and comparable in magnitude to previously reported test–retest estimates of ABV (Naim et al., 2015). Finally, based on the entire pool of RTs for correct responses, the estimated parameters of the ex-Guassian distribution were calculated for each participant using the ex-Gauss MATLAB toolbox for fitting the ex-Gaussian distribution to response time data (Zandbelt, 2014).

Data Analysis

We used SPSS (Version 25) for all analyses. The assumptions in Kruijt et al. (2016) were evaluated by calculating Pearson correlation coefficients between (a) standard deviation and ABV and (b) mean RT and ABV. Further, we performed separate hierarchical regression analyses on PTSD symptom severity measured by either the CAPS or PCL. The basic elements describing the RT distribution (i.e., standard deviation, mean RT, dummy ABV, or the parameters of the ex-Gaussian distribution) were entered into the models in Step 1, and ABV was entered into the models in Step 2. These regressions were used to evaluate the unique contribution of ABV to the prediction of PTSD symptom severity. Finally, to assess potential multicollinearity between the predictors in the regression models, we calculated the variation inflation factor (VIF) and computed Spearman correlation coefficients for these predictors. There were no missing data in the current sample.

Results

Do Simulation Results Replicate in Real Data?

In their simulations, Kruijt et al. (2016) found that (a) as standard deviation increases, ABV increases, and (b) as mean RT increases, ABV decreases. In accord with the simulated

Table 1
Mean and Standard Deviation for Reaction Times in the Dot-Probe Task

	Neutral Trials		Threat Trials		All Trials	
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*
Participant *M* RT	660.27	222.51	656.72	216.02	658.26	218.58
Participant *SD* of RTs	139.14	93.85	141.59	95.78	140.38	93.70

Note. $N = 95$. Reaction times are reported in milliseconds. RT = reaction time.

results, the correlation between standard deviation and ABV was significant, $r(94) = .65$, $p < .001$; namely, a larger standard deviation was positively correlated with increased ABV. However, contrary to the simulated results, mean RT was also positively correlated with ABV, $r(94) = .28$, $p = .006$. Further analysis indicated that there was a positive dependency between mean RT and the standard deviation of RTs, $r(97) = .71$, $p < .001$; thus, manipulating standard deviation and RT independently, as was done by Kruijt et al., does not appear to accurately reflect response patterns from real participants. Indeed, when we artificially controlled for participants' standard deviation on the association between mean RT and ABV, the simulated pattern of results emerged with a negative and significant partial correlation, $r(92) = -.34$, $p < .001$.

Does ABV Uniquely Predict PTSD Symptoms Beyond the Basic Properties of the RT Distribution?

In the current sample, ABV was positively correlated with PTSD symptom severity as measured by both CAPS, $r(94) = .34$, $p < .001$, and PCL, $r(94) = .50$, $p < .001$. We further tested whether ABV uniquely predicts symptom severity beyond the basic properties of the RT distribution. To test for potential multicollinearity between predictors, we calculated VIF for each predictor in each regression model (see Tables 3–6). In addition, we calculated Spearman correlation coefficients between the different predictors (see Table 2). As shown, all VIFs ranged from 1.04 to 2.04, indicating that there is no multicollinearity between the predictors (Alin, 2010). In the same vein, the magnitude of the correlation coefficients between the predictors of each model was moderate at most and did not exceed the absolute value of .70, which is typically considered a cutoff for multicollinearity concerns (Dormann et al., 2013).

In Table 3, we present estimated coefficients for the regression models predicting the effects of standard deviation and ABV on PTSD symptoms as measured by the CAPS and PCL. In total, 7.9% of the variance in CAPS scores, $F(1, 92) = 8.20$, $p = .005$, and 8.0% of the variance in PCL scores, $F(1, 92) = 10.15$, $p = .002$, were uniquely accounted for by ABV beyond the variance explained by the standard deviation of RTs. Although the regression model for the PCL scores in Step 1 was significant, $F(1, 93) = 22.07$, $p < .001$, $R^2 = .19$, the regression model for the CAPS scores in Step 1 was not significant, $F(1, 93) = 3.38$, $p = .069$, $R^2 = .035$; namely, standard deviation alone predicted PTSD symptoms assessed by the self-report PCL but not by the clinician-evaluated CAPS.

In Table 4, we present estimated coefficients for the hierarchical regressions on CAPS and PCL scores predicted by mean RT in Step 1 and ABV in Step 2. In total, 10.5% of the variance in CAPS scores, $F(1, 92) = 10.93$, $p = .001$, and 22.6% of the variance in PCL scores were uniquely accounted for by ABV beyond mean RT, $F(1, 92) = 27.81$, $p < .001$. Both regression

Table 2
Spearman Bivariate Correlation Matrix of the Different Variables in the Current Study

	1	2	3	4	5	6	7	8	9	10
1. *SD* of RTs	–	.78**	.11	.46**	.63**	.49**	.12	.28**	.43**	.89**
2. *M* RT		–	.07	.15	.33**	.09	.17	.69**	.56**	.79**
3. CAPS			–	.46**	.28**	.12	.03	−.08	.07	.15
4. PCL				–	.47**	.38**	.01	− .15	.11	.35**
5. ABV					–	.53**	− .01	− .12	.12	.55**
6. Dummy-ABV						–	− .11	− .36**	− .03	.42**
7. Attention bias							–	.16	.07	.11
8. Mu								–	.59**	.24*
9. Sigma									–	.27**
10. Tau										–

Note. $N = 95$. RT = reaction time; CAPS = Clinician-Administered PTSD Scale; PCL = PTSD Checklist; ABV = attention bias variability.
* $p < .05$. ** $p < .01$.

Table 3
Summary of Hierarchical Regression Analyses for Standard Deviations and Attention Bias Variability (ABV) as Predictors of Posttraumatic Stress Disorder (PTSD) Symptoms

DV	Predictor	*B*	*SE*	95% CI	*t*	*df*	*p*	VIF
CAPS								
Step 1	*SD* of RTs	0.04	0.02	[0.01, 0.08]	1.84	93	.069	1.00
Step 2	*SD* of RTs	− 0.01	0.03	[− 0.06, 0.04]	− 0.40	92	.671	1.74
	ABV	188.69	64.14	[56.32, 311.07]	2.86	92	.005	1.74
PCL								
Step 1	*SD* of RTs	0.06	0.01	[0.04, 0.09]	4.69	93	< .001	1.00
Step 2	*SD* of RTs	0.03	0.02	[− 0.01, 0.06]	1.65	92	.103	1.74
	ABV	134.02	42.07	[56.47, 217.56]	3.19	92	.002	1.74

Note. VIF = variation inflation factor; RT = reaction time.

models were not significant in Step 1, Fs(1, 93) = 0.65–2.33, ps = .130–.421. Mean RT alone did not predict the magnitude of PTSD symptoms. Kruijt et al. (2016) simulated the effects of standard deviation and RT separately. Nonetheless, when performing hierarchical regressions in which both RT and standard deviation were entered together in Step 1 and ABV was entered in Step 2, ABV still significantly accounted for 7.5% of the variance in CAPS scores, $F(1, 91) = 7.68$, $p = .007$, and 4.9% of the variance in PCL scores, $F(1, 91) = 6.24$, $p = .014$.

In Table 5, we present estimated coefficients for the hierarchical regressions predicting PTSD symptoms, as assessed using the CAPS and PCL, with the dummy ABV index entered as a predictor in Step 1 and ABV entered into the model in Step 2. In total, 10.9% of the variance in CAPS scores, $F(1, 92) = 11.51$, $p = .001$, and 10.1% of the variance in PCL scores, $F(1, 92) = 12.63$, $p < .001$, were uniquely predicted by ABV beyond the dummy ABV index. The dummy ABV could predict PTSD symptoms assessed by the PCL only, $F(1, 93) = 18.09$, $p < .001$, $R^2 = .16$, and not by the CAPS, $F(1, 93) = 1.43$, $p = .234$, $R^2 = .02$.

In Table 6, we present estimated coefficients for the hierarchical regressions predicting PTSD symptoms, as assessed using the CAPS and PCL, with the estimated parameters of the ex-Gaussian distribution (i.e., mu, sigma, and tau) as predictors in Step 1 and ABV as another predictor in Step 2. In total, 4.7% of the variance in CAPS scores, $F(1, 90) = 4.80$, $p = .031$, and 12.0% of the variance in PCL scores, $F(1, 90) = 14.59$, $p < .001$, were uniquely predicted by ABV beyond the elements of the ex-Gaussian distribution. These elements could significantly account for PTSD symptom severity as assessed by the PCL only, $F(3, 91) = 5.06$, $p = .003$, $R^2 = .14$, and not by the CAPS, $F(3, 91) = 2.39$, $p = .074$, $R^2 = .07$.

Discussion

In the present study, we examined the validity of the ABV index as it correlates with PTSD symptom severity, in light of a recent criticism (Kruijt et al., 2016) that was based on simulated data. Although the simulated data suggested that ABV might fail to provide relevant information about the dynamic fluctuations in threat-related attention bias beyond mean RT and standard deviation, the current results, based on data in patients, suggest that ABV predicts clinician-rated and self-reported PTSD symptom severity beyond the variability explained by mean RT or standard deviation.

Table 4
Summary of Hierarchical Regression Analyses for Mean Reaction Time (RT) and Attention Bias Variability (ABV) as Predictors of Posttraumatic Stress Disorder (PTSD) Symptoms

DV	Predictor	*B*	*SE*	95% CI	*t*	*df*	*p*	VIF
CAPS								
Step 1	*M* RT	0.007	0.008	[− 0.01, 0.24]	0.81	93	.421	1.00
Step 2	*M* RT	− 0.001	0.008	[− 0.02, 0.02]	− 0.12	92	.907	1.09
	ABV	167.55	50.67	[66.90, 268.19]	3.31	92	.001	1.09
PCL								
Step 1	*M* RT	0.009	0.006	[− 0.003, 0.02]	1.53	93	.130	1.00
Step 2	*M* RT	0.001	0.006	[− 0.01, 0.01]	0.18	92	.862	1.09
	ABV	177.64	33.69	[110.73, 244.55]	5.41	92	< .001	1.09

Note. VIF = VIF = variation inflation factor; RT = reaction time.

Table 5
Summary of Hierarchical Regression Analyses for the Dummy Attention Bias Variability (ABV) and the ABV Indices as Predictors of Posttraumatic Stress Disorder (PTSD) Symptoms

DV	Predictor	*B*	*SE*	95% CI	*t*	*df*	*p*	VIF
CAPS								
Step 1	Dummy ABV	47.63	39.77	[− 31.35, 126.60]	1.19	93	.234	1.00
Step 2	Dummy ABV	−55.15	48.37	[− 151.21, 40.90]	− 1.14	92	.257	1.65
	ABV	210.12	61.94	[87.10, 333.13]	3.39	92	.001	1.65
PCL								
Step 1	Dummy ABV	112.88	26.53	[60.19, 165.57]	4.25	93	< .001	1.00
Step 2	Dummy ABV	41.43	32.09	[− 22.31, 105.17]	1.29	92	.200	1.65
	ABV	146.06	41.10	[64.44, 227.69]	3.55	92	< .001	1.65

Note. VIF = VIF = variation inflation factor.

Additionally, ABV predicted a unique and significant portion of the variance in PTSD symptoms beyond variables that better represent the entire RT distribution rather than a single element of it; namely, the dummy ABV index and the parameters of the ex-Gaussian distribution. Whereas in the original ABV, attention bias scores represent the difference between mean RT in neutral and threat trials and thus reflect fluctuations in threat-related attention bias, the dummy ABV was calculated following exactly the same equations but by randomly reassigning trials as neutral or threat regardless of their actual valence. Thus, attention bias scores in the dummy ABV index do not reflect more than the properties of raw RTs for a specific participant. The current results show that ABV predicted PTSD symptom severity while controlling for dummy ABV. In the same vein, ABV uniquely predicted PTSD symptom severity beyond the parameters of the ex-Gaussian distribution, which are derived from all the RTs of correct trials and which better delineate the shape of the RT distribution compared to the general standard deviation and mean of the RT distribution (Swick & Ashley, 2017). These results indicate that even when all RTs of correct trials, without removing outlier RTs as is customary in ABV research (Badura-Brack et al., 2015; Bardeen et al., 2016; Iacoviello et al., 2014; Naim et al., 2015) are included, the ABV index still captures unique and significant portions of PTSD symptom severity not accounted for by RT artifacts.

Taken together, these results suggest that ABV captures, at least in part, the temporal dynamics of attention allocation to

Table 6
Summary of Hierarchical Regression Analyses for Ex-Gaussian Components and the Attention Bias Variability (ABV) Index as Predictors of Posttraumatic Stress Disorder (PTSD) Symptoms

DV	Predictor	*B*	*SE*	95% CI	*t*	*df*	*p*	VIF
CAPS								
Step 1	Mu	− 0.02	0.02	[− 0.06, .01]	− 1.81	91	.074	1.53
	Sigma	0.03	0.06	[− 0.08, 0.13]	0.45	91	.651	1.82
	Tau	0.02	0.01	[0.01, 0.04]	2.03	91	.046	1.36
Step 2	Mu	− 0.02	0.02	[− 0.05, 0.02]	− 0.87	90	.385	1.79
	Sigma	0.02	0.05	[− 0.09, 0.12]	0.34	90	.736	1.83
	Tau	0.01	0.01	[− 0.02, 0.03]	0.41	90	.681	2.05
	ABV	139.12	63.49	[12.98, 265.26]	2.19	90	.031	1.68
PCL								
Step 1	Mu	− 0.02	0.01	[− 0.05, − 0.01]	− 2.17	91	.033	1.53
	Sigma	0.04	0.04	[− 0.03, 0.12]	1.16	91	.25	1.82
	Tau	0.02	0.01	[0.01, .04]	2.89	91	.005	1.36
Step 2	Mu	− 0.01	0.01	[− 0.03, 0.02]	− 0.69	90	.489	1.79
	Sigma	0.04	0.04	[− 0.03, 0.11]	1.02	90	.309	1.83
	Tau	0.002	0.01	[− 0.02, 0.02]	0.30	90	.764	2.05
	ABV	160.66	42.06	[77.10, 244.22]	3.82	90	< .001	1.68

Note. VIF = variation inflation factor.

threat versus neutral stimuli. The ABV index appears to have a predictive power in real data that overcomes the possible artifacts that might inflate its magnitude (Badura-Brack et al., 2015; Bardeen et al., 2016; Iacoviello et al., 2014; Naim et al., 2015; Swick & Ashley, 2017). In addition, the current results suggest that findings about the increased intrapersonal variability in RTs in the context of PTSD (Swick & Ashley, 2017) could not exclusively account for the increased ABV observed among individuals with PTSD.

Though the current results suggest that ABV does capture the temporal dynamics of attention allocation to threat, they also show that irrelevant factors representing the manual RT distribution (i.e., mean RT and standard deviation of RTs, or the parameters of the ex-Gaussian distribution) also affect the magnitude of ABV and account for a significant portion of PTSD symptom severity. Specifically, as indicated by the simulated data, standard deviation positively correlates with ABV independently of fluctuations in attention bias. This implies that ABV captures simultaneously the desired "signal" (i.e., attention bias fluctuations) alongside "noise" (i.e., artifacts stemming from manual responses). These results are in line with previous studies that have shown general increased response variability in PTSD (Swick, Honzel, Larsen, & Ashley, 2013), possibly stemming from a more general executive dysfunction (Aupperle, Melrose, & Paulus, 2012). Thus, future studies could attempt to better characterize the targeted signal over the extant noise. Specifically, studies could inspect the relation between ABV and PTSD symptoms using hierarchical regressions, entering a factor representing the distribution of RTs in Step 1 and ABV in Step 2, as applied in the current study. Such factors could be standard deviation and mean RT, as suggested by Kruijt et al. (2016); intra-individual coefficient of variation, as suggested by Swick and Ashley (2017); the neutral-ABV index, as suggested by Bardeen et al. (2016); or the parameters of the ex-Gaussian distribution or the dummy-ABV measure, as applied in the current study. Such practice could distinguish between the roles of manual response artifacts and ABV in predicting PTSD symptoms. Moreover, this practice could be extended to other indices of dynamic attention bias in PTSD, such as the trial-level bias score (Schäfer et al., 2016) to establish their validity in relation to PTSD and their unique contribution to PTSD symptom severity. In addition, it could be of interest to investigate the interplay between fluctuations in attention bias to threat assessed by ABV and dysfunctions in more general cognitive capacities.

Despite its improved and significant psychometric properties compared to traditional attention bias scores, ABV's internal consistency in the current sample was still quite low. Importantly, the current ABV measurement design was not ideal for estimation of internal consistency given that calculations relied on a small number of trials. It is conceivable that increasing the number of trials would improve the captured internal consistency. In addition to increasing the number of trials in ABV measurements, future studies are encouraged to investigate whether alternative measures of attention bias with acceptable reliability (e.g., Lazarov, Abend, & Bar-Haim, 2016; Waechter, Nelson, Wright, Hyatt, & Oakman, 2014; Zvielli, Bernstein, & Koster, 2015) predict PTSD severity among clinical populations.

Of note, although ABV was sensitive to mean RT, the current results were in the opposite direction compared to the simulated results reported by Kruijt et al. (2016). Whereas the simulations predicted that mean RT would increase as ABV decreased (Kruijt et al., 2016), our data showed that as mean RT increased, ABV increased. This discrepancy between simulated and real data is not surprising given that RTs in the simulations were drawn from a normal distribution in which standard deviation and mean RT are independent, whereas in real data, there is a positive correlation between these two parameters (McCormack & Wright, 1964; Ratcliff, 1993; Rouder et al., 2005; Swick & Ashley, 2017). The current results highlight the need for careful interpretation of simulated data, as conclusions drawn from such simulations may be limited to the veracity of the parameters used by the simulators (Lewandowsky, 1993).

The current data also revealed some unexpected and difficult-to-interpret differences between clinician-rated (CAPS) and self-report (PCL) measures of PTSD symptoms. Specifically, the results suggest that the basic distribution parameters of standard deviation, dummy ABV, and the ex-Gaussian distribution could predict PTSD symptom severity only when assessed by self-report and not when assessed by clinician rating. We had no a priori reason to assume this pattern of results, as PCL and CAPS scores presumably measure the same theoretical construct. Speculatively, however, it could be that there is a common variability element in PCL reporting and manual responses in the dot-probe task, potentially stemming from aberrations in executive function or other cognitive processes and that variability stemming from such a factor is filtered when an external clinician rates symptom severity. Certainly, more research is needed to shed light on the causes of these rater-related differences.

In conclusion, despite the limitations of the ABV index, the current results indicate that it does carry potential as a behavioral marker in the context of PTSD. In the present study, ABV emerged again as a replicable correlate of PTSD that captured a unique portion of the variance in PTSD symptom severity beyond the basic properties of the RT distribution from which the ABV index is derived. As the field has been challenged in establishing behavioral markers for PTSD (Zoladz & Diamond, 2013), the current results hold promise for advancing PTSD research. The current results also suggest that simulated results should be interpreted with caution and validated using real patient data.

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