## Introduction

Impulsivity is a leading diagnostic criterion across psychiatric disorders (Whiteside & Lynam, 2001), often linked with dire outcomes, including early onset of alcohol use, alcohol dependence, difficulty with smoking cessation (Riley et al., 2016), suicidal ideation (Auerbach et al., 2017), and suicide attempts (Kasen et al., 2011). Emotion-driven impulsivity (EDI), defined as disadvantageous rash behaviors during states of heightened affect (Carver & Johnson, 2018), is separable from other forms of impulsivity and has discriminant validity (Sharma et al., 2014). Compared to other forms of impulsivity, EDI is consistently more strongly related to psychopathology, such as depression, substance use, eating disorders, aggression, and suicidality (Berg et al., 2015). Here, I investigate how personality traits and momentary changes in affect might explain suicidal ideation.

Although EDI is a transdiagnostic symptom, hazardous behaviors during overwhelming negative affect, such as substance use, self-harm, and interpersonal reactivity, are prevalent and persistent in borderline personality disorder (BPD) (Jopling et al., 2018). BPD is characterized by severe emotion dysregulation, abrupt and strong mood swings, disinhibition, and interpersonal hypersensitivity (D'Agostino et al., 2018, p. 201). Impulsivity in BPD is often consistent over time and is a strong predictor of borderline psychopathology across time (Links et al., 1999), explaining 64% of the variation in BPD symptoms (Whiteside & Lynam, 2001). The biosocial model of BPD suggests that a genetic predisposition to strong affective experiences and disinhibition, the two key components of EDI, combined with traumatic environments characterized by emotional neglect and uncontrollability, might lead to the development of BPD (Crowell et al., 2009). Notably, individuals with BPD often strongly experience EDI, more than other types of impulsivity (Johnson et al., 2017, p. 201).

A history of emotional neglect predisposes individuals with BPD to a fear of abandonment (Meyer et al., 2001). Moreover, a feared loss of interpersonal connection is prominent in BPD, accentuating the prioritization of interpersonal cues (Santangelo et al., 2014), especially emotional changes in others (Domes et al., 2008). Such prioritization can facilitate more accurate empathic responses, enabling individuals to establish deeper connections and navigate complex social dynamics (Derntl et al., 2010). However, interpersonal stressors are the strongest predictor of heightened negative affect (Pearson et al., 2017, p. 201) and impulsivity (Berenson et al., 2016) in BPD, with responses to interpersonal cues being reactive and insensitive to situational demands (Beeney et al., 2019). Such reactivity has been associated with as an increased likelihood of drinking (Fleming et al., 2021), suicidal ideation (Kaurin et al., 2020), and suicide attempts (Victor et al., 2019).

Building on the existing literature, we hypothesize that momentary changes in negative affect (e.g., sadness, anger) during interpersonal interactions, combined with trait EDI (i.e., Negative Affectivity and Disinhibition) will predict suicidal ideation. We propose that this explanation can offer insights into the temporal triggers associated with suicidal ideation in individuals who are vulnerable to the hazardous effects of interpersonal distress. This study will address several gaps in our understanding of EDI. First, the associations between established survey measures of EDI and lab-based behavioral tasks have been limited, showing low predictions of impulsive behaviors outside of the lab (Elliott et al., 2023). We will use ecological momentary assessment (EMA) data in conjunction with self-report measures of EDI. By examining EDI at the trait level and negative affect and impulsive actions at the state level through the EMA data, we will test the direct associations between trait and state variability in negative affect and impulsivity. Second, most studies of impulsivity to date have relied on summary statistics. This approach condenses variability in behavior into a singular value, eliminating any fluctuations in behaviors (see Haines et al., 2023). Here, examining within-person fluctuations in negative affect and impulsive behaviors reported during the EMA protocol, we will capture the temporal dynamics associated with EDI.

