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A machine learning approach to modeling PTSD and difficulties in emotion regulation

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ABSTRACT

Despite evidence for the association between emotion regulation difficulties and posttraumatic stress disorder (PTSD), less is known about the specific emotion regulation abilities that are most relevant to PTSD severity. This study examined both item-level and subscale-level models of difficulties in emotion regulation in relation to PTSD severity using supervised machine learning in a sample of U.S. adults (N=570). Participants were recruited via Amazon's Mechanical Turk (MTurk) and completed self-report measures of emotion regulation difficulties and PTSD severity. We used five different machine learning algorithms separately to train each statistical model. Using ridge and elastic net regression results in the testing sample, emotion regulation predictor variables accounted for approximately 28% and 27% of the variance in PTSD severity in the item- and subscale-level models, respectively. In the item-level model, four predictor variables had notable relative importance values for PTSD severity. These items captured secondary emotional responding, experiencing emotions as out-of-control, difficulties modulating emotional arousal, and low emotional granularity. In the subscale-level model, lack of access to effective emotion regulation strategies, lack of emotional clarity, and emotional nonacceptance subscales had the highest relative importance to PTSD severity. Results from analyses modeling a probable diagnosis of PTSD based on DERS items and subscales are presented in supplemental findings. Findings have implications for developing more efficient, targeted emotion regulation interventions for PTSD.

1. Introduction

In the last two decades, there has been increasing interest in the role of emotion regulation difficulties in the development and maintenance of posttraumatic stress disorder (PTSD; Seligowski et al., 2015). Most studies in this area have provided support for relations between various aspects of emotion regulation and PTSD severity (Tull et al., 2020); however, less is known about the specific emotion regulation abilities that may be most likely to contribute to the severity of PTSD symptoms. Thus, the present study used a machine learning analytic method to identify the specific emotion regulation abilities that are most central to PTSD severity.

PTSD includes a set of symptoms characterized by frequent, intrusive, and distressing memories or reexperiencing, as well as avoidance, negative alterations in cognitions or mood, and alterations in reactivity and arousal following traumatic event exposure (American Psychiatric Association, 2013). Although almost 70% of U.S. adults will experience at least one potentially traumatic event in their lifetime (Goldstein et al., 2016), most will not develop PTSD. Indeed, Goldstein et al. (2016) estimated that only 7% of all U.S. adults will develop PTSD in their lifetime. Consequently, considerable research has been conducted in an attempt to identify individual difference factors that may contribute to the development and maintenance of PTSD among individuals exposed to a traumatic event. This body of research has identified multiple risk factors for the development of PTSD following traumatic exposure (e.g., younger age at the time of the traumatic event, female gender, exposure to an interpersonal traumatic event, history of other psychiatric disorders; Brewin et al., 2000; Xue et al., 2015). However, given (a) theoretical models emphasizing the central role of deficits in emotional processing in PTSD (Foa et al., 1989; Foa and Kozak, 1986), (b) the presence of intense and persistent negative emotions (e.g., fear, anxiety, shame, guilt, anger) in PTSD, and (c) conceptualizations of PTSD as a disorder of emotion (Frewen and Lanius, 2006; McLean and Foa, 2017; Tull et al., 2020), increasing research has explored the role of difficulties in the regulation of emotion in the development and maintenance of PTSD.

Gratz and Roemer (2004) conceptualize emotion regulation as a multidimensional construct involving the (a) awareness, understanding,

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and acceptance of emotions; (b) ability to control impulsive behaviors and engage in goal-directed behaviors when experiencing negative emotions; (c) flexible use of non-avoidant, situationally-appropriate strategies to modulate the intensity and duration of emotional responses in order to meet individual goals and situational demands; and (d) willingness to experience negative emotions in pursuit of meaningful activities in life. This model of emotion regulation broadly focuses on the ability to respond to emotions in a manner that promotes the functional use of emotions as information and the pursuit of valued actions and desired goals; thus, difficulties in any of these areas may increase risk for psychopathology or maladaptive behaviors (Gratz and Roemer, 2004). The vast majority of the scientific literature on emotion regulation abilities and PTSD has relied on self-report measures, primarily the Difficulties in Emotion Regulation Scale (DERS; Gratz and Roemer, 2004). Based in this model of emotion regulation, elevated difficulties in emotion regulation in general have consistently been associated with more severe PTSD symptoms in cross-sectional investigations (McDermott et al., 2009; Miles et al., 2016; Tull et al., 2007; Weiss et al., 2013). Further, prospective studies have shown that difficulties in emotion regulation predict the development of more severe PTSD symptoms following traumatic event exposure (Bardeen et al., 2013; Forbes et al., 2020). Moreover, research shows that difficulties in emotion regulation may underlie the association between PTSD and a wide variety of maladaptive behaviors, such as risk-taking behaviors (Weisset al., 2012; Weiss et al., 2014), nonsuicidal self-injury (Dixon-Gordon et al., 2014), impulsive aggression (Miles et al., 2016), and substance use (Bonn--Miller et al., 2011; Tripp et al., 2015).

