



Machine Learning Modeling of Adaptive and Maladaptive Personality Traits from Passively Sensed Behavior

Runze Yan^a, Whitney R. Ringwald^b, Julio Vega Hernandez^c, Madeline Kehl^b, Sang Won Bae^d, Anind K. Dey^e, Carissa Low^c, Aidan G.C. Wright^b, Afsaneh Doryab^a

^a*School of Engineering and Applied Science, University of Virginia, United States*

^b*Department of Psychology, University of Pittsburgh, United States*

^c*Mobile Sensing + Health Institute, Center for Behavioral Health, Media, and Technology, University of Pittsburgh, United States*

^d*School of Systems and Enterprises, Stevens Institute of Technology, United States*

^e*Information School, University of Washington, United States*

Abstract

Continuous passive sensing of daily behavior from mobile devices has the potential to identify behavioral patterns associated with different aspects of human characteristics. This paper presents novel analytic approaches to extract and understand these behavioral patterns and their impact on predicting adaptive and maladaptive personality traits. Our machine learning analysis extends previous research by showing that both adaptive and maladaptive traits can be predicted from passively sensed behavior providing initial evidence for the utility of this type of data to study personality and its pathology. The analysis also provides insights into the underlying behavior patterns that link adaptive and maladaptive variants consistent with contemporary models of personality pathology.

Keywords: Mobile and Wearable Sensing, Machine Learning, Data Mining, Behavior Modeling, Personality Prediction

1. Introduction

Personality refers to an individual's typical patterns of motivations, thoughts, feelings, and behavior that serve the functional roles of adaptively navigating the environment [18, 71]. As such, personality pathology (i.e., personality disorder) refers to typical patterns of motivations, thoughts, feelings, and behavior that are persistently and pervasively maladaptive, such that they result in dysfunctional patterns of day-to-day behavior [49]. These maladaptive patterns of behavior are thought to account for associations between personality pathology and poor psychosocial and physical health outcomes [20, 47, 69]. Clinical psychology and psychiatry are undergoing a paradigm shift from classifying personality pathology using a finite set of discrete categorical diagnoses to continuously distributed dimensional traits, and growing evidence suggests traits are more valid, reliable, and clinically useful [31]. Despite these recent advances, little is known about the specific, everyday, behavioral expressions of pathological traits that may contribute to poor psychosocial functioning and outcomes.

Most research on dimensional models has relied on cross-sectional, global self-report data, which are not well-suited to measure the dynamic moment-to-moment processes underlying personality and its pathology [26, 70]. Although the use of ecological momentary assessment (EMA) and intensive longitu-

nal studies to collect data from people in their naturalistic settings has remedied some of these issues, heavy reliance on self reports, which can be prone to bias and lack of engagement, can affect the quality and validity of the collected data [61]. Passive sensing via a participant's smartphone or wearable devices has the potential to address these concerns through continuous and contextualized measures of behavior [42]. Smartphone sensing combined with machine learning has been used to predict personality traits from smartphone devices [29]. However, to our knowledge, no existing research has investigated the feasibility of passive sensing to predict adaptive and maladaptive personality traits and to extract the shared and unique behavioral patterