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ORIGINAL ARTICLE

Does Hopelessness Accurately Predict How Bad You Will Feel in the Future? Initial Evidence of Affective Forecasting Errors in Individuals with Elevated Suicide Risk

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Abstract

Background Forecasts about the future can dictate actions and behaviors performed in the present moment. Given that periods of elevated acute suicide risk often consist of elevated negative affect and hopelessness, individuals during these periods may more bias-prone and make decisions (e.g., suicide attempts) based on inaccurate affective forecasts about their futures (e.g., overestimating future pain/psychiatric symptom severity). The aim of this study was to examine the accuracy of hopelessness in predicting future feelings—an important step for understanding possible decision-making biases that may occur near elevated periods of acute suicide risk.

Methods Secondary longitudinal data analyses were performed on two randomized clinical trial samples of active-duty military personnel (*N*s = 97 and 172) with past-week suicide ideation and/or a lifetime suicide attempt history.

Results Results were consistent with the affective forecasting literature; in both samples, individuals overestimated future pain.

Conclusions Results from two studies offer preliminary evidence for the existence of affective forecasting errors near the time of a suicide attempt/during periods of elevated suicide risk.

Keywords Suicide · Cognitive biases · Heuristics · Affective forecasting · Decision making

Individuals create experiential projections not only for what events will occur in the future but also how future events will make them *feel* (Martin et al., 2020). Unfortunately, these projections (i.e., affective forecasts) are based on error-prone cognitive processes that reliably result in inaccurate predictions, even among healthy individuals (Wilson & Gilbert, 2003, 2005). Although people can accurately predict if they will experience positive or negative emotions, people tend to be inaccurate in predicting the intensity and duration of their future emotions (Gilbert & Wilson, 2007; Gilbert et al., 1998), especially for novel and severe events (e.g. in response to the onset of a disability; Bagenstos & Schlanger, 2007), and those further away in time (Gilber et al., 2002). Several hypotheses have been posited for why these errors (e.g., overestimating the severity of future affect [impact bias]; Buechel et al., 2017) occur, including state emotions affecting future outlooks (i.e., projection biases; Loewenstein et al., 2003), focusing too heavily on a single event (i.e., focalism; Wilson et al., 2000), neglecting one's natural unconscious psychological immune system (i.e., immune neglect; Gilbert et al., 1998; Wilson & Gilbert, 2005), and imagining future events without temporal information (i.e., atemporal representation; Gilbert et al., 2002). Critically, people make decisions and take actions based, in part, on their affective forecasts (Charpentier

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et al., 2016; Sharot & Sunstein, 2020), with evidence suggesting that these predictions guide behavior in the present (DeWall et al., 2016; Mellers & McGraw, 2001). Therefore, people may base their decisions on mispredictions. Although many of these forecasts may yield trivial outcomes (e.g., not experiencing joy after buying a product), for people with extremely negative views of the future (e.g., individuals with major depressive disorder), these forecasts could result in serious outcomes (e.g., suicide attempts).

Although people in general display affective forecasting biases, there are significant differences in how clinical samples (e.g., depressed individuals) display these errors. In the depression literature, researchers have focused on understanding how individuals with depression view both the likelihood that events will happen as well as how these future events will feel (i.e., affective forecasting). Research in this domain finds that what separates dysphoric individuals from control participants is their underestimation of positive future events (i.e., predicting less positive events will occur) as well as their predictions that if these positive future events occur they will experience less positive emotion (Marroquín & Nolen-Hoeksema, 2015). In another study, dysphoric individuals with a history of a suicide attempt were distinguished from dysphoric nonattempters by their overestimation of future negative events and underestimation of future positive affect (Marroquín et al., 2013). These findings suggest that affective forecasting errors have unique contributions to different mental health symptoms.

Hopelessness is a related, but distinct, construct from affective forecasting that is primarily defined by a dysphoric, bleak, and pessimistic view of the future (Beck et al., 1974). Although everyone experiences hopelessness at times during their life, for some, hopelessness is severe. For instance, hopelessness is an essential component of many theories of depression (Abramson et al., 1989, 2002) and is a key symptom of major depressive disorder (American Psychiatric Association [APA], 2013). Similar to affective forecasting errors, hopelessness has been shown to strongly correlate with a lack of positive thoughts about future positive events and a greater amount of anticipated future negative events (MacLeod et al., 2005). These studies mainly utilize the Beck Hopelessness Scale, which has several items that directly relate to affective forecasting (e.g., "When I look ahead to the future, I expect I will be happier than I am now."), suggesting that this scale may be a strong proxy for measuring affective forecasting errors. The most extreme cases of hopelessness may be found in individuals who experience suicidal ideation, with hopelessness being a core feature of many classic and modern theories of suicide (Beck et al., 2006; Klonsky & May, 2014; Van Orden et al., 2010). Suicide attempts often occur during a suicidal crisis (short periods of elevated acute suicide risk), which consists of a sudden and rapid increase in severe negative emotional experiences (Rogers et al., 2017) and is often preceded by a life-stressor (e.g., job loss) or with a life-stressor looming in the future (Dempsey et al., 2018; Hedegaard et al., 2018). Given the existence of hopelessness and stressors being present near the time of a suicide attempt, people likely base their decision to attempt suicide (in part) on predictions they make about their futures. However, by and large, these affective forecasts may be incorrect. This line of reasoning is consistent with the Fluid Vulnerability Theory of Suicide (Rudd, 2006), which posits that stressors can trigger dynamic-interactions between state-based (e.g., hopelessness) and trait-level (e.g., cognitive rigidity) constructs to create suicide risk. Investigating the accuracy of affective forecasting during times of elevated suicide risk is an overlooked aspect of suicide research that warrants further research.

Suicidal individuals may be at increased risk for inaccurate predictions about their futures, including the severity of their psychiatric symptoms (e.g., depression, anxiety, suicidal ideation), because predictions (e.g., extreme hopelessness about the future) are often influenced by a person's current state. People's predictions about the future often follow mood-congruent patterns. Individuals in a current negative mood state will estimate negative events to be more likely to occur, both when the negative mood state was experimentally-induced (DeSteno et al., 2000) or due to a clinically depressive state (Marroquín & Nolen-Hoeksema, 2015). Additionally, there is strong evidence that negative events—such as stressors that occur near the time of a suicide attempt—elicit stronger and more rapid cognitive, emotional, and behavioral reactions than do positive events (Baumeister et al., 2001; Taylor, 1991; Voichek & Novemsky, 2021), and it has been suggested that anticipated negative events might create this effect (Macleod et al., 2005). Dysphoric individuals also rely more heavily on negative emotion for information than non-dysphoric individuals (MacLeod & Byrne, 1996; Marroquín & Nolen-Hoeksema, 2015; Strunk et al., 2006) and feel more confident about their predictions (Andersen & Lyon, 1987). Given that suicidal crises often consist of elevated negative affect and hopelessness, people in crisis may more bias-prone and make decisions (e.g., suicide attempts) based on inaccurate (yet confident) forecasts about their futures (e.g., future mood and symptoms). Therefore, understanding whether hopelessness accurately predicts future feelings is an important step for understanding possible decision-making biases that may be present near the time of a suicidal crisis. If affective forecasting errors (inaccurate predictions about the future) are present in individuals at high risk for suicide, this could indicate that cognitive heuristics and biases may play an important role in suicide-related decisions. Importantly, if such evidence were supported, it could increase the nomological network of suicide theory by connecting it to decision-making theories like prospect theory (Barberis, 2013) and behavioral economics (Thaler, 2018), and thus potentially benefit from interventions within these areas that can help mitigate the influence of heuristics and biases on peoples' decisions (e.g., nudges).

In the following two sets of secondary analyses, we explore the relationship between hopelessness and future mood and/or symptoms using two clinically relevant samples—active-duty military at elevated risk for suicide. Specifically, because hopelessness is significantly associated with affective forecasting errors such as overestimating future negative events (e.g., likelihood of frequency, likelihood of value) and underestimating future positive events (Macleod et al., 2005; Marroquín et al., 2013; Marroquín & Nolen-Hoeksema, 2015), we sought to understand if hopelessness might act as a proxy for affective forecasting and display similar errors in predicting future outcomes. We investigated this question by using data from two randomized clinical trials (Bryan et al., 2017; Rudd et al., 2015). Both samples consisted of military personnel presenting for emergency behavioral health appointments. Each sample collected data on hopelessness, mood, and psychiatric symptoms across multiple time points, allowing for the analysis of hopelessness as a predictor of future mood. We hypothesized that (1) predictions about the future (i.e., hopelessness) would be significantly associated with current mood and psychiatric symptoms but not future mood and symptom severity (i.e., projection bias). This hypothesis was based on evidence that hopelessness is strongly associated with a lack of positive future events (e.g., improved mood and psychiatric condition; Macleod et al., 2005; Marroquín et al., 2013; Marroquín & Nolen-Hoeksema, 2015). In addition, given the findings indicating that events further in the future are more difficult to predict because individuals often imagine future events without temporal information (Gilbert et al., 1998, 2002; Wilson & Gilbert, 2005) we hypothesized that (2) predictive accuracy would be poor, especially from baseline to future time points and (3) overall, forecasts would be less accurate the more temporally distant they were from a future mood or symptom time point. To our knowledge, no prior studies have examined the existence of affective forecasting errors in the context of suicide risk. If forecasting errors are present in periods closely following a suicidal crisis, it is possible that they may be stronger and more impactful during the height of a suicidal crisis. Thus, these findings may offer preliminary insights into relevant decision-making biases close to the time of an attempt. Importantly, if findings support our hypotheses, these results would provide a target for future clinical interventions—helping reduce affective forecasting biases during the course of therapy to help reduce this bias during elevated periods of suicide risk.