Although the association between PTSD and emotion regulation difficulties in general is well-established (Bardeen et al., 2013; McDermott et al., 2009; Miles et al., 2016; Tull et al., 2007; Weiss et al., 2013), relations between DERS subscales and PTSD symptoms are less clear. Specifically, whereas one correlational evaluation of undergraduates found that all six DERS subscales (i.e., lack of emotional awareness, difficulties controlling impulsive behaviors when distressed, difficulties engaging in goal-directed behavior when distressed, emotional nonacceptance, lack of emotional clarity, and limited access to effective emotion regulation strategies) were associated with PTSD total and subscale scores (Tripp et al., 2015), other studies of traumatic event-exposed college students found that only five of six DERS subscales (all but lack of emotional awareness) were significantly associated with PTSD total and symptom cluster scores (O'Bryan et al., 2015; Tull et al., 2007) and only four (all but lack of emotional awareness and clarity) were significantly associated with probable PTSD (vs. non-PTSD) group status (Weiss et al., 2012). Further, using hierarchical multiple regression analyses, O'Bryan et al. (2015) found that only two subscales evidenced unique associations with PTSD symptom clusters after accounting for trauma history and negative affect, as only emotional nonacceptance was uniquely associated with PTSD avoidance and only lack of emotional awareness and emotional nonacceptance were uniquely associated with PTSD hyperarousal (O'Bryan et al., 2015). Finally, in a sample of patients with substance dependence, difficulties controlling impulsive behaviors when distressed was the only DERS subscale to predict PTSD (vs. non-PTSD) group status (Weiss et al., 2013).

Given inconsistent findings with regard to the relation between specific emotion regulation difficulties and PTSD, additional research is needed to examine the item- and subscale-level associations between the DERS and PTSD severity, in order to elucidate the specific emotion regulation abilities that are most relevant to PTSD symptom severity. Such research could highlight specific emotion regulation deficits that require attention in PTSD interventions, facilitating the development of more efficient PTSD treatments. To this end, the aim of the present study was to model PTSD symptom severity using item-level responses to a widely employed measure of emotion regulation difficulties using advanced statistical methods. Given the complexity of both PTSD and the associations of PTSD severity with specific emotion regulation difficulties, reliance on General Linear Model (GLM) computational methods (which require a priori hypothesis testing) may restrict examinations of these relations, as these models identify when to reject if there is no effect, but they are not designed to examine complex interconnectedness among variables. In contrast, machine learning can examine probabilistic relations among variables and uses repeated cross validation techniques to test reliability of results (Hastie et al., 2016). Therefore, we used supervised machine learning to model PTSD severity using item-level emotion regulation responses on the DERS; we subsequently repeated these analyses using emotion regulation subscale scores. Supervised machine learning involves training a statistical model using example/training data, in order to recognize patterns to subsequently use in modeling a new dataset (Hastie et al., 2016; LeCun et al., 2015). Because of this approach's focus on training data and application to test data, supervised machine learning has often outperformed traditional statistical algorithms (Jordan and Mitchell, 2015). In fact, machine learning has been increasingly used in psychology and psychiatry research (Shatte et al., 2019). Furthermore, we used specific machine learning algorithms (described below) that overcome important limitations inherent in traditional statistics. Finally, although previous research has used classification-based machine learning to model PTSD as a categorical diagnostic variable based on numerous psychological and demographic predictor variables (Galatzer-Levy et al., 2014, 2017; Karstoft et al., 2015; Karstoft et al., 2015; Schultebraucks et al., 2020), we primarily used regression-based symptom forecasting, a type of supervised machine learning for modeling a continuous dependent variable. Given the American Psychiatric Association's promotion of dimensional models of PTSD (American Psychiatric Association, 2013), as well as increasing evidence for a dimensional structure of PTSD (Tsai et al., 2015), examining the influence of emotion regulation on the severity of PTSD symptoms (vs. only a categorical representation of PTSD) is in-line with current recommendations and empirical literature.

2. Method

2.1. Participants

In order to achieve a sample size large enough to split into training and test groups to conduct analyses, we pooled data from two nationwide online surveys of community adult participants recruited from Amazon's Mechanical Turk (MTurk) internet labor market (a platform often used for data collection in social science research; Shapiro et al., 2013). Institutional Review Board approval was granted prior to data collection, in accordance with the Declaration of Helsinki. Data collection via MTurk is at least as reliable as other traditional methods (Buhrmester et al., 2011; Shapiro et al., 2013) and affords advantages over other sampling approaches (Buhrmester et al., 2011; Landers and Behrend, 2015), producing a sample representative of mental health prevalence in the general population (Shapiro et al., 2013; van Stolk--Cooke et al., 2018).