# Methods

## Study Participants

This project used an existing dataset from a longitudinal study. Participant recruitment for the broader study was conducted through inpatient and outpatient medical facilities and community outreach via advertisements in the surrounding area of Pittsburgh, Pennsylvania. Exclusion criteria were: lifetime history of psychotic or bipolar disorders; clinical evidence of organic brain disease, including seizure disorder, acquired brain injury, or developmental deficits; medical conditions or treatments with known psychiatric consequences (e.g., lupus, steroids); and IQ below 70 as assessed by the Wechsler Test of Adult Reading (WTAR; (Wechsler, 2001). All participants ($N$ = 114, ) were between 18 to 45 years old at enrollment. Enrollment into the study was based on the presence of a probable or definite diagnosis for BPD on the International Personality Disorders Examination (Loranger, 1999) and a definite diagnosis for BPD on the Diagnostic Interview for Borderline Patients –Revised (Zanarini et al., 1989). Healthy control participants had no lifetime history of psychiatric disorders or suicide attempts, as determined by the SCID/DSM-IV. Questions surrounding differential diagnoses were resolved via clinical consensus discussions using all available data. Participants completed self-report measures of EDI at enrollment, following the clinical interviews to determine group assignments. Then, they completed a 21-day EMA protocol. In this study, participants from the two groups were pooled into a single sample to allow for continuous data analysis across a range of symptom severity.

## Materials

***Personality Inventory for DSM-5 (PID-5)****:* The PID-5 is a 120-item measure assessing five broad domains of personality dysfunction (as proposed in the personality trait model by Krueger et al. (2012), outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (American Psychiatric Association, 2013). The five domains in the scale are Negative Affect, Detachment, Antagonism, Disinhibition, and Psychoticism. Each domain is further divided into three facets, with each facet measured by eight items. The reliability of the domains, as measured by Cronbach's alpha (Cronbach, 1951), was initially reported as follows: Negative Affect ($\alpha$ = .93), Detachment ($\alpha$ = .96), Antagonism ($\alpha$ = .94), Disinhibition ($\alpha$ = .84), and Psychoticism ($\alpha$ = .96).

## Ecological Momentary Assessments (EMA)

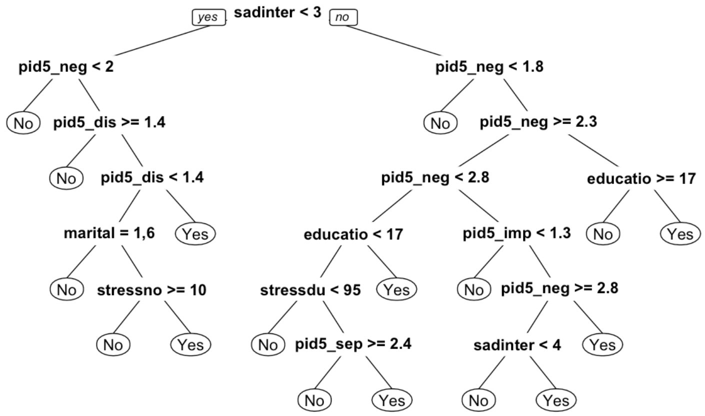
To assess fluctuations in mood and impulsive behaviors, participants completed a 21-day EMA protocol using the MetricWire smartphone app. They completed surveys in the morning and at night, reporting their mood. Additionally, they received push notifications six times daily over a 12-hour period determined based on their sleep schedules. The notifications were at least 90 minutes apart, participants had 60 minutes to complete each survey upon getting the notification.