Study 1 Methods

Participants and Procedures

The following series of secondary data analyses were performed on a randomized clinical trial sample consisting of 97 active-duty U.S. Army personnel who voluntarily presented with active suicide ideation (i.e., past week) and/or a lifetime suicide attempt history to a military medical clinic for an emergency behavioral health evaluation (Bryan et al., 2017). The only exclusion criterion was a psychiatric or medical condition that would impair mental status and thus preclude informed consent (e.g., acute intoxication, psychosis, mania). Participants were recruited from either the emergency department ($n=8$, 8.2%), a large hospital-based outpatient behavioral health clinic ($n=55$, 56.7%), or smaller behavioral health clinics ($n=34$, 35.1%) located at Fort Carson, CO, from January to December 2013 and January 2015 to February 2016. Participants were mainly male ($n=78\%$) and between the ages of 19 and 53-years-old ($M=25.84$, $SD=5.78$). For a detailed description of participant characteristics, inclusion criteria, and overall study design, see Bryan et al. (2017).

Participants at elevated suicide risk—those who reported active ideation and/or a lifetime suicide attempt history at the emergency department or behavioral health clinic for a voluntary emergency behavioral health appointment—were referred to a research therapist and underwent a suicide risk assessment (via the Beck Scale for Suicidal Ideation, described below). Participants meeting eligibility criteria were randomly assigned to one of three interventions: (1) contract for safety, (2) standard crisis response plan, and (3) enhanced crisis response plan. The contract for safety consisted of suicide risk assessment, supportive listening, provision of crisis resources, referral to a mental health professional, and a verbal contract for safety (Bryan et al., 2017, p. 67). The standard crisis response plan intervention included the same elements of the contract for safety condition except for the verbal contract for safety. Further, the standard crisis response plan included a collaborative discussion between the patient and therapist to identify warning signs for an impending emotional crisis, coping skills, and sources of social support. The enhanced crisis response plan was identical to the standard crisis plan but added an explicit discussion about the patient's reasons for living (see Bryan et al., 2017 for more information regarding intervention details and participant flow).

Posttreatment assessments were conducted at 1-, 3-, and 6-month follow-up time points. During these follow-up time periods, participants were assessed for suicide attempts, suicidal ideation, and mental health service use.

All procedures were approved by the appropriate Institutional Review Board.

Measures

Visual Analogue Mood Scale (VAMS, Bryan, 2019). Two VAMS scales measured degree of anxiety and happiness. The VAMS asked participants to "show how extreme you are experiencing each of the feelings and moods right now, at the current moment." Scores for each item ranged from 0 ("none") to 100 ("extreme"), with the default position of the slider being at 50. The VAMS is a reliable method of ascertaining multiple dimensions of suicide risk (Bryan, 2019) and current mood/affect (e.g., Happiness, Anxiety; Williams et al., 2010). The VAMS was collected at baseline, 1-month, 3-month, and 6-month follow-up time points. Happiness was added to have a positive mood measure in addition to negative mood measures. Evidence for construct validity for these scales was supported by happiness VAMS scores positively correlating with other happiness time points and negatively relating with other mood symptoms (e.g., anxiety). Similarly, anxiety VAMS scores were positively associated with other anxiety time points and positively correlated with other mood symptoms (e.g., depression; see Supplemental Table 2).

Beck Depression Inventory, Second Edition (BDI-II, Beck et al., 1996). The BDI-II is a 21-question, self-report inventory that is a valid and reliable measure of depressive symptoms over the previous two weeks. BDI-II items are summed to provide an overall score of depressive symptom severity. The BDI-II was used to further assess future mood and depressive symptoms. The BDI-II has shown strong validity and reliability (Beck et al., 1996; Dozois et al., 1998). The BDI-II was collected at baseline, 3-month, and 6-month time points. In this study, the BDI-II showed excellent internal reliability at baseline ($\alpha = 0.90$), 3-month ($\alpha = 0.94$), and 6-month (($\alpha = 0.95$).

Beck Hopelessness Scale (BHS, Beck et al., 1974). The BHS is a 20-item, self-report inventory that measures feelings about the future, loss of motivation and expectations over the past week. Items are scored using a true/false scale and summed to provide an overall score for hopelessness. Example items include, "All I can see ahead of me is unpleasantness rather than pleasantness", "It is very unlikely that I will get any real satisfaction in the future." The BHS has shown excellent reliability and validity (Beck et al., 1988a, 1988b; McMillan et al., 2007; Steed, 2001). The BHS was collected at baseline, 3-month, and 6-month time points. In this study, the BHS showed excellent internal consistency ($\alpha = 0.90$), 3-month ($\alpha = 0.91$), and 6-month ($\alpha = 0.91$).

Beck Scale for Suicide Ideation (BSSI; Beck et al., 1988a, 1988b). The BSSI is a 19-item interviewer-administered scale to assess the intensity of a participant's behaviors, attitudes, and attitudes, and plans to enact a suicide attempt. Each item is scored on a 3-point scale; higher scores indicate greater suicide risk. All items are summed to provide a metric of suicide risk severity. In the present study, the BSSI had good internal consistency at baseline ($\alpha = 0.84$), and excellent internal consistency at 3-month ($\alpha = 0.98$), and 6-month ($\alpha = 0.98$).

Data Diagnostics

All study variables showed acceptable skew and kurtosis (i.e., < 1.00; George & Mallery, 2003) except happiness at both baseline (skew $= 1.801$) and 1-month time points (skew $= 1.249$). Happiness was transformed across all time points using a square root transformation, resulting in acceptable skew for both baseline happiness (0.753) and happiness at 1-month follow-up (0.472). To ease interpretation, untransformed variables are used for the descriptive statistics (see Supplemental Table 1). Using z-scores and Mahalanobis Distance (Mahalanobis 1936), no outliers were detected. Multicollinearity was assessed using the variance inflation factor VIF; all values were < 5.0 for all analyses. All variables were centered prior to analyses.

Analytic Strategy

All statistical analyses were performed using R 4.0.2 (R Core Team, 2020) and the *lavaan* package (Roessel, 2012). We chose to employ *lavaan* specifically because of its native integration with R packages that estimate multiple imputation models to handle missingness and maximize statistical power (e.g., *mice*; van Buuren & Groothuis-Oudshoorn, 2011). We used descriptive statistics to report sample characteristics.

To test our first hypothesis that BHS (hopelessness) would be associated with current mood, we conducted one multiple linear regression model and two hierarchical multiple linear regression models. The first model contained baseline BSSI, BDI, and VAMS Happiness and VAMS Anxiousness scores as predictors and baseline BHS scores as the outcome variable. The second and third models controlled for baseline symptoms in Step 1 and then entered current symptoms for the respective time point (i.e., Model 2: 3-month, Model 3: 6-month) in Step 2, with current BHS scores (i.e., 3-month and 6-month, respectively) as the outcome variable. This first hypothesis would be supported if current symptoms were significantly associated with current BHS above and beyond baseline symptoms.

To test our second hypothesis that hopelessness would be unable to predict future symptoms, we then conducted a series of cross-lagged panel models (Little et al., 2007) with nested model comparisons to assess change in fit as a function of model respecification. First, we compared a freely estimated panel model assessing only autoregressive effects to account for stability within each construct (e.g., Adachi & Willoughby, 2015). We compared this to a more parsimonious simplex model to determine whether stability constants for each construct varied as a function of wave. After determining an optimal model to control for stability in our variables over time, we constructed a model with all lagged BHS paths (i.e., baseline, 1-month, 3- month); that is, we allowed earlier scores on BHS to predict all later symptom scores after accounting for within-person stability (i.e., the autoregressive paths). We compared this "full" model using an iterative approach in which successive models restricted the slope of BHS time points and tested for loss of fit using nested comparisons. We employed likelihood ratio tests (e.g., Chou & Bentler, 1990) with a standard decision rule: the more parsimonious model was retained if model fit did not significantly decrease as evidenced by a one-way analysis of variance (ANOVA) test between models. We used multiple fit indices to assess model fit, as considering multiple indices is the preferred approach to ascertain best-fitting models (Chen et al., 2008). Additional fit indices used were the Tucker-Lewis Index (TLI), comparative fit index (CFI), root mean square error of approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Good model fit is indicated by a non-significant chi-square statistic, TLI $\geq$ 0.95, CFI $\geq$ 0.90, and SRMR $\leq$ 0.08 (Hu & Bentler, 1999). Several values for RMSEA have been suggested: $\leq$ 0.06 indicates good fit, $\leq$ 0.08 adequate fit, and $\geq$ 0.10 poor fit (Browne & Cudeck, 1992; Hu & Bentler, 1999; Yu, 2002). If model fit is improved by including BHS into the models, this would suggest that BHS is a significant predictor of future symptom and would be evidence against our hypothesis that people's predictions about the future (e.g., hopelessness) are inaccurate.

Our third hypothesis was that BHS would be more accurate in predicting future symptoms that are closer in time. That is, baseline BHS scores would be better at predicting 1-month symptoms than 6-month symptoms. To assess this hypothesis, we examined correlation coefficients and comparing correlation coefficients using Fisher's r to z transformations.

Due to the high number of analyses, we used the Benjamini–Hochberg procedure to adjust for false discoveries/spurious findings (Benjamini & Hochberg, 1995). A conservative false discovery rate of $Q = 0.05$ was used for all p-values associated with regression coefficient estimates and correlation coefficients.

Study 1 Results

Missing Data

At baseline, there were no missing data for any variables. At 1-month follow-up, all VAMS scales (i.e., anxiousness, happiness) had two missing data points (2.1%). At the 3-month assessment, 32 (33.7%) participants did not provide information on the BHS or BDI, and 31 (32.6%) did not provide data for the VAMS scales. At 6-month follow-up, 57 (60%) participants did not complete the BDI-II or BHS and 55 (57%) did not complete the VAMS scales. Little's missing completely at random (MCAR) was not significant ($p = 0.742$). Further, data were not missing due to condition or study procedures (see Bryan et al., 2017 for more details on dropouts by treatment condition). Missing data were handled in R using the MICE package v. 3.8 (van Buuren & Groothuis-Oudshoorn, 2011). MICE uses a Fully Conditional Specification (FCS) algorithm (see van Buuren & Groothuis-Oudshoorn, 2011), where each continuous variable has its own imputation model using predictive mean matching. Due to the high proportion of missing data, a total of 20 imputations were performed (Enders, 2010; Graham et al., 2007), resulting in complete data across all time points, except for the BDI and BHS, which were not collected at 1-month follow-up.