In the first sample, data were collected between July and September 2018. Participants were required to be over the age of 18, live in the United States, and speak/read English. They were provided with $3.00 (U.S.) for completing a survey battery that took approximately 60 minutes to complete. Five-hundred and fifteen individuals participated; however, data from 150 participants were excluded due to incorrect responses on one or more attention check items embedded within the survey, providing a nonsensical response to an open-ended question, and/or if their completion time was shorter than one-third of the median response time. The final sample consisted of 365 participants. In the second sample, data were collected between March and May 2019. Participants were required to be over the age of 18, live in the United States, speak/read English, and endorse engaging in at least one self-damaging behavior in the past year. They were provided $3.00 (US) for completing a survey battery that took approximately 90 minutes. Five-hundred and eighty-four individuals participated; however, 141 were excluded for incorrectly responding to embedded attention check items, providing a nonsensical response to an open-ended question, and/or if their completion time was shorter than one-third of the median response time, leaving a sample of 443. Both studies obtained informed consent electronically via Qualtrics immediately before participants began the surveys.

The remaining data from both online surveys were pooled, resulting in a full sample of 808 subjects. We excluded 238 individuals from analysis, including 150 who did not endorse at least one lifetime traumatic event and an additional 88 whose endorsed traumatic event did not satisfy DSM-5's PTSD criterion A (American Psychiatric Association, 2013). Of the remaining 570 participants (the "effective" sample), 65.1% (n=371) were women, 34.7% (n=196) were men, and < 1% identified as transgender or other (n=3). Most respondents were White, 82.3% (n=469), Native American/American Indian, 9.8% (n=56), or Asian 4.4% (n=24). The average age was 39.91 years (SD= 11.95; range= 21-87). The most commonly endorsed index (i.e., most salient, distressing) traumatic events were sexual assault (16.8%), life-threatening illness or injury (13.9%), and natural disaster (12.8%).

2.2. Measures

The Life Events Checklist (LEC-5; Weathers et al., 2013) is a 17-item self-report measure designed to screen for lifetime exposure to traumatic events. The first 16 items assess specific traumatic events, with a final item assessing other stressful events. For each event listed on the LEC-5, individuals were asked to indicate their experience on a 6-point nominal scale (1 = *happened to me*, 2 = *witnessed it*, 3 = *learned about it*, 4 = *experienced as part of job*, 5 = *not sure*, and 6 = *does not apply*), with endorsement of any of the first four ranks indicating a positive Criterion A traumatic event (American Psychiatric Association, 2013). Following these 17 items, respondents were asked to identify and briefly describe their most distressing traumatic event (i.e., their index event). The LEC-5 demonstrates convergent validity with other similar measures (Weathers et al., 2013).

The PTSD Checklist-5 (PCL-5; Weathers et al., 2013) consists of 20 self-report items designed to assess current (i.e., past month) PTSD symptoms. Although the PCL-5 is the gold-standard instrument for assessing self-reported PTSD symptom severity, it was not designed nor is it recommended to be used as a sole indicator of a PTSD diagnosis (Weathers et al., 2013). However, sensitivity and specificity analyses have found that a score of 33 or greater on the PCL-5 may be indicative of a probable PTSD diagnosis (Bovin et al., 2016). Participants were instructed to complete the PCL-5 in response to the index trauma identified in the LEC-5. The PCL-5 uses a 5-point Likert scale from 0 (*not at all*) to 4 (*extremely*). Item summation results in a total score of PTSD symptom severity, with higher scores indicative of greater PTSD symptom severity. The PCL-5 has consistently demonstrated excellent validity and reliability (Blevins et al., 2015; Bovin et al., 2016; Wortmann et al., 2016) when compared to other measures of PTSD. Internal consistency in the current sample was acceptable (Cronbach's α= .97).

The Difficulties in Emotion Regulation Scale (DERS; Gratz and Roemer, 2004) is a 36-item self-report measure assessing individuals' typical levels of emotion regulation difficulties. Items are rated on a 5-point Likert-type scale (1 = *almost never*; 5 = *almost always*), with higher scores indicating greater difficulties with emotion regulation. The DERS includes six subscales: (a) nonacceptance of negative emotional responses (i.e., Nonacceptance), (b) difficulties engaging in goal-directed behaviors when distressed (i.e., Goals), (c) difficulties controlling impulsive behaviors when distressed (i.e., Impulse), (d) lack of emotional awareness (i.e., Awareness), (e) limited access to effective emotion regulation strategies (i.e., Strategies), and (f) lack of emotional clarity (i.e., Clarity). The DERS demonstrates good reliability and construct and convergent validity and is significantly associated with objective measures of emotion regulation (Gratz et al., 2007; Gratz and Roemer, 2004; Vasilev et al., 2009). Internal consistency for the total score and each subscale score in this sample was acceptable (αs = .96 for the total score and .84 to .94 for the subscale scores).