The surveys that were delivered by push notifications inquired about interpersonal interactions. If the participant reported that an interaction had occurred, they were asked to report on their interaction partner's behavior and briefly describe the encounter. Then, they rated negative (i.e., nervous, sad, irritated, angry) and positive (i.e., happy, content, excited) emotions they felt during the interactions (e.g., "How [emotion] did you feel during the interaction?") on a scale from 1 (Very Slightly or Not at all) to 5 (A great deal), based on the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988). Additionally, they rated how they perceived their interaction partner (e.g., "Please rate how the other person behaved toward you during this interaction.") using two questions regarding dominance and warmth, measured on a continuum from -50 to +50. The dominance scale extended from "Accommodating/Submissive/Timid" at one end to "Assertive/Dominant/Controlling" at the other. Similarly, the warmth scale spanned from "Cold/Distant/Hostile" to "Warm/Friendly/Caring." They answered additional items asking about their impulsivity (i.e., "How would you describe your behavior during the interaction?, 0 ("In Control") to 100 ("Impulsive") and stress (e.g., How stressful was this interaction when it happened?, 0 ("Not at all") to 100 ("Extremely")) during the interaction. They reported their stress related to the interaction (i.e., How stressful is it now?), how much they had thought about it since the interaction (i.e., How much have you thought about this interaction since it happened?), and the extent to which they tried to stop thoughts related to the interaction (i.e., How much have you tried to STOP thinking about this interaction since it happened?) on a scale of 0 ("Not at all") to 100 ("Extremely"). Suicidal ideation was assessed by two dichotomous items: "Since the interaction," "Have you wished you were dead or wished you could go to sleep and not wake up?" and "Have you actually had any thoughts of killing yourself?" derived from the suicidal ideation subscale of the Columbia-Suicide Severity Rating Scale (C-SSRS; (Posner et al., 2007).

## Results

## 1. Decision trees with CART

First, I fit a decision tree (CART, specifically) to see the most predictive variables in my data. Decision trees identify clusters of individuals based on the outcome, showing which of their qualities predict the outcome best. The biggest predictors of suicidal ideation were feeling sad during the interaction (>3) and Negative Affectivity (>2.3) (Figure 1a.). Then, I got the complexity parameter to see if my model overfit the data and could improve by pruning. The complexity parameter was very small (cp = 0.011), indicating that the model did not suffer from complexity. However, I used the complexity parameter that was determined via k-fold cross-validation to re-plot the tree to further validate my model. When I examined the prediction error of the full tree and the pruned tree with the test dataset, I got different results. Specifically, the misclassification rate of the full tree was 0.052. The model missed 33 instances of suicidal ideation and gave a false alarm for 24 instances. The pruned tree had a misclassification rate of .55, and missed 41 instances of suicidal ideation and gave a false alarm for 20 instances. Due to the higher misclassification rate in the pruned tree, I retained the full tree.




a.

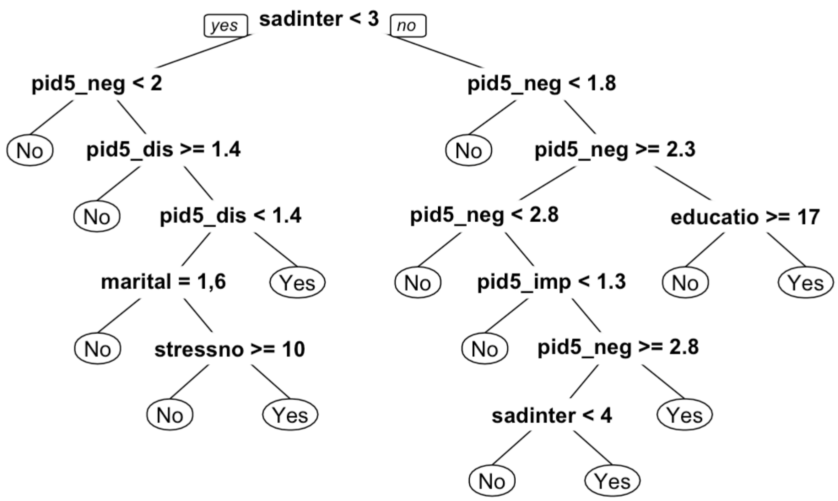



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Figure 1. Decision trees with CART.