Main Analyses[1]

Of the sample, 54.7% ($n = 52$) reported a lifetime suicide attempt history.[1] Zero-order correlations, means, standard deviations, and ranges between all self-report measures are presented in Supplemental Table 2. Correlation coefficients between hopelessness and symptoms (i.e., BDI, BSSI, VAMS Anxiety, VAMS Happiness) appeared descriptively strongest when correlating hopelessness with current symptoms ($r_{range} = 0.28$ to 0.78, $r_{mean} = 0.53$, $r_{median} = 0.53$, $n = 12$), followed by symptoms that were 1-month in the future ($r_{range} = 0.38$ to 0.60, $r_{mean} = 0.49$, $r_{median} = 0.49$, $n = 2$), then three months ($r_{range} = 0.02$ to 0.63, $r_{mean} = 0.36$, $r_{median} = 0.34$, $n = 8$), closely followed by the associations between baseline symptoms and 6-month symptoms, which showed the weakest associations ($r_{range} = 0.15$ to 0.43, $r_{mean} = 0.34$, $r_{median} = 0.39$, $n = 4$). Due to the high number of statistical tests conducted, for brevity, results will be summarized in the text.

[1] Our pattern of findings remained the same across all models when examining suicide attempt history as a moderator.

Hierarchical Regressions to Assess the Relationships Between Current Symptoms and Current Hopelessness

See Table 1 for complete statistics. Baseline mood and symptom scores (BDI, VAMS Happiness, BSSI, VAMS Anxiousness) were significantly associated with baseline hopelessness (BHS; $F[4,92] = 30.665$, $p < 0.001$, $R^2 = 0.570$), 3-month ($F[5,91] = 8.308$, $p < 0.001$, $R^2 = 0.336$), and 6-month follow-up ($F[5,91] = 9.427$, $p < 0.001$, $R^2 = 0.303$). The addition of current symptoms significantly increased the variance explained, above and beyond baseline symptoms, for both 3-month ($\Delta R^2 = 0.37$, $p < 0.001$) and 6-month time points (($\Delta R^2 = 0.233$, $p = 0.003$).

Cross-Lagged Panel Models and Nested Model Comparisons

First, we tested two models to assess if autoregressive slopes for each variable varied significantly across time points (see Supplemental Table 3). In one model, slopes were freely estimated over time points and in the simplified model autoregressive estimates were fixed to equality for each variable (i.e., BHS, BDI, BSSI, VAMS Happiness, VAMS Anxiousness). The likelihood ratio model comparison was significant ($F[7,155.36] = 2.44$, $p = 0.017$), indicating a significant loss in model fit. Therefore, the freely estimated panel model was retained for analysis. All subsequent models contained freely estimated autoregressive to account for variance explained by previous time points (i.e., stability within each construct).

Second, we used an iterative approach to test increasingly complex models to investigate if model fit improved by adding lagged BHS variables (e.g., predictions about the future) into the model (see Table 2 and Supplemental Figs. 1, 2). Model 1 contained only dependent variables with no BHS variables predicting any paths. Model 2 added baseline BHS to predict future symptoms and the third contained both baseline BHS and 3-month BHS variables to understand the association between previous BHS scores and future symptoms. Nested model comparisons indicated the likelihood ratio tests comparing Model 1 to Model 2 was significant, $F(14,320.37) = 1.79$, $p = 0.033$, but not Model 2 to Model 3, $p = 0.252$). All fit indices indicated poor model fit (see Table 4 for complete fit statistics). A close investigation of regression paths indicated that baseline BHS was significantly associated with 1-month VAMS Happiness scores in Model 1 ($B = -0.314$, $p = 0.029$) and Model 2 ($B = -0.310$, $p = 0.034$) but was not significantly associated with any other future symptoms. Adding treatment as a covariate did not change the pattern of these results.

Study 1 Discussion

In support of our main hypothesis, current symptom severity was significantly related to current hopelessness, above and beyond baseline symptom severity at every time point. These results are in line with a wealth of research suggesting that hopelessness is positively related to a range of psychiatric symptoms (Alloy et al., 1990; Hallensleben et al., 2019; Metalsky & Joiner, 1992). Patients' BHS scores were significantly associated with future mood and symptom severity in only 2 out of the 24 (8.33%) instances evaluated. The removal of baseline BHS scores did cause a significant loss of fit, indicating that BHS is likely related to future symptoms. However, the addition of these BHS scores (for any time point) did not significantly improve model fit. These findings are in line with our second hypothesis, indicating that hopelessness alone may be a poor predictor of future symptom severity and mood. Together, these findings point to an effect similar to affective forecasting errors, specifically projection bias. That is, in this sample, results indicate that the amount of pain people were experiencing in the current moment adversely influenced the accuracy of their projections about the future.

A few interesting patterns emerged. First, BHS scores were unable to accurately predict symptoms after 3-month follow-up. In addition, as indicated by the correlation statistics, BHS appeared to be a stronger predictor of future symptom/mood when follow-up periods were shorter. That is, early time points (e.g., baseline, 1-month) were related to one another but were less correlated with later time points (e.g., 3-month, 6-month). Scores on all symptom and mood measures dropped over time, indicating that participants were likely to overpredict the severity of their future emotional pain (i.e., impact bias).

Study 2 Methods

Participants and Procedures

The following secondary analyses were conducted on 152 active-duty military personnel participating in a randomized controlled trial (see Rudd et al., 2015).[2] Inclusion criteria included military personnel at elevated suicide risk, specifically having suicidal ideation with intent to die within the past week or a recent suicide attempt (i.e., in the past month). Soldiers were identified during weekly behavioral health treatment team meetings or through daily emergency

[2] A total of 172 participants completed baseline measures and 152 were eligible (Rudd et al., 2012). We used all 172 participants in our analyses and imputed missing data points.

Table 1 Multiple linear and hierarchical regression models testing projection bias in Study 1

Variable	*B*	*SE*	*t*	*p*	R^2	*F*
Baseline hopelessness						
					0.570	29.25(4.92)**
BDI0	0.231	0.038	6.144	< .001		
Happy0	− 0.085	0.018	− 4.664	< .001		
BSSI0	0.343	0.174	1.976	0.016‡		
Anxious0	0.014	0.012	1.210	0.202		
Hopelessness at 3-month follow-up						
					0.336	8.308(5.91)**
BDI0	0.029	0.067	0.434	0.666		
Happy0	0.006	0.032	0.189	0.851		
BSSI0	0.219	0.261	0.836	0.407		
Anxious0	0.010	0.019	0.547	0.587		
BHS0	0.501	0.156	3.212	0.002		
					0.706**	26.576(9.87)**
BDI0	− 0.017	0.051	− 0.324	0.747		
Happy0	0.022	0.027	0.817	0.419		
BSSI0	0.161	0.197	0.819	0.418		
Anxious0	− 0.002	0.014	− 0.116	0.908		
BHS0	0.380	0.127	3.004	0.005		
BDI3	0.237	0.046	5.156	< .001		
Happy3	− 0.036	0.019	− 1.900	0.030‡		
BSSI3	0.166	0.206	0.804	0.427		
Anxious3	− 0.017	0.017	− 0.999	0.324		
Hopelessness at 6-month follow-up						
					0.303	9.427(5.91)**
BDI0	− 0.021	0.089	− 0.235	0.816		
Happy0	0.015	0.048	0.318	0.755		
BSSI0	− 0.339	0.495	− 0.685	0.507		
Anxious0	− 0.004	0.022	− 0.178	0.860		
BHS0	0.597	0.273	2.191	0.047‡		
					0.701**	16.777(9.85)**
BDI0	− 0.048	0.077	− 0.623	0.539		
Happy0	0.006	0.047	0.119	0.907		
Burden0	− 0.150	0.394	− 0.379	0.710		
Anxious0	− 0.008	0.021	− 0.374	0.711		
BHS0	0.610	0.254	1.811	0.006		
BDI6	0.432	0.073	1.896	0.016‡		
Happy6	− 0.016	0.030	− 0.527	0.606		
BSSI6	0.148	0.275	0.539	0.597		
Anxious6	0.013	0.026	0.490	0.630		

Numbers correspond to time point (i.e., 0 = Baseline, 1 = 1-month follow-up, 3 = 3-month follow-up, 6 = 6-month follow-up). Estimates are pooled estimates from 20 imputed data sets using Rubin's (1987) rules

BHS Beck Hopelessness Scale total scores, *BDI* Beck Depression Inventory-II total scores, *Anxious* Visual Analogue Mood Scale for Anxiety, *Happy* Visual Analogue Mood Scale for Happiness, *BSSI* Beck Scale for Suicidal Ideation total scores

**$p < 0.05$. **$p < 0.01$

‡No longer significant after Benjamini–Hochberg correction. Represents pooled statistics from 20 imputed data sets

Table 2 Study 1 nested models comparing different hopelessness time points

Models	χ^2	F	Δ df	CFI	TLI	RMSEA	SRMR
No BHS	197.372**	–	–	0.678	0.566	0.179	0.263
Baseline BHS	175.623**	1.975*	10	0.711	0.568	0.179	0.211
Baseline and T1 BHS	180.259**	1.34	4	0.716	0.555	0.182	0.2

Nested models were compared sequentially and are listed in the order that they were compared. Best fitting model in italics

CFI Comparative fit index, *TLI* Tucker–Lewis Index, *RMSEA* root mean square error of approximation, *SRMR* standardized root mean square residual

*$p < 0.05$. **$p < 0.01$

department reports at Fort Carson, CO, between January 2011 and September 2012. Participants were identified during behavioral health treatment team meetings and emergency department reports. All soldiers admitted to inpatient psychiatric hospitalization for either suicidal ideation with intent to die or for a suicide attempt were referred to research assistants upon discharge to determine if soldiers were eligible to participate in a randomized controlled trial. Soldiers were excluded if they had a current medical or psychiatric condition that would preclude informed consent (e.g., psychosis, mania). Participants were mainly male ($n = 152$; 86.9%) with an average age of 27.53 years ($SD = 6.26$).