2.3. Analysis

Minimal missing data were detected, with 19 respondents (3.33%) missing only one item (5%) on the PCL-5. No DERS item-level data were missing. Maximum likelihood estimation procedures with the expectation-maximization algorithm (Graham, 2009) were used to estimate item-level missing data. We summed item responses to form scale scores. Scale scores and all DERS items were normally distributed, with the largest absolute skewness value of 1.33 and kurtosis values of 1.13. We used R software, version 3.6.1 (R Core Team, 2020), implementing R's *caret* package for machine learning. We randomly shuffled the sample of 570 data rows (participants), using a fixed seed for subsequent, consistent replication. The effectiveness of supervised machine learning is maximized when the training sample is as large as possible to train the statistical model before applying it to the test sample (Hastie et al., 2016; Kuhn and Johnson, 2013); in the literature, these models commonly use a 70%-30% training-test sample split. Thus, we randomly selected 70% of participants (n = 399) as the training sample, and the remaining 30% (n = 171) as the external test sample. After allocating participants to training and test samples (Kuhn and Johnson, 2013), we preprocessed the predictor and dependent variables by centering and scaling values (as z-scores) separately for the two samples.

We tested five machine learning algorithms separately. We used three penalty algorithms – ridge, lasso, and elastic net regression – which impose a penalty constraint on regression coefficients for complex models of predictors that are too highly correlated, reducing variance by introducing bias. This approach offsets challenges in traditional regression from collinearity, which we expect for emotion regulation items and subscales. Ridge regression shrinks coefficients toward (but not exactly to) zero; lasso and elastic net regression shrink coefficients toward or exactly to zero if applicable – the latter involving empirical subset selection of a reduced set of predictors (Zou and Hastie, 2005). We also used an ensemble machine learning algorithm – extreme gradient boosting – in which many weak learners, or random subsets of predictors and research participants, are iteratively tested (fixing prior errors) to form an aggregated strong model, reducing overfitting in the process. Finally, we used a support vector machine algorithm with a radial basis function kernel, capable of mapping predictor-dependent variable relations in three-dimensional space for improved linear separability in the dependent variable based on predictors. These algorithms are discussed in detail elsewhere (Hastie et al., 2016). We compared algorithms using the root mean square error (RMSE), mean absolute error (MAE) and R-square values, and pairwise statistical tests.

We first trained our regression model using the training sample (n = 399), using repeated cross-validation for data simulation, splitting the training sample into 5 unique folds/subsets, training the first four folds and testing on the fifth fold. We conducted this process so that each of the 5 folds served as the simulated test sample once. Then, we repeated this process another 9 times, for a total of 50 cross-validations. We used a fixed number seed for these replications, to facilitate consistent replication. Finally, we applied the aggregated final trained model (across the 50 cross-validations) to the external test sample of 171 participants for additional validation.

3. Results

Descriptive statistics for the PCL-5 and all DERS items and subscales are displayed in Table 1. We present machine learning results modeling DERS items on PTSD severity, compared across algorithms for the training and test samples, in Table 2 (see Item-Level Model). Better fit is judged by lower values for RMSE and MAE and higher values on R-squared. In training, the ridge regression algorithm performed best on RMSE and R-square, whereas support vector machine performed best on

Table 1
Means and standard deviations for all DERS items, subscales, and PTSD severity.

Variable		Mean (SD)
PCL-5 Total		21.39 (21.05)
DERS Subscale	**Nonacceptance**	14.68 (7.01)
Item Number:	11	2.44 (1.31)
	12	2.37 (1.33)
	21	2.42 (1.35)
	23	2.56 (1.39)
	25	2.39 (1.35)
	29	2.50 (1.34)
	Goals	13.87 (5.40)
	13	2.76 (1.35)
	18	2.84 (1.29)
	20	2.82 (1.23)
	26	2.77 (1.32)
	33	2.69 (1.31)
	Impulse	12.99 (5.85)
	3	2.28 (1.29)
	14	1.92 (1.19)
	19	2.15 (1.31)
	24	2.60 (1.22)
	27	2.07 (1.19)
	32	1.97 (1.21)
	Awareness	14.77 (5.46)
	2	2.14 (1.07)
	6	2.36 (1.15)
	8	2.19 (1.15)
	10	2.48 (1.17)
	17	2.58 (1.26)
	34	3.04 (1.28)
	Strategies	19.49 (8.67)
	15	2.28 (1.34)
	16	2.39 (1.43)
	22	2.75 (1.26)
	28	2.21 (1.28)
	30	2.53 (1.37)
	31	2.16 (1.30)
	35	2.51 (1.32)
	36	2.66 (1.39)
	Clarity	10.13 (4.34)
	1	2.22 (1.06)
	4	1.78 (1.08)
	5	1.91 (1.17)
	7	2.31 (1.12)
	9	1.91 (1.11)

MAE; elastic net regression performed second best across three indices. Using Bonferroni-adjusted *p*-values for statistical pairwise comparisons (training analyses), ridge regression performed significantly better than all other algorithms on RMSE and R-square, and elastic net regression performed better than the remaining algorithms. For MAE, support vector machine and elastic net were not significantly different from each other, and were both significantly better than some of the remaining algorithms. In the testing sample, ridge regression performed best on all fit indices, with predictor variables accounting for 28% of the variance in PTSD severity.