## 2. Ensemble Methods

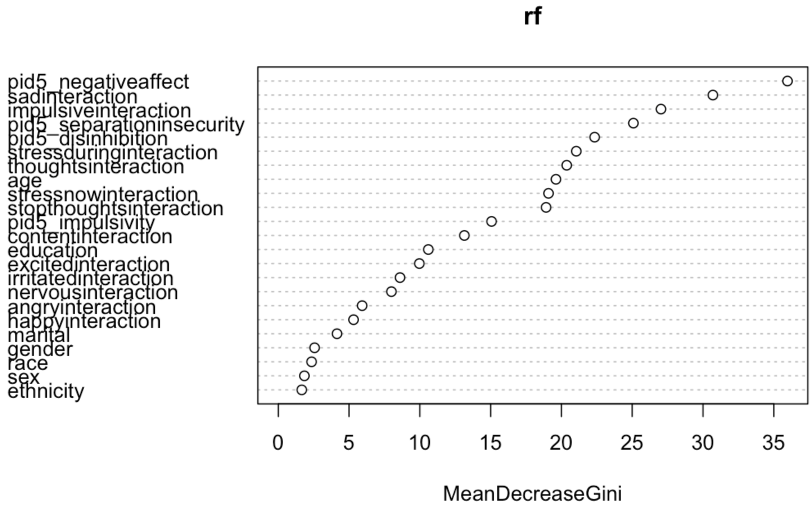
While CART identifies the most predictive variables, it favors continuous variables and a more predictive categorical variable might not show up at the top of the tree. To test whether sex, marital status, race and ethnicity predict the outcome, I then tried another method that would not have such a bias toward continuous predictors. As such, I used ensemble models since they improve on prediction accuracy and stability over decision trees. Ensemble models were preferred over Conditional Inference Decision Trees for that reason. Among different ensemble models, I used random forest instead of bagging since I have variables that are highly correlated (e.g., negative affectivity and impulsivity). Random forests allow for highly correlated variables to appear, whose effects may have otherwise been obscured. I also used conditional inference random forests to increase model generalizability and compared both of them to bagging.

The random forest algorithm initially gave me an error due to a misalignment in levels across training and testing datasets (Error in checkData(oldData, RET) :Levels in factors of new data do not match original data). I investigated the data structure and found that the sample only had one Native American participant, who was split into the training dataset. With that, the two datasets had different numbers of levels in the race variable, interfering with model fitting. To resolve the issue, I excluded that participant from the dataset and ran the model successfully.

I used random forest *without* conditional inference (Figure 2a.) and bagging (Figure 2b), using randomForest. Bagging uses all available predictors, which yielded a misclassification rate of 0 in this case. That is, using all variables in the dataset as a predictor of suicidal ideation, bagging accurately identified all instances of suicidal ideation and lack thereof. Variable importance measures showed Negative Affectivity as the stronger predictor of suicidal ideation, followed by sadness during the interaction, impulsivity during the interaction, trait Impulsivity, and Separation Insecurity.

Then, I fit a random forest model with 7 random variables to split on and 800 trees grown in bootstrapped datasets. This model had a prediction error rate of < .002, missed no incident of ideation, and gave a false alarm in 1 instance. Variable importance measures showed Negative Affectivity as the stronger predictor of suicidal ideation, followed by sadness during the interaction, impulsivity during the interaction, Separation Insecurity, and trait Disinhibition. I used 5-fold cross-validation to determine the tuning parameters for the random forest, which would minimize prediction error in the left-out fold. This identified the number of candidate predictors to split on to maximize accuracy (i.e., mtry) as 9. Using the tuning parameter did not change the results (Figure 2c.). Next, I added ID as a cluster variable to account for the hierarchical structure of my data. Using 9 random variables to split on and 800 trees grown in bootstrapped datasets, the most important predictors were as follows: Negative Affectivity, sadness during the interaction, ID, impulsivity during the interaction, Separation Insecurity, and stress during the interaction (Figure 2d.). Adding ID as a cluster variable improved model accuracy with a misclassification rate below .001, missing no incident of ideation, and gave a false alarm in 1 instance.