Participants were randomly assigned to either brief cognitive behavioral therapy (B-CBT) or treatment as usual. Treatment as usual consisted of individual and group psychotherapy, psychiatric medication, substance abuse treatment, and/or support groups as determined by participants' mental health care providers. B-CBT consisted of treatment as usual as well as 12 outpatient individual psychotherapy sessions, which included an assessment of the recent suicidal episode/attempt, crisis planning, cognitive strategies to reduce suicide-related beliefs and assumptions (e.g., hopelessness, perceived burdensomeness), and relapse prevention. Symptom data (e.g., anxiety, depression, suicidal ideation) were collected from participants at baseline and 3-, 6-, 9-, 12-, 18-, and 24-month follow-up time points. All procedures were approved by the appropriate Institutional Review Board. Due to missing data at later time points, only data up to 9-month follow-up were used for analyses.

Measures

Beck Anxiety Inventory (BAI, Beck et al., 1988a, 1988b). The BAI is a 21-question, self-report measure of anxiety severity. Items in the BAI are composed of a list of common symptoms of anxiety (e.g., "Numbness or tingling" and "Heart pounding/racing") and a 4-point Likert scale for responses ranging from 0 ("Not at all") to 3 ("Severely—it bothered me a lot"). Responses are summed and larger numbers indicate higher overall anxiety; scores of 0–21 = low anxiety, 22–35 = moderate anxiety, and 36 and above = potentially concerning levels of anxiety. The BAI was completed at baseline and 1-, 3-, and 6-month time points. The BAI has been shown to have excellent internal consistency (α = 0.92) and good one week test–retest reliability (0.75). In this sample, the BAI showed excellent reliability at baseline (α = 0.94), time 1 (α = 0.95), time 2 (α = 0.95), and time 3 (α = 0.94).

Beck Scale for Suicide Ideation (BSSI, Beck et al., 1988a, 1988b). In this sample, the BSSI had good reliability at baseline (α = 0.88), time 1 (α = 0.87), and time 2 (α = 0.87), and excellent reliability at time 3 (α = 0.95).

Beck Depression Inventory-II (BDI-II). In this sample, the BDI-II demonstrated excellent reliability at baseline (α = 0.94), time 1 (α = 0.96), time 2 (α = 0.95), and time 3 (α = 0.95).

Beck Hopelessness Scale (BHS, Beck et al., 1974). In this sample, the BHS showed excellent reliability at baseline (α = 0.93), good reliability at time 1 (α = 0.87) and time 2 (α = 0.87), and excellent at time 3 (α = 0.95).

Data Analytic Plan

Descriptive statistics revealed that BSSI scores at 3-, 6-, and 9-month time points were positively skewed. Based on recommendations by Strerne et al. (2009), a square root transformation was performed prior to multiple imputation, reducing skewness for all variables to < 0.5. To identify multivariate outliers, we used Mahalanobis Distance values with a chi-square distribution. Two multivariate outliers were detected. However, because these data points were not extreme and represented less than 2% of the data, these points were retained and used for all analyses (Cohen et al. 2003). Multicollinearity was assessed using VIF; all values were < 5.0 for all models.

Analytic Strategy

We used the same analytic strategy as outlined in the Study 1 Analytic Strategy section to test our hypotheses. The only major differences being that (1) the BAI was used as a measure of anxiety instead of VAMS Anxiousness, (2) all measures were collected across baseline, 3-month, 6-month, and 9-month time points, and (3) no measure of happiness was included in the analyses (was not administered).

Study 2 Results

Missing Data

Of the original sample ($N=171$), $<1\%$ of data was missing from baseline data collection. However, missing data for our independent and dependent variables at subsequent time points ranged from 47.4 to 56.7% at 3-month follow-up, 46.8% to 63.7% at 6-month follow-up, and 50.3 to 78.9% at 9-month follow-up. Little's (MCAR) test was not significant ($p=0.184$). Multiple imputation techniques have been shown to significantly reduce parameter estimate bias for missing longitudinal data, even those with high levels of missing data (e.g., 75%; Newman, 2003). Missing data for dependent and independent variables were addressed using the MICE package v.3.8 (van Buuren & Groothuis-Oudshoorn, 2011); see Study 1 Results for more details. A total of 20 imputations were computed, resulting in complete data for all time points. Rubin's (1987) were used to pool point and SE estimates across all 20 imputed data sets and calculate degrees of freedom for statistical tests and confidence intervals.

Descriptive Statistics and Zero-Order Correlations

Among this sample, 134 (77%) reported a lifetime suicide attempt history.[3] See Supplemental Table 4 for zero-order correlations between all self-report measures and descriptive statistics from the full imputed data. Correlation coefficients between hopelessness and symptoms (i.e., BDI, BAI, BSSI) appeared strongest when correlating hopelessness with current symptoms ($r_{range}=0.36$ to 0.75, $r_{mean}=0.53$, $r_{median}=0.51$, $n=12$), followed by symptoms three months in the future ($r_{range}=0.15$ to 0.38, $r_{mean}=0.25$, $r_{median}=0.22$, $n=9$), then six months ($r_{range}=0.06$ to 0.28, $r_{mean}=0.16$, $r_{median}=0.16$, $n=6$), and associations between baseline symptoms and 9-month symptoms showing the weakest associations ($r_{range}=0.03$ to 0.07, $r_{mean}=0.05$, $r_{median}=0.05$, $n=3$).

[3] Similar to Study 1, our pattern of findings remained the same across all models when examining suicide attempt history as a moderator.

Hierarchical Regressions to Assess the Relationships Between Current Symptoms and Current Hopelessness

Baseline

See Table 3 for all statistics for regression models. Baseline symptom scores (i.e., BDI, BAI, BSSI) were significantly associated with baseline hopelessness (BHS; $F[3,172]=50.581$, $p<0.001$, $R^2=0.469$).

3-Month Follow-Up

Step 1 (baseline BDI, BSSI, BAI, and BHS scores) was significant in predicting 3-month BHS scores ($F[4,171]=8.910$, $p<0.01$, $R^2=0.167$) At Step 2, current BDI, BAI, and BSSI scores were added to the model. The addition of current symptoms in Step 2 led to a statistically significant change the variance explained ($\Delta R^2=0.520$, $p<0.001$).

6-Month Follow-Up

Step 1 (baseline symptoms and hopelessness) was significant, however, no individual predictors significantly predicted 6-month BHS scores. The addition of current symptoms in Step 2 again led to a significant change in the variance explained ($\Delta R^2=0.453$, $p<0.001$).

9-Month Follow-Up

Step 1 (baseline symptoms and hopelessness) was significant, however, similar to the 6-month model, no individual predictor variables significantly predicted 9-month BHS scores. The addition of current symptoms in Step 2 significantly increased the variance explained ($\Delta R^2=0.394$, $p<0.001$).

Cross-Lagged Panel Models and Nested Model Comparisons

First, we tested two models to assess if autoregressive slopes for each variable varied significantly across time points (see Supplemental Table 5). In one model, slopes were freely estimated over time points and in the simplified model, autoregressive estimates were fixed to equality for each variable (i.e., BHS, BDI, BAI, BSI). The likelihood ratio model comparison was not significant ($F[8, 287.66]=0.997$, $p=0.438$), indicating no significant loss in model fit. Therefore, the more parsimonious model simplex model with a constant rate of change was retained for analysis. All subsequent models contained autoregressive paths at fixed slope estimates to account for variance explained by previous timepoints (i.e., stability within each construct).

Table 3 Multiple linear/hierarchical regressions for projection bias in Study 2

BHS baseline

Variable	b	SE	t	p	R^2	F
					0.469	50.581**(3.172)
BDI0	0.221	0.037	6.027	<.001		
BAI0	0.002	0.031	0.062	0.950		
BSSI0	0.195	0.045	4.307	<.001		

BHS 3-month

Variable	*b*	*SE*	*t*	*p*	R^2	*F*
					0.167	8.910** (4.171)
BDI0	− 0.106	0.091	− 1.176	0.252		
BAI0	0.092	0.066	1.392	0.176		
BSSI0	0.195	0.093	2.092	0.0445‡		
BHS0	0.185	0.150	1.236	0.226		
					0.687**	53.140**(7.168)
BDI0	− 0.209	0.066	− 3.154	0.005		
BAI0	0.057	0.043	1.309	0.201		
BSSI0	0.198	0.064	1.160	0.255		
BHS0	0.247	0.101	2.447	0.021		
BDI3	0.298	0.046	6.489	0.000		
BAI3	0.045	0.041	1.103	0.278		
BSSI3	0.086	0.085	1.005	0.324		

BHS 6-month

Variable	*b*	*SE*	*t*	*p*	R^2	*F*
					0.065	3.545 (4.171)
BDI0	− 0.018	0.081	− 0.223	0.825		
BAI0	0.059	0.061	0.966	0.341		
BSSI0	0.116	0.116	1.000	0.329		
BHS0	− 0.040	0.138	− 0.288	0.775		
					0.518**	26.485 (7.168)
BDI0	− 0.087	0.075	− 1.164	0.258		
BAI0	<.001	0.049	0.003	0.997		
BSSI0	− 0.005	0.078	− 0.069	0.946		
BHS0	0.121	0.113	1.069	0.293		

BHS 9-month

Variable	*b*	*SE*	*t*	*p*	R^2	*F*
					0.073	3.629** (4, 171)
BDI0	− 0.020	0.088	− 0.228	0.821		
BAI0	− 0.008	0.083	− 0.102	0.920		
BSSI0	0.044	0.117	0.379	0.709		
					0.467**	21.979**(7,168)
BDI0	− 0.087	0.092	− 0.945	0.358		
BAI0	− 0.027	0.082	− 0.332	0.745		
BSSI0	0.035	0.106	0.331	0.745		
BHS0	0.197	0.159	1.233	0.234		
BDI9	0.186	0.110	1.689	0.116		
BAI9	0.077	0.108	0.709	0.492		
BSSI9	0.231	0.155	1.492	0.153		

Table 3 (continued)

BHS 6-month						
Variable	*b*	*SE*	*t*	*p*	R^2	*F*
BDI6	0.220	0.055	3.968	<.001		
BAI6	0.062	0.048	1.283	0.209		
BSSI6	0.201	0.108	1.865	0.074		

Statistics calculated from 20 imputed data sets

BHS Beck Hopelessness Scale, *BDI* Beck Depression Inventory-II, *BSSI* Beck Scale for Suicidal Ideation, *BAI* Beck Anxiety Inventory. Numbers correspond to time point (i.e., 0 = Baseline. 3 = 3-month follow-up, 6 = 6-month follow-up, 9 = 9-month follow-up)

**$p < 0.05$. **$p < 0.01$

Second, we used an iterative approach to test increasingly complex models to investigate if model fit improved by adding lagged BHS variables (e.g., predictions about the future) into the model (see Table 4 and Supplemental Figs. 3–5). The first model contained only dependent variables with no BHS variables predicting any paths. The second model added baseline BHS to predict future symptoms, the third contained both baseline BHS and 3-month BHS variables, and the fourth model contained all previous BHS variables to understand the association between previous BHS scores and future symptoms. Nested model comparisons indicated that all likelihood ratio tests (testing all possible combinations of models) were non-significant (*p*s > 0.89). Furthermore, only RMSEA indicated good model fit (range = 0.045 to 0.056) whereas all other fit indices indicated poor model fit. A close investigation of regression paths indicated no significant effect of prior BHS scores on subsequent symptoms. When treatment was added as a covariate the pattern of results did not change. Together, these results suggest that the addition of previous BHS variables offered no significant improvement in model fit.