We present variable importance estimates for ridge and elastic net regression algorithms, interpreted as standardized regression coefficients because of z-score standardization of predictor and dependent variables. Variable importance estimates show the relative contribution of each predictor variable on the dependent variable. Fig. 1 displays the relative importance of predictors using ridge regression, and Fig. 2 displays estimates for elastic net regression. We display only the 15 most important variables in the figures. Across these two machine learning algorithms, DERS items 23 ("When I am upset, I feel like I am weak") and 16 ("When I am upset, I believe I will end up feeling very depressed") had the highest relative importance values for PTSD severity, followed by items 4 ("I have no idea how I am feeling"), and 35 ("When I am upset, it takes me a long time to feel better"). All four items were positively associated with PTSD severity (*r*s range .39-.49, all *p*s $< .001$). Using a third algorithm that shrinks regression coefficients to zero for

Table 2
Comparison of five machine learning-based regression algorithms in modeling emotion regulation items and subscales in relation to PTSD severity, reported separately for the training sample using repeated cross-validation and the external test sample.

	Mean Model Fit Findings Over Repeated Cross-Validations in the Training Sample			Model Fit Findings in the Test Sample		
	RMSE (SD)	**MAE (SD)**	**R^2 (SD)**	**RMSE**	**MAE**	**R^2**
Item-Level Model						
Lasso	.8280 (.0662)	.6389 (.0453)	.3210 (.0744)	.8569	.6349	.2753
Ridge	.8113 (.0634)	.6338 (.0421)	.3506 (.0753)	.8513	.6375	.2774
Elastic Net	.8198 (.0655)	.6324 (.0446)	.3347 (.0745)	.8558	.6317	.2782
Support Vector Machine	.8263 (.0598)	.6211 (.0404)	.3298 (.0565)	.8630	.6476	.2811
Extreme Gradient Boosting	.8512 (.0698)	.6566 (.0499)	.2894 (.0749)	.8904	.6539	.2404
Subscale-Level Model						
Lasso	.8256 (.0660)	.6384 (.0443)	.3259 (.0740)	.8613	.6471	.2658
Ridge	.8246 (.0650)	.6408 (.0437)	.3280 (.0737)	.8595	.6490	.2666
Elastic Net	.8248 (.0654)	.6399 (.0439)	.3275 (.0738)	.8603	.6497	.2650
Support Vector Machine	.8430 (.0693)	.6250 (.0434)	.3086 (.0612)	.8621	.6299	.2876
Extreme Gradient Boosting	.8636 (.0715)	.6610 (.0452)	.2715 (.0662)	.8724	.6535	.2519
Lasso	.8256 (.0660)	.6384 (.0443)	.3259 (.0740)	.8613	.6471	.2658

Note. Because of the subtle differences found between the algorithms, estimates were rounded to four decimal places. RMSE=root mean squared error; MAE=mean absolute error.

statistically unimportant variables (i.e., lasso regression), our results suggest that only the following DERS items are important to PTSD severity: items 23, 4, 16, 19, 35, 21, 33, 8, 9, 24, 3, 34, 36, 18, 20, 27, 28, and 22.

We repeated the machine learning analyses for DERS subscale scores. There were not as clear findings for the top performing algorithms as with the item-level data; yet, ridge and elastic net regression were among the top performing algorithms on most indices for training and test samples, displayed in Table 2 (see Subscale-Level Model). These algorithms accounted for approximately 27% of the variance in PTSD severity in the test sample. Fig. 3 shows variable importance for ridge regression, and Fig. 4 shows variable importance indices for elastic net regression. Across these two algorithms, the DERS subscales of limited access to effective emotion regulation strategies, lack of emotional clarity, and nonacceptance of emotions were the most important subscale-level variables in modeling PTSD severity. Results from analyses modeling a probable diagnosis of PTSD based on DERS items and subscales are presented in supplemental findings.

4. Discussion

We used a machine learning approach to determine relative importance of specific emotion regulation difficulties in relation to PTSD symptom severity. Previous PTSD studies have established a clear link between difficulties in emotion regulation and PTSD symptom severity; however, examinations of item- and subscale-level dimensions driving this association have produced inconsistent results. These inconsistencies may be partially attributed to the primary use of a GLM framework, which may introduce error due to collinearity of closely

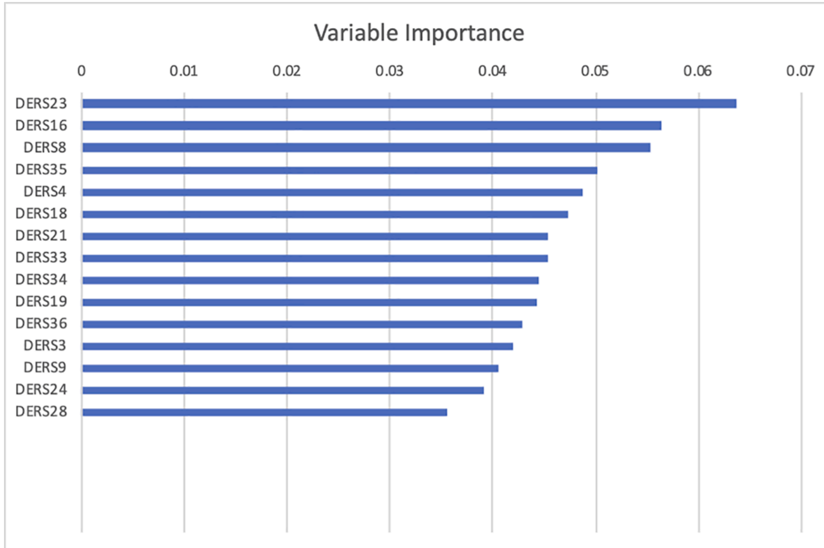

Fig. 1. Variable importance for the ridge regression model's top fifteen variables, predicting PTSD severity.