Finally, I ran this final model with a conditional inference random forest to prevent variable selection bias in the tree construction. I included participant ID as a cluster variable, 9 random variables to split on, and 800 trees grown in bootstrapped datasets. In this model, we had a misclassification rate of .055, missing 55 instances of suicidal ideation and giving a false alarm in 6 instances. Negative Affectivity was the strongest predictor of suicidal ideation, followed by ID, sadness during the interaction, Separation Insecurity, and age (Figure 2e.). The previously specified tuning routine identified the optimal model as the one that has 24 variables to split on. Using this, the variables of most importance were as follows: Negative Affectivity, sadness during the interaction, ID, and Separation Insecurity (Figure 2f.). This model had a misclassification rate of .059, missing 57 instances of suicidal ideation and giving a false alarm in 8 instances.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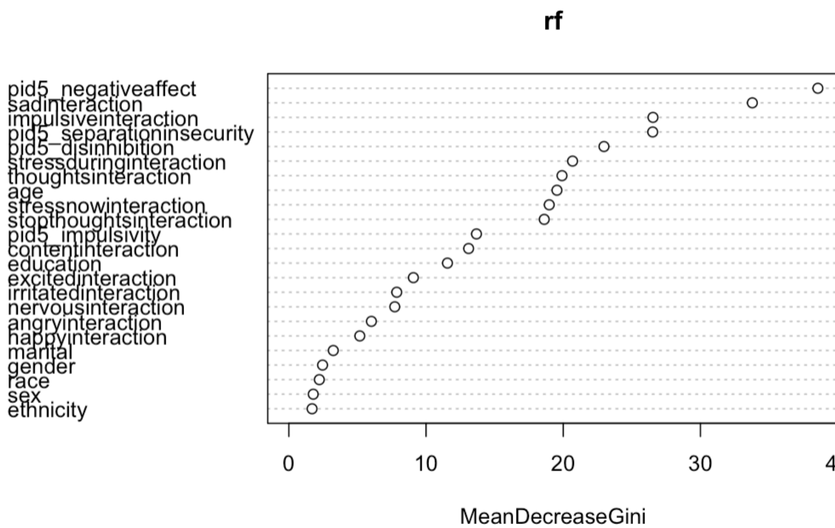
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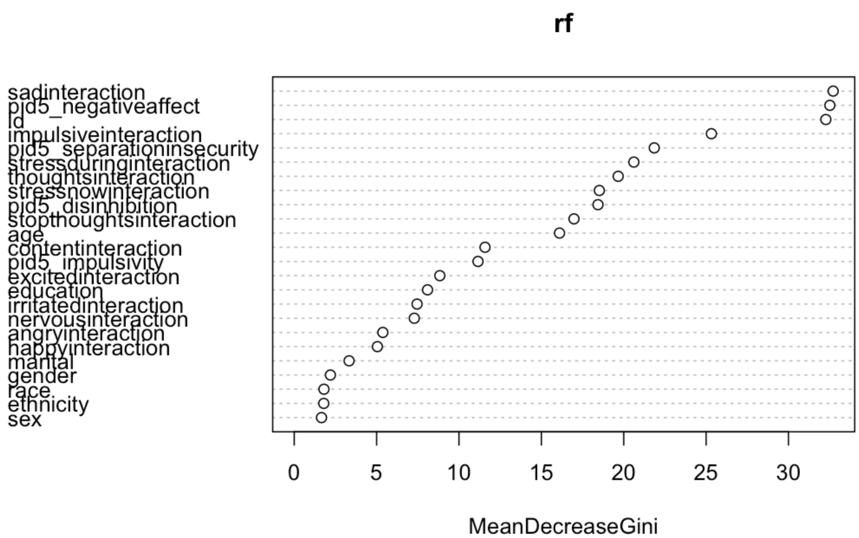
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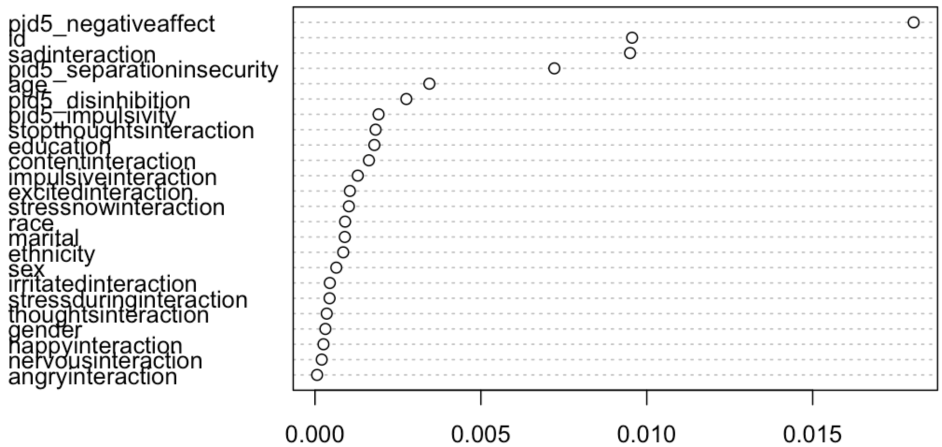