Study 2 Discussion

Ultimately, hopelessness scores were not significantly associated with any future symptoms after statistically controlling for previous symptom scores. Furthermore, the addition of hopelessness did not significantly improve model fit at any time point. Hopelessness was overwhelmingly inaccurate in predicting future symptoms. Notably, patients' baseline hopelessness was significantly correlated with only 2 of 9 future symptom scores, each of which exhibited a weak correlation coefficient. Also similar to Study 1, in this sample, correlations revealed that hopelessness was more poorly related to symptoms and mood the further away they were in time. That is, in this sample, patients' predictions about their futures during their initial appointments were inaccurate estimates of their future symptom severity. Like our previous results, all linear regression models found that current symptom severity was significantly associated with current hopelessness, above and beyond baseline symptom severity for all time points. This finding may again indicate the influence of projection bias, whereby individuals' inaccuracy is largely driven by how badly they currently feel. These results are again in line with the long program of research showing relationships between hopelessness, anxiety, depression, and suicidal ideation (Alloy et al., 1990; Hallensleben et al., 2019; Metalsky & Joiner, 1992).

Table 4 Nested models comparing different hopelessness time points

Models	χ2	*F*	Δ df	CFI	TLI	RMSEA	SRMR
No BHS	137.21*	–	–	0.827	0.794	0.045	0.214
Baseline BHS	131.271**	0.133	9	0.812	0.755	0.049	0.213
Baseline and T1 BHS	128.431**	0.369	6	0.797	0.717	0.053	0.201
Baseline, T1, and T2 BHS	129.315**	0.19	3	0.779	0.68	0.056	0.203

Nested models were compared sequentially and are listed in the order that they were compared. Best fitting model in italics

CFI Comparative fit index, *TLI* Tucker–Lewis Index, *RMSEA* Root mean square error of approximation, *SRMR* Standardized Root Mean Square Residual

$^*p < 0.05$. $^{**}p < 0.01$

General Discussion

Suicidal crises are periods of increased suicide risk characterized by elevated levels of negative affect and marked hopelessness about the future. Although the relationship between suicide and hopelessness has been well-documented, the accuracy of hopelessness in predicting future feelings has received far less attention. A nearly universal human experience is making predictions about how we will *feel* in reaction to future events; however, these affective forecasts are error-prone and can often be inaccurate (Gilbert et al., 1998; Wilson & Gilbert, 2005). Because humans make decisions in the present based on how they expect to feel in the future, examining the accuracy of hopelessness in relation to future symptoms and mood may be important in understanding decision-making processes during the time surrounding periods of increased suicide risk. Thus, the current study represents a preliminary investigation into the accuracy of hopelessness in predicting future mood and symptoms to understand if these relationships share similar characteristics with well-known affective forecasting errors.

Using hopelessness as a proxy for affective forecasting, our hypotheses for this study were generally supported in two samples of military service members presenting to mental health clinics at elevated suicide risk. In both samples, current mood and symptoms were significantly associated with current hopelessness. However, hopelessness was a weak predictor of future symptoms and mood. Furthermore, hopelessness at any time point was most strongly correlated with symptoms that were closest to it in time (e.g., time 1 and time 2) and were less strongly associated with future mood and symptoms the further they were from a given hopelessness time point (e.g., time 1 and time 3). Together, these results offer initial evidence that affective forecasting errors, as measured by the proxy of hopelessness, may be present in patients at increased risk for suicide.

Results from both samples supported our hypothesis that present symptoms and mood would be associated with simultaneous predictions about the future (i.e., hopelessness). Further, the overwhelming majority of predictions about the future (i.e., previous hopelessness scores) were not associated with future mood or symptom scores). Although the lack of significant findings in these latter results do not directly support our second hypothesis, the pattern of our results in combination resemble common affective forecasting errors. Specifically, although hopelessness was largely inaccurate at predicting future mood and symptoms in both samples, it was significantly associated with current symptom severity and mood at all time points. This pattern may reflect the presence of projection bias (Loewenstein et al., 2003). That is, when patients were making predictions about a future event—in this case, their lives in the future—they see their futures being commensurate with how it is at the current time due to their current mood. These results are made more interesting by the fact that all individuals from both studies received treatment aimed at reducing suicidal thoughts and behaviors. Although treatment did not attempt to intervene on hopelessness/affective forecasting errors directly, it is interesting that receiving psychological treatment did not decrease hopelessness nor increase the predictive accuracy of future mood and psychiatric symptoms, and could imply that an additional treatment element that targets affective forecasting errors (or hopelessness) directly is needed to curtail inaccurate predictions. Although these results are preliminary, given that hopelessness is a central variable to suicidal crises (Klonsky & May, 2015; Rogers et al., 2017; Tucker et al., 2016; Van Orden et al., 2010) and thus clinically relevant, future mechanistic studies on hopelessness and its association with mood are warranted.

Patients tended to overestimate that their futures would be poor; however, participants steadily improved on all measures over time regardless of treatment condition. Furthermore, and in support of our third hypothesis, the strength of the association between hopelessness and future mood/symptom severity was generally greater for those closer in time, and weaker for those further away in time. These results are in line with past research finding that negative affective forecasting is more accurate for events that are closer in time (Finkenhauer et al., 2007). In addition, these findings are analogous to several affective forecasting errors. First, these findings may reflect an impact bias, where patients are overestimating the intensity of the negative emotional impact of certain events on their future (Wilson & Gilbert, 2005). Unfortunately, negative predictions tend to produce more biased estimates (Finkenhauer et al., 2007; Gilbert et al., 1998). Important for suicide research, impact bias has been documented not only when predicting future events, but also shortly after events occur (Gilbert et al., 1998). Life stressors are often present around the time of a suicidal crisis, either acting as a catalyst or as a looming negative event (Dempsey et al., 2018; Hedegaard et al., 2018). Due to this, people may make inaccurate predictions about how they will feel in the future in reaction to these events, leading to engagement in suicidal behaviors. These mispredictions may be especially important as several studies have found that predicted rewards and punishments have been shown to determine decision-making behaviors (Charpentier et al., 2016; DeWall et al., 2016; Mellers & McGraw, 2001).

Several explanations for the existence of affective forecasting errors, such as the impact bias, have been posited. One being focalism, which occurs when people focus too much on a current event and neglect all the other events, which impacts how they feel (Wilson et al., 2000). Given that suicide risk has been associated with depression and higher levels of pessimistic views (Beck et al. 2007), people with such characteristics may focus even more heavily on a negative event and predicted negative future events, failing to take into account more positive pieces of information. Another possible mechanism for the misprediction found in our samples could be due to people suffering from immune neglect. Immune neglect is the tendency for individuals to neglect their own unconscious psychological immune system that reduces negative affect over time (Gilbert et al., 1998; Hoerger et al., 2009). This concept is related to hedonic adaption, which posits that people tend to return to an affect baseline following unfavorable (and favorable) circumstances (Frederick & Loewenstein, 1999). In the current study, on average, participants in both samples felt better over time (i.e., decreased psychiatric symptoms, increased happiness), which might suggest that people are unable to predict their own ability to reduce pain and suffering.

Our findings also align with studies showing that biased decisions are more common when estimates are further out in time (Finkenhauer et al., 2007). Construal level theory suggests that distant events are conceptualized more abstractly than events closer in time (Liberman et al., 2002). Therefore, people tend to rely on generalized representations, which often exclude concrete details, leading to inaccurate mental representations (Wesp et al., 2009). In our samples, baseline hopelessness only predicted future mood and symptoms in 2 out of 48 (4.2%) possible instances. Baseline hopelessness, symptom, and mood scores were highest at baseline across both studies. In addition, hopelessness was unable to predict future mood and symptom severity past six months. What these results may suggest is that people near a suicidal crisis (e.g., coming to an appointment or emergency room due to elevated suicide risk) are overestimating how badly they will feel in the future—possibly due to a combination of how bad they are feeling in the moment (i.e., projection bias), an inability to focus on future events that will positively impact their well-being (i.e., focalism), and being unaware of the impact of their psychological immune system (i.e., immune neglect). Although these mechanisms are unable to be tested in the current studies, our findings do show that prior hopelessness (our affective forecast proxy) was a poor predictor of future mood and symptom severity, mainly because participants over-predicted how negative they would feel in the future. Overall, how hopeless participants felt did not predict how bad they felt in the future, especially when they first came in for an appointment. However, what appeared to influence hopelessness/outlooks on the future the most was how they were feeling *in that moment*.