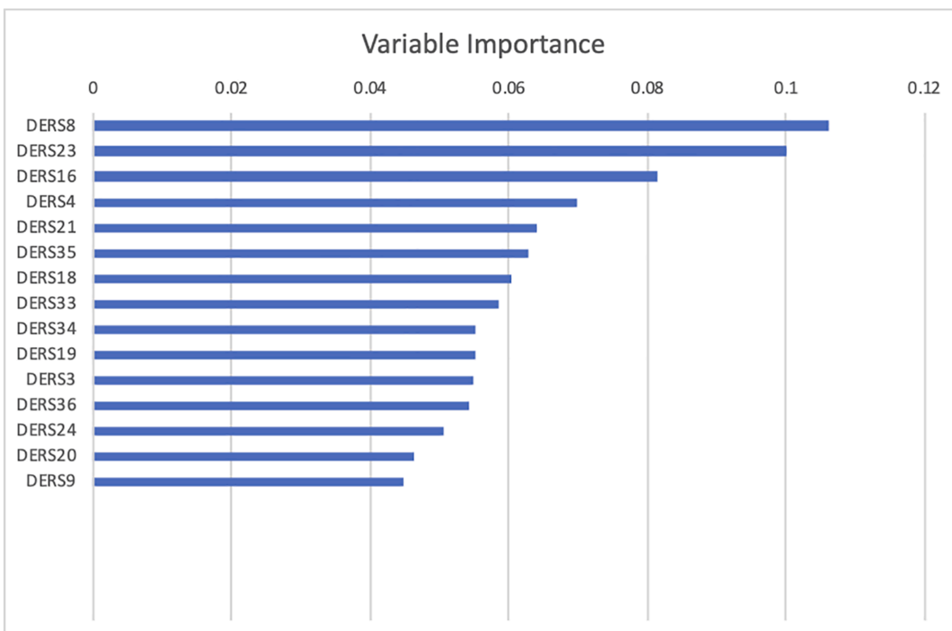

Fig. 2. Variable importance for the elastic net regression model's top fifteen variables, predicting PTSD severity.

related variables and by providing an average solution versus pursuing consistent results across individuals. The use of machine learning methods in the present study attempts to address these concerns, as this approach does not rely on GLM and can establish if the resulting models are accurate across participants, rather than on the aggregate (Aliferis et al., 2010; Mohri et al., 2018).

Using a machine learning approach, we first fit a regression model explaining PTSD symptom severity in a training sample, then simulated that model to an external test sample. We fit regression models for both DERS item- and subscale-level emotion regulation predictors. The ridge regression algorithms accounted for approximately 35% (training) and 28% (testing) of the variance in PTSD symptom severity in the item-level model, and 33% (training) and 27% (testing) of the variance in the subscale-level model. This degree of variance (R-squared) is similar to, but slightly lower than, studies that implemented linear regression without machine learning to examine the relations between emotion regulation difficulties and PTSD severity (R-squared ranges from 0.31 to 0.47; Barlow et al., 2017; Tull et al., 2007; Weiss et al., 2013; Weiss et al., 2013). It is also important to note that these studies accounted for additional psychological and demographic variables (e.g., mood/anxiety disorders and symptoms, childhood traumatic event exposure, income level, negative affect) in their models. The exclusion of additional predictors in our analyses may account for the slightly lower amount of variance explained in our models.

In the DERS item-level model, four items appeared particularly relevant to PTSD severity. Interestingly, these items belong to three separate subscales of the DERS (e.g., emotional nonacceptance, limited access to effective emotion regulation strategies, and lack of emotional clarity), suggesting that the phenomena assessed by these items may have unique contributions to PTSD severity that are not adequately captured when using only subscale-level analyses. To illustrate, all four items capture maladaptive responses to emotional experiences, although