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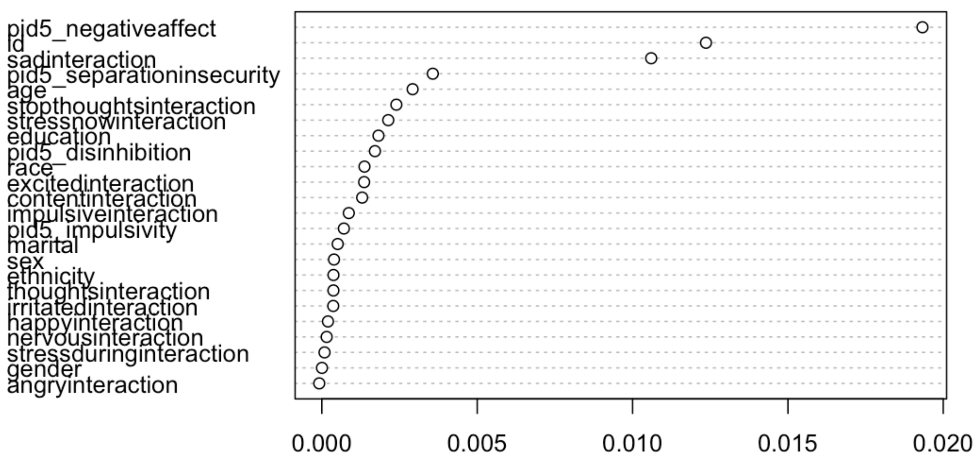


f.

Figure 2. Ensemble Model variable importance measures

**3. Final Model**

The model comparison suggests that random forest without conditional inference and with ID as a cluster variable is the best-fitting model. While bagging had a misclassification rate of 0, it used all available variables, which might limit the interpretation of my findings since my variables are highly correlated. Random forest accounts for that high collinearity and showed high sensitivity and specificity, while the random forest with conditional inference led to a decrease in sensitivity and specificity. The random forest that considered the hierarchical structure of the data revealed ID as an important predictor.

## Discussion

In this study, we investigated how personality traits and momentary changes in negative affect predict suicidal ideation in the context of interpersonal interactions. The results showed that the strongest predictors of suicidal ideation were a combination of personality traits (i.e., Negative Affectivity and Separation Insecurity), and momentary changes in negative affect (sadness) as well as feeling impulsive during the interaction, as expected. Importantly, participant ID was a predictor of suicidal ideation, showing that those who have higher averages of suicidal ideation are more likely to experience suicidal ideation in a given moment. These results show that personality traits pose vulnerability and changes in negative affect trigger suicidal ideation. Having ID as an important variable is due to accounting for the hierarchical structure of the data.

### Limitations

Unfortunately, I had to exclude the only Native American participant in the sample, which is a limitation of this study given that suicide rates are higher than the average in the population among Native American communities. Studies should make an effort to recruit representative samples. Further, the algorithms used in this study require omitting missing data. Given that heightened emotions may have interfered with survey completion, it is likely that we missed important data points.

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