This study leveraged secondary data analyses to conduct an initial investigation into the possible effects of affective forecasting errors within the context of suicide risk. Although there were several strengths of this study—including replication from a second sample, longitudinal study designs, and sampling from a high-risk group in a real-world setting—there are important limitations. First, there was a high percentage of missing data in both samples. Multiple imputation methodologies have been shown to produce reliable estimates even with high proportions of missing data (Lee & Huber, 2011) and is nearly always advisable above ignoring missing data (Janssen et al., 2010; Sterne et al., 2009). However, because of the high number of missing data at distant time points, findings should be interpreted with caution until further replications have been conducted. Second, due to the nature of the study, there was no true control group for studying affective forecasting differences specifically. Although healthy adults with low suicide risk display stable, low levels of symptoms severity, mood, and hopelessness, future studies should include a healthy sample to more precisely understand the degree of prediction error and accuracy. Similarly, due to the design of these studies, we were unable to test possible mechanisms for prediction errors (e.g., focalism). Future studies should examine different hypotheses for the possible existence of affective forecasting errors in samples at increased risk for suicide. Third, although the BHS contains items related to affective forecasting (i.e., predicting future feelings), it is not a stringent measure designed for affective forecasting per se. The BHS includes more than just mood and symptoms, which were our outcome variables in this study. Further, past affective forecasting research most often studies single concrete, predictable events. Conversely, in the current study, we treated continuing to live life as the “event” that the BHS was measuring. Additionally, people's hope about their futures often include factors other than their future mood and symptoms. Hopelessness was assessed across time points that spanned months, yet hopelessness is state-based and influenced by several factors. Future studies should examine potential affective forecasting using intensive measurement strategies (e.g., ecological momentary assessment [EMA]) to better understand how state-based emotions might influence short-term versus long-term predictions. Lastly, all participants received some sort of intervention to reduce suicidal thoughts and behaviors which impacted their hopelessness scores and ability to cope. This limits the generalizability of our findings to individuals not receiving treatment.

Despite these constraints, it is easy to assume that individuals would want to feel less anxiety, depression, and suicidal ideation in their future, and experience more happiness. Furthermore, the relationship between our study variables from all models did not deviate from patterns commonly found in studies investigating affective forecasting errors (Finkenauer et al., 2007; Gilbert et al., 1998). In addition, there may be sizeable complications to truly studying affective forecasting—at least with regards to how it has been traditionally studied—in the context of suicide. Previous research has relied on measuring forecasts about *impending* events (e.g., elections) or highly likely future events (e.g., romantic break-ups between college freshman). Suicide is a rare phenomenon and the catalysts for a suicidal crisis vary widely. Thus, measuring perceptions of a single event (e.g., job loss) before it takes place with an adequately powered sample of individuals at high-risk for suicide may prove challenging. Lastly, this study only collected data on state hopelessness (as measured by the BHS) and did not collect data on enduring trait features. Individuals who are persistently pessimistic about the future may perform differently than those experiencing more state-based, momentary forms of hopelessness. For example, it is possible that people with trait pessimism exhibit *greater* accuracy in their forecasts because they are more prone to future negative affectivity (Chioqueta & Stiles, 2005), especially in reaction to stressors (Bromberger & Matthews, 1996). Future work should examine the possible unique associations between state and trait-based hopelessness and affective forecasting errors. Ultimately, more work and better methodologies are needed to better test the possibility of affective forecasting errors being present in individuals at elevated risk for suicide.

There are several important implications of these results. Our findings suggest that patients at heightened risk for suicide may be overestimating how poorly they will feel in the future. These overestimations are likely greater at the peak of a suicidal crisis, as suicidal crises likely create an environment for decision-making biases to thrive (see Bauer & Capron, 2020). Although further research is needed that more directly investigates affective forecasting errors and associated mechanisms, the mechanisms underlying these errors may represent tangible targets for clinical and public health interventions. For example, if focalism is somewhat responsible for errors in emotional prediction, diary interventions in which people make short lists (e.g., taking less than 3 min) of activities they perform on a typical weekday, the amount of time they take, and the level of enjoyability of those activities could reduce the effects of affective forecasting errors during a suicidal crisis. These simple diary interventions have shown to reduce the effects of impact bias in several studies (Hoerger et al., 2010; Sevdalis & Harvey, 2009). Similarly, current treatments for suicidal behaviors may already contain modules that help reduce focalism and may be one mechanism for their success. For instance, B-CBT (Bryan & Rudd, 2018) frequently focuses on considering a broad range of options other than suicidal behaviors and crisis response planning (Bryan et al., 2017) lists a menu of self-regulatory strategies, thereby helping individuals remember that they have several options available. However, mechanistic and dismantling studies are needed to understand if these strategies target focalism and if these components are effective on their own.

Conclusion

In conclusion, preliminary findings from two samples of active-duty military personnel at elevated risk for suicide suggest that hopelessness is not significantly associated with future mood (e.g., happiness) and psychiatric symptoms (e.g., depressive symptoms). Our results align with the affective forecasting literature and indicate that affective forecasting errors such as projection bias and impact bias may be present during high-risk periods (e.g., behavioral health appointments for suicide risk). In particular, how people feel in the present moment may dictate how they expect to feel in the future; however, these predictions appear to be largely inaccurate. Understanding how affective forecasting may motivate suicidal behaviors proximal to an attempt, as well as what affective forecasting errors may be common during high risk periods, may increase our understanding of proximal suicide risk. Such information may also illuminate tangible targets for interventions and situate this area of suicide research within the larger nomological network of bounded rationality and cognitive heuristics/biases. However, additional studies using direct measurements of affective forecasting are necessary before arriving at such conclusions. Of immediate consequence, our results may offer the following preliminary evidence for health professionals to share with their patients who are experiencing suicidal thoughts: people near the time of a suicidal crisis do not appear to be accurate in their affective forecasts. This thesis may be especially powerful for patients to hear because cognitive biases are an inherent feature in human functioning and does not imply any deficit or weakness within an individual.

Open Science Statement

In line with open research practices, the authors have provided the following information: Both of the experiments were pre-registered (omitted for masked review). Due to the propriety nature of these data and materials, all data and materials will be provided on a case-by-case basis through individual requests. The script for analyses can be found at the [omitted OSF link for blind review].

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Author Contributions BWB developed the manuscript concept. Study design and data collection were performed by CJB and MDR. BWB, MAH, ATK, and LAK performed the data analyses. BWB, MAH, and ATK drafted the paper and DWC and CJC provided critical revisions. All authors approved the final version of the manuscript for submission.

Declarations

Conflict of Interest Brian W. Bauer, Melanie A. Hom, Aleksandr T. Karnick, Caroline J. Charpentier, Lucas A. Keefer, Daniel W. Capron, M. David Rudd, and Craig J. Bryan declare that they have no conflict of interest.

Informed Consent Informed consent was obtained from all individual participants included in the study.

Animal Rights No animals were used in these studies.

References

Abramson, L. Y., Alloy, L. B., Hogan, M. E., Whitehouse, W. G., Gibb, B. E., Hankin, B. L., & Cornette, M. M. (2002). The hopelessness theory of suicidality. *Suicide science* (pp. 17–32). Kluwer Academic Publishers.

Abramson, L. Y., Metalsky, G. I., & Alloy, L. B. (1989). Hopelessness depression: A theory-based subtype of depression. *Psychological Review, 96*(2), 358.

Adachi, P., & Willoughby, T. (2015). Interpreting effect sizes when controlling for stability effects in longitudinal autoregressive models: Implications for psychological science. *European Journal of Developmental Psychology, 12*(1), 116–128. https://doi.org/10.1080/17405629.2014.963549

Alloy, L. B., Kelly, K. A., Mineka, S., & Clements, C. M. (1990). Comorbidity of anxiety and depressive disorders: a helplessness-hopelessness perspective.

American Psychiatric Association, & American Psychiatric Association. (2013). Diagnostic and statistical manual of mental disorders: DSM-5.

Andersen, S. M., & Lyon, J. E. (1987). Anticipating undesired outcomes: The role of outcome certainty in the onset of depressive affect. *Journal of Experimental Social Psychology, 23*(5), 428–443. https://doi.org/10.1016/0022-1031(87)90039-4

Bagenstos, S. R., & Schlanger, M. (2007). Hedonic damages, hedonic adaptation, and disability. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.928883

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives, 27*(1), 173–196.

Bauer, B. W., & Capron, D. W. (2020). How behavioral economics and nudges could help diminish irrationality in suicide-related decisions. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science, 15*(1), 44–61. https://doi.org/10.1177/1745691619866463

Baumeister, R. F. (1990). Suicide as escape from self. *Psychological Review, 97*(1), 90–113. https://doi.org/10.1037/0033-295X.97.1.90

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology, 5*(4), 323–370. https://doi.org/10.1037/1089-2680.5.4.323

Baumeister, R. F., Zell, A. L., & Tice, D. M. (2007). How emotions facilitate and impair self-regulation. *Handbook of Emotion Regulation*, 408–426.

Beck, A. T., Brown, G., Berchick, R. J., Stewart, B. L., & Steer, R. A. (2006). Relationship between hopelessness and ultimate suicide: A replication with psychiatric outpatients. *Focus, 4*(2), 291–296. https://doi.org/10.1176/foc.4.2.291

Beck, A. T., Epstein, N., Brown, G., & Steer, R. A. (1988a). An inventory for measuring clinical anxiety: Psychometric properties. *Journal of Consulting and Clinical Psychology, 56*(6), 893–897. https://doi.org/10.1037//0022-006x.56.6.893

Beck, A. T., Steer, R. A., & Brown, G. K. (1996). *Beck depression inventory (BDI-II)* (Vol. 10, p. 13). Pearson.

Beck, A. T., Steer, R. A., & Ranieri, W. F. (1988b). Scale for suicide ideation: Psychometric properties of a self-report version. *Journal of Clinical Psychology, 44*(4), 499–505.

Beck, A. T., Weissman, A., Lester, D., & Trexler, L. (1974). The measurement of pessimism: The hopelessness scale. *Journal of Consulting and Clinical Psychology, 42*(6), 861–865. https://doi.org/10.1037/h0037562

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological), 57*(1), 289–300.