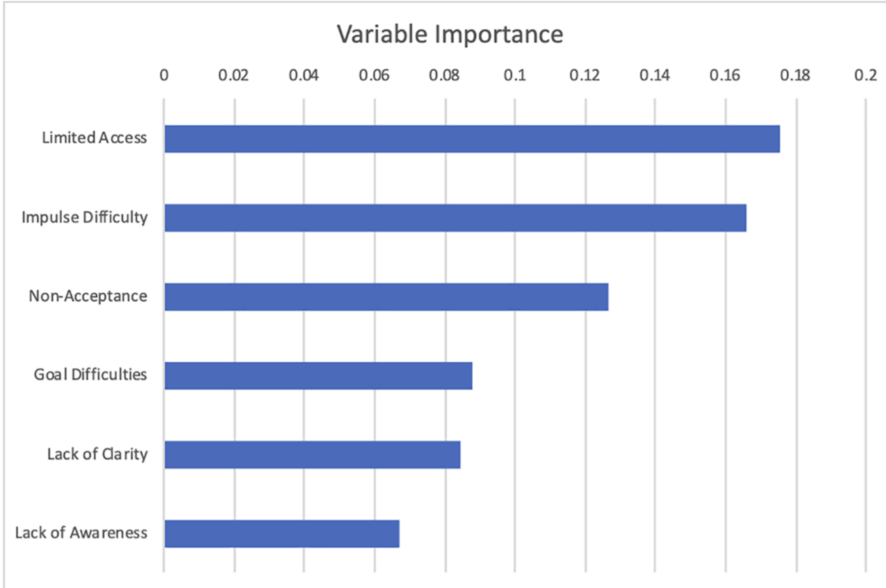

Fig. 3. Variable importance for the ridge regression model's subscales, predicting PTSD severity.

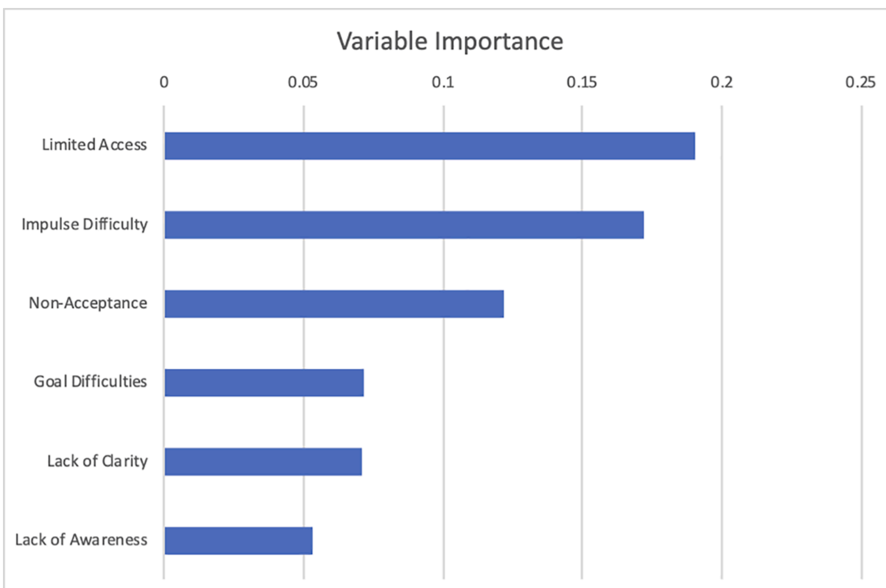

Fig. 4. Variable importance for the elastic net regression model's subscales, predicting PTSD severity.

the precise nature of the maladaptive response varies across the items. Specifically, one of the items with the largest statistical contribution to PTSD severity, "when I'm upset, I feel like I am weak" (item 23), captures the experience of secondary emotional responding, which has been suggested to contribute to increased threat perceptions and the exacerbation of PTSD symptoms (Ehlers and Clark, 2000; Harman and Lee, 2010; Resick, 2001). According to Ehlers and Clark (2000), if individuals do not evaluate symptoms or emotions as an expected, normal, or understandable aspect of recovering from a traumatic experience, these experiences may be perceived as an indication that symptoms are worsening, recovery is not possible, or a permanent reduction in functioning has occurred. Conversely, both item 16 ("when I'm upset, I believe that I'll end up feeling very depressed") and item 35 ("when I'm upset, it takes me a long time to feel better") capture difficulties modulating emotional arousal, which has been theoretically and empirically linked to both PTSD and PTSD symptom severity (Lanius et al., 2010; Liberzon and Sripada, 2007; Shepherd and Wild, 2014; Tull et al., 2020). Item 16 also appears to capture the experience of emotions as out of control, which has been linked to a variety of negative interpersonal, emotional, and psychological outcomes (Ford and Gross, 2019). Finally, the fourth DERS item-level variable found to be relevant to PTSD severity, "I have no idea how I am feeling" (item 4), may reflect inattention to or confusion regarding emotions low granularity of emotions, which may interfere with emotional processing and contribute to increased severity of PTSD symptoms (Foa and Kozak, 1991; Suvak et al., 2020). In addition to highlighting particular emotion regulation difficulties that may be especially relevant to PTSD symptoms, these item-level findings may inform the development of a brief version of the DERS specific to individuals with traumatic exposure. Indeed, although a brief version of the DERS has been developed (Bjureberg et al., 2016), results of the present study could facilitate the development of a streamlined version of the DERS of particular relevance to PTSD sequelae.