Brezo, J., Paris, J., & Turecki, G. (2006). Personality traits as correlates of suicidal ideation, suicide attempts, and suicide completions: A systematic review. *Acta Psychiatrica Scandinavica, 113*(3), 180–206. https://doi.org/10.1111/j.1600-0447.2005.00702.x

Bromberger, J. T., & Matthews, K. A. (1996). A longitudinal study of the effects of pessimism, trait anxiety, and life stress on depressive symptoms in middle-aged women. *Psychology and Aging, 11*(2), 207.

Brosch, T., Scherer, K. R., Grandjean, D., & Sander, D. (2013). The impact of emotion on perception, attention, memory, and decision-making. *Swiss Medical Weekly, 143*, w13786. https://doi.org/10.4414/smw.2013.13786

Brown, G. K., Beck, A. T., Steer, R. A., & Grisham, J. R. (2000). Risk factors for suicide in psychiatric outpatients: A 20-year prospective study. *Journal of Consulting and Clinical Psychology, 68*(3), 371–377. https://doi.org/10.1037//0022-006X.68.3.371

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research, 21*(2), 230–258.

Bryan, C. J. (2019). A preliminary validation study of two ultra-brief measures of suicide risk: The Suicide and Perceived Burdensomeness Visual Analog Scales. *Suicide and Life-Threatening Behavior, 49*(2), 343–352.

Bryan, C. J., Mintz, J., Clemans, T. A., Leeson, B., Burch, T. S., Williams, S. R., Maney, E., & Rudd, M. D. (2017). Effect of crisis response planning vs. contracts for safety on suicide risk in U.S. Army Soldiers: A randomized clinical trial. *Journal of Affective Disorders, 212*, 64–72. https://doi.org/10.1016/j.jad.2017.01.028

Bryan, C. J., & Rudd, M. D. (2018). *Brief cognitive-behavioral therapy for suicide prevention*. Guilford Publications.

Buechel, E. C., Zhang, J., & Morewedge, C. K. (2017). Impact bias or underestimation? Outcome specifications predict the direction of affective forecasting errors. *Journal of Experimental Psychology: General, 146*(5), 746.

Cavanagh, J. T. O., Carson, A. J., Sharpe, M., & Lawrie, S. M. (2003). Psychological autopsy studies of suicide: A systematic review. *Psychological Medicine, 33*(3), 395–405. https://doi.org/10.1017/s0033291702006943

Chang, H. B., Munroe, S., Gray, K., Porta, G., Douaihy, A., Marsland, A., Brent, D., & Melhem, N. M. (2019). The role of substance use, smoking, and inflammation in risk for suicidal behavior. *Journal of Affective Disorders, 243*, 33–41. https://doi.org/10.1016/j.jad.2018.09.005

Charpentier, C. J., De Neve, J. E., Li, X., Roiser, J. P., & Sharot, T. (2016). Models of affective decision making: How do feelings predict choice? *Psychological Science, 27*(6), 763–775.

Chen, F., Curran, P. J., Bollen, K. A., Kirby, J., & Paxton, P. (2008). An empirical evaluation of the use of fixed cutoff points in RMSEA test statistic in structural equation models. *Sociological Methods & Research, 36*(4), 462–494.

Chioqueta, A. P., & Stiles, T. C. (2005). Personality traits and the development of depression, hopelessness, and suicide ideation. *Personality and Individual Differences, 38*(6), 1283–1291.

Chou, C., & Bentler, P. M. (1990). Model modification in covariance structure modeling: A comparison among likelihood ratio, Lagrange multiplier, and Wald tests. *Multivariate Behavioral Research, 25*(1), 115–136. https://doi.org/10.1207/s/15327906mbr2501_13

Cohen, L. J., Ardalan, F., Yaseen, Z., & Galynker, I. (2018). Suicide crisis syndrome mediates the relationship between long-term risk factors and lifetime suicidal phenomena. *Suicide & Life-Threatening Behavior, 48*(5), 613–623. https://doi.org/10.1111/sltb.12387

Conaghan, S., & Davidson, K. M. (2002). Hopelessness and the anticipation of positive and negative future experiences in older parasuicidal adults. *The British Journal of Clinical Psychology, 41*(Pt 3), 233–242. https://doi.org/10.1348/014466502760379208

Conner, K. R., Bridge, J. A., Davidson, D. J., Pilcher, C., & Brent, D. A. (2019). Metaanalysis of mood and substance use disorders in proximal risk for suicide deaths. *Suicide & Life-Threatening Behavior, 49*(1), 278–292. https://doi.org/10.1111/sltb.12422

Dempsey, C., Benedek, D., Nock, M., Ng, T., Riggs, C., Aliaga, P., Caulfield, N., & DeStefano, S. (2018). *Recent stressful experiences and resilience among US Army soldiers at risk for suicide.* Poster presented at the Anxiety and Depression Association of America in Washington, DC.

DeSteno, D., Petty, R. E., Wegener, D. T., & Rucker, D. D. (2000). Beyond valence in the perception of likelihood: The role of emotion specificity. *Journal of Personality and Social Psychology, 78*(3), 397–416. https://doi.org/10.1037//0022-3514.78.3.397

DeWall, C. N., Baumeister, R. F., Chester, D. S., & Bushman, B. J. (2016). How often does currently felt emotion predict social behavior and judgment? A meta-analytic test of two theories. *Emotion Review, 8*(2), 136–143.

Dozois, D. J., Dobson, K. S., & Ahnberg, J. L. (1998). A psychometric evaluation of the Beck Depression Inventory-II. *Psychological Assessment, 10*(2), 83.

Enders, C. K. (2010). *Applied missing data analysis*. Guilford Press.

Finkenauer, C., Gallucci, M., van Dijk, W. W., & Pollmann, M. (2007). Investigating the role of time in affective forecasting: Temporal influences on forecasting accuracy. *Personality and Social Psychology Bulletin, 33*(8), 1152–1166. https://doi.org/10.1177/0146167207303021

Frederick, S., & Loewenstein, G. (1999). 16 Hedonic adaptation. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Well-being. The foundations of Hedonic Psychology* (pp. 302–329). Russell: Sage.

George, D., & Mallery, P. (2003). SPSS for Windows step by step: Answers to selected exercises. *A Simple Guide and Reference, 63*, 1461–1470.

Gilbert, D. T., Gill, M. J., & Wilson, T. D. (2002). The future is now: Temporal correction in affective forecasting. *Organizational Behavior and Human Decision Processes, 88*(1), 430–444.

Gilbert, D. T., Pinel, E. C., Wilson, T. D., Blumberg, S. J., & Wheatley, T. P. (1998). Immune neglect: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology, 75*(3), 617–638. https://doi.org/10.1037/0022-3514.75.3.617

Gilbert, D. T., & Wilson, T. D. (2007). Prospection: Experiencing the future. *Science, 317*(5843), 1351–1354. https://doi.org/10.1126/science.1144161

Graham, J. W., Olchowski, A. E., & Gilreath, T. D. (2007). How many imputations are really needed? Some practical clarifications of multiple imputation theory. *Prevention Science, 8*(3), 206–213.

Hallensleben, N., Glaesmer, H., Forkmann, T., Rath, D., Strauss, M., Kersting, A., & Spangenberg, L. (2019). Predicting suicidal ideation by interpersonal variables, hopelessness and depression in real-time. An ecological momentary assessment study in psychiatric inpatients with depression. *European Psychiatry, 56*(1), 43–50.

Hedegaard, H., Curtin, S. C., & Warner, M. (2018). Suicide mortality in the United States, 1999–2017. *NCHS Data Brief, 330*, 1–8.

Hoerger, M. (2012). Coping strategies and immune neglect in affective forecasting: Direct evidence and key moderators. *Judgment and Decision Making, 7*(1), 86–96.

Hoerger, M., Quirk, S. W., Chapman, B. P., & Duberstein, P. R. (2012). Affective forecasting and self-rated symptoms of depression, anxiety, and hypomania: Evidence for a dysphoric forecasting bias. *Cognition & Emotion, 26*(6), 1098–1106. https://doi.org/10.1080/02699931.2011.631985

Hoerger, M., Quirk, S. W., Lucas, R. E., & Carr, T. H. (2009). Immune neglect in affective forecasting. *Journal of Research in Personality, 43*(1), 91–94. https://doi.org/10.1016/j.jrp.2008.10.001

Hoerger, M., Quirk, S. W., Lucas, R. E., & Carr, T. H. (2010). Cognitive determinants of affective forecasting errors. *Judgment and Decision Making, 5*(5), 365.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55.

Janssen, K. J. M., Donders, A. R. T., Harrell, F. E., Vergouwe, Y., Chen, Q., Grobbee, D. E., & Moons, K. G. M. (2010). Missing covariate data in medical research: To impute is better than to ignore. *Journal of Clinical Epidemiology, 63*(7), 721–727. https://doi.org/10.1016/j.jclinepi.2009.12.008

Klonsky, E. D., & May, A. M. (2014). Differentiating suicide attempters from suicide ideators: A critical frontier for suicidology research. *Suicide and Life-Threatening Behavior, 44*(1), 1–5.

Klonsky, E. D., & May, A. M. (2015). The Three-Step Theory (3ST): A new theory of suicide rooted in the "Ideation-to-Action" framework. *International Journal of Cognitive Therapy, 8*(2), 114–129. https://doi.org/10.1521/ijct.2015.8.2.114

Lee, J. H., & Huber, J. H. (2011). Multiple imputation with large proportions of missing data: How much is too much? *United Kingdom Stata Users' Group Meetings, 2011*, 23.

Liberman, N., Sagristano, M. D., & Trope, Y. (2002). The effect of temporal distance on level of mental construal. *Journal of Experimental Social Psychology, 38*(6), 523–534. https://doi.org/10.1016/S0022-1031(02)00535-8

Little, T. D., Preacher, K. J., Selig, J. P., & Card, N. A. (2007). New developments in latent variable panel analyses of longitudinal data. *International Journal of Behavioral Development, 31*(4), 357–365.

Loewenstein, G., & Lerner, J. S. (2003). The role of affect in decision making. *Handbook of Affective Science*, pp. 619–642.