Though statistically less clear, in the DERS subscale-level model, the subscales reflecting limited access to emotion regulation strategies perceived as effective, lack of emotional clarity, and emotional nonacceptance were the most relevant subscales in modeling PTSD severity. There is some support for the association between PTSD and lack of access to effective emotion regulation strategies (O`Bryan et al., 2015; Tull et al., 2007; Weiss et al., 2012). These findings are also consistent with evidence that PTSD is associated with a greater reliance on putatively maladaptive emotion regulation strategies (e.g., emotional avoidance, rumination; Seligowski et al., 2015), as well as associations between low emotion regulation flexibility and PTSD severity among individuals exposed to a traumatic event (Levy-Gigi et al., 2016). Given that emotional clarity is a closely related construct to emotional granularity, our findings regarding lack of emotional clarity also align with the theorized inverse relation between emotional granularity and PTSD severity (Suvak et al., 2020). Moreover, lack of emotional clarity, as well as emotional nonacceptance, may interfere with emotional processing of the trauma and trauma related sequelae (Foa and Kozak, 1991). Specifically, deficits in these dimensions of emotion regulation may contribute to a greater reliance on emotion regulation strategies that are geared towards the avoidance or escape of distressing stimuli without concern for the potentially long-term negative consequences of engaging in such strategies. Although these strategies may be effective in reducing distress in the short-term, they may prevent functional exposure to trauma-related stimuli in the long-term, interfering with emotional processing and contributing to the exacerbation or maintenance of PTSD symptoms.

The present study provides a novel approach to conceptualizing emotion regulation difficulties within PTSD through the use of machine learning techniques, which offer several advantages over traditional statistics (Jordan and Mitchell, 2015). This study contributes to the extant literature on the link between emotion regulation difficulties and PTSD, and, to our knowledge, is the first use of machine learning to model item- and subscale-level emotion regulation variables in relation to PTSD severity. Specifically, although past research has used machine learning to predict PTSD diagnoses from a number of psychological and demographic variables (Galatzer-Levy et al., 2014, 2017; Karstoft et al., 2015; Karstoft et al., 2015; Schultebraucks et al., 2020), ours is the first to examine PTSD symptoms dimensionally (consistent with growing evidence supporting the utility of dimensional classifications of psychopathology; Tsai et al., 2015) and to explore the specific emotion regulation difficulties most relevant to PTSD severity.

Nonetheless, findings must be evaluated in the context of study limitations. First, ours was a convenience, nonclinical sample obtained from an internet platform, averaging mild PTSD severity scores and slightly elevated overall difficulties in emotion regulation. Although the mean PTSD symptom severity score was below the recommended cutoff for a probable PTSD diagnosis, 29.3% of our sample had severity scores above this cutoff. This distribution is consistent with past trauma-exposed Mturk samples (Price et al., 2019; Van Stolk-Cooke et al., 2018), which tend to have lower rates of PTSD than Veteran or clinical samples but higher rates of PTSD compared to typical undergraduate samples. Consequently, it should not be assumed that findings would necessarily translate to more severe or clinical populations with PTSD. Future studies would benefit from efforts to replicate our findings within inpatient and outpatient samples with subthreshold and threshold PTSD. Second, our outcomes were based solely on participant self-report. Self-report measures are subject to bias (e.g., social desirability), and there may be limitations in the assessment of emotion regulation abilities through self-report. Specifically, individuals may have limited awareness of the ways in which they regulate and respond to their emotions, especially if they struggle with emotional clarity and awareness. Future studies would benefit from the use of diagnostic interviews to assess PTSD, as well as laboratory-based emotion regulation paradigms (Gratz et al., 2006; Levy-Gigi et al., 2016). Moreover, our study design was cross-sectional, so causal inferences cannot be made. Prospective studies evaluating the extent with which specific emotion regulation difficulties predict the worsening of PTSD symptoms are needed. Finally, co-occurring psychopathology (e.g., anxiety and depression) and history of psychiatric interventions were not assessed; thus, it is not possible to evaluate whether the observed relations may be better explained by psychopathology in general.

Findings from this study support the relevance of multiple facets of emotion regulation difficulties to PTSD severity. These results may be particularly helpful in refining our understanding of the precise emotion regulation difficulties most relevant to PTSD and the most efficient treatment targets for emotion-based PTSD interventions. With regard to the latter, by delineating the associations of both specific (DERS items) and more overarching (DERS subscales) emotion regulation abilities to PTSD symptom severity, these findings may inform the development of more targeted interventions for PTSD. Specifically, results suggest that interventions focused on reducing secondary emotional responding and negative beliefs about emotions, as well as increasing emotional clarity, emotional acceptance, and emotion regulation repertoires, may be particularly useful for addressing PTSD. These findings may also aid future research in this area by highlighting key targets of further examination in investigations of emotion regulation difficulties in PTSD.

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CRediT authorship contribution statement

Nicole M. Christ: Conceptualization, Formal analysis, Project administration, Writing - original draft, Writing - review & editing. **Jon D. Elhai:** Conceptualization, Formal analysis, Methodology, Visualization, Writing - original draft, Writing - review & editing. **Courtney N. Forbes:** Data curation, Funding acquisition, Writing - review & editing. **Kim L. Gratz:** Data curation, Funding acquisition, Writing - review & editing. **Matthew T. Tull:** Conceptualization, Data curation, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors have no commercial interests to disclose.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2021.113712.

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