Loewenstein, G., O'Donoghue, T., & Rabin, M. (2003). Projection bias in predicting future utility. *The Quarterly Journal of Economics, 118*(4), 1209–1248. https://doi.org/10.1162/003355303322552784

MacLeod, A. K., & Byrne, A. (1996). Anxiety, depression, and the anticipation of future positive and negative experiences. *Journal of Abnormal Psychology, 105*(2), 286–289. https://doi.org/10.1037//0021-843x.105.2.286

MacLeod, A. K., Pankhania, B., Lee, M., & Mitchell, D. (1997). Parasuicide, depression and the anticipation of positive and negative future experiences. *Psychological Medicine, 27*(4), 973–977. https://doi.org/10.1017/s003329179600459x

MacLeod, A. K., Rose, G. S., & Williams, J. M. G. (1993). Components of hopelessness about the future in parasuicide. *Cognitive Therapy and Research, 17*(5), 441–455. https://doi.org/10.1007/BF01173056

MacLeod, A. K., Tata, P., Tyrer, P., Schmidt, U., Davidson, K., & Thompson, S. (2005). Hopelessness and positive and negative future thinking in parasuicide. *The British Journal of Clinical Psychology, 44*(Pt 4), 495–504. https://doi.org/10.1348/014466505X35704

Marroquín, B., & Nolen-Hoeksema, S. (2015). Event prediction and affective forecasting in depressive cognition: Using emotion as information about the future. *Journal of Social and Clinical Psychology, 34*(2), 117–134. https://doi.org/10.1521/jscp.2015.34.2.117

Marroquín, B., Nolen-Hoeksema, S., & Miranda, R. (2013). Escaping the future: Affective forecasting in escapist fantasy and attempted suicide. *Journal of Social and Clinical Psychology, 32*(4), 446–463. https://doi.org/10.1521/jscp.2013.32.4.446

Martin, S. M., Gerhart, J. I., Rochefort, C., Perry, L., & Hoerger, M. (2020). Affective forecasting in health psychology. *The Wiley Encyclopedia of Health Psychology*, pp. 293–300.

McIntosh, D. N., Silver, R. C., & Wortman, C. B. (1993). Religion's role in adjustment to a negative life event: Coping with the loss of a child. *Journal of Personality and Social Psychology, 65*(4), 812–821.

McMillan, D., Gilbody, S., Beresford, E., & Neilly, L. I. Z. (2007). Can we predict suicide and non-fatal self-harm with the Beck Hopelessness Scale? A meta-analysis. *Psychological Medicine, 37*(6), 769–778.

Mellers, B. A., & McGraw, A. P. (2001). Anticipated emotions as guides to choice. *Current Directions in Psychological Science, 10*(6), 210–214. https://doi.org/10.1111/1467-8721.00151

Metalsky, G. I., & Joiner, T. E. (1992). Vulnerability to depressive symptomatology: A prospective test of the diathesis-stress and causal mediation components of the hopelessness theory of depression. *Journal of Personality and Social Psychology, 63*(4), 667.

Miranda, R., Fontes, M., & Marroquín, B. (2008). Cognitive content-specificity in future expectancies: Role of hopelessness and intolerance of uncertainty in depression and GAD symptoms. *Behaviour Research and Therapy, 46*(10), 1151–1159. https://doi.org/10.1016/j.brat.2008.05.009

Miranda, R., Gallagher, M., Bauchner, B., Vaysman, R., & Marroquín, B. (2012). Cognitive inflexibility as a prospective predictor of suicidal ideation among young adults with a suicide attempt history. *Depression and Anxiety, 29*(3), 180–186. https://doi.org/10.1002/da.20915

Newman, D. A. (2003). Longitudinal modeling with randomly and systematically missing data: A simulation of ad hoc, maximum likelihood, and multiple imputation techniques. *Organizational Research Methods, 6*(3), 328–362.

O'Connor, R. C., Fraser, L., Whyte, M.-C., Machale, S., & Masterton, G. (2008). A comparison of specific positive future expectancies and global hopelessness as predictors of suicidal ideation in a prospective study of repeat self-harmers. *Journal of Affective Disorders, 110*(3), 207–214. https://doi.org/10.1016/j.jad.2008.01.008

O'Connor, R. C., Smyth, R., Ferguson, E., Ryan, C., & Williams, J. M. G. (2013). Psychological processes and repeat suicidal behavior: A four-year prospective study. *Journal of Consulting and Clinical Psychology, 81*(6), 1137–1143. https://doi.org/10.1037/a0033751

R Core Team. (2020). *R: A language and environment for statistical computing*. https://www.R-project.org

Roessel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36.

Rogers, M. L., Galynker, I., Yaseen, Z., DeFazio, K., & Joiner, T. E. (2017). An overview and comparison of two proposed suicide-specific diagnoses: Acute suicidal affective disturbance and suicide crisis syndrome. *Psychiatric Annals, 47*(8), 416–420. https://doi.org/10.3928/00485713-20170630-01

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys Wiley*.

Rudd, M. D. (2006). Fluid vulnerability theory: A cognitive approach to understanding the process of acute and chronic suicide risk. In T. E. Ellis (Ed.), *Cognition and suicide: Theory, research, and therapy* (pp. 355–368). American Psychological Association.

Rudd, M. D., Bryan, C. J., Wertenberger, E. G., Peterson, A. L., Young-McCaughan, S., Mintz, J., Williams, S. R., Arne, K. A., Breitbach, J., Delano, K., Wilkinson, E., & Bruce, T. O. (2015). Brief cognitive-behavioral therapy effects on post-treatment suicide attempts in a military sample: Results of a randomized clinical trial with 2-year follow-up. *The American Journal of Psychiatry, 172*(5), 441–449. https://doi.org/10.1176/appi.ajp.2014.14070843

Sargalska, J., Miranda, R., & Marroquín, B. (2011). Being Certain about an absence of the positive: Specificity in relation to hopelessness and suicidal ideation. *International Journal of Cognitive Therapy, 4*(1), 104–116. https://doi.org/10.1521/ijct.2011.4.1.104

Sevdalis, N., & Harvey, N. (2009). Reducing the impact bias in judgments of post-decisional affect: Distraction or task interference? *Judgment and Decision Making, 4*(4), 287.

Sharot, T., & Sunstein, C. R. (2020). How people decide what they want to know. *Nature Human Behaviour, 4*(1), 14–19.

Simon, H. A. (1973). Organization man: Rational or self-actualizing? *Public Administration Review, 33*(4), 346. https://doi.org/10.2307/975114

Steed, L. (2001). Further validity and reliability evidence for Beck Hopelessness Scale scores in a nonclinical sample. *Educational and Psychological Measurement, 61*(2), 303–316.

Stensman, R. (1985). Severely mobility-disabled people assess the quality of their lives. *Scandinavian Journal of Rehabilitation Medicine, 17*(2), 87–99.

Sterne, J. A. C., White, I. R., Carlin, J. B., Spratt, M., Royston, P., Kenward, M. G., Wood, A. M., & Carpenter, J. R. (2009). Multiple imputation for missing data in epidemiological and clinical research: Potential and pitfalls. *BMJ (Clinical Research Ed.), 338*, b2393. https://doi.org/10.1136/bmj.b2393

Strunk, D. R., Lopez, H., & DeRubeis, R. J. (2006). Depressive symptoms are associated with unrealistic negative predictions of future life events. *Behaviour Research and Therapy, 44*(6), 861–882. https://doi.org/10.1016/j.brat.2005.07.001

Taylor, S. E. (1991). Asymmetrical effects of positive and negative events: The mobilization-minimization hypothesis. *Psychological Bulletin, 110*(1), 67–85. https://doi.org/10.1037/0033-2909.110.1.67

Thaler, R. H. (2018). From cashews to nudges: The evolution of behavioral economics. *American Economic Review, 108*(6), 1265–1287.

Tucker, R. P., Michaels, M. S., Rogers, M. L., Wingate, L. R., & Joiner, T. E. (2016). Construct validity of a proposed new diagnostic entity: Acute Suicidal Affective Disturbance (ASAD). *Journal of Affective Disorders, 189*, 365–378. https://doi.org/10.1016/j.jad.2015.07.049

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software, 45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Van Orden, K. A., Witte, T. K., Cukrowicz, K. C., Braithwaite, S. R., Selby, E. A., & Joiner, T. E. (2010). The interpersonal theory of suicide. *Psychological Review, 117*(2), 575–600. https://doi.org/10.1037/a0018697

Voichek, G., & Novemsky, N. (2021). Asymmetric hedonic contrast: Pain is more contrast dependent than pleasure. Psychological Science, 0956797621991140.

Wesp, R., Sandry, J., Prisco, A., & Sarte, P. (2009). Affective forecasts of future positive events are tempered by consideration of details. *The American Journal of Psychology, 122*(2), 167–174.

Williams, V. S. L., Morlock, R. J., & Feltner, D. (2010). Psychometric evaluation of a visual analog scale for the assessment of anxiety. *Health and Quality of Life Outcomes, 8*, 57. https://doi.org/10.1186/1477-7525-8-57

Wilson, T. D., & Gilbert, D. T. (2003). Affective forecasting. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (Vol. 35, pp. 345–411). Elsevier Academic Press. https://doi.org/10.1016/S0065-2601(03)01006-2

Wilson, T. D., & Gilbert, D. T. (2005). Affective forecasting. *Current Directions in Psychological Science: A Journal of the American Psychological Society, 14*(3), 131–134. https://doi.org/10.1111/j.0963-7214.2005.00355.x

Wilson, T. D., Wheatley, T., Meyers, J. M., Gilbert, D. T., & Axsom, D. (2000). Focalism: A source of durability bias in affective forecasting. *Journal of Personality and Social Psychology, 78*(5), 821–836.

Yu, C. Y. (2002). *Evaluating cutoff criteria of model fit indices for latent variable models with binary and continuous outcomes*. University of California.

Yuan, J. W., & Kring, A. M. (2009). Dysphoria and the prediction and experience of emotion. *Cognition and Emotion, 23*(6), 1221–1232. https://doi.org/10.1080/02699930802416445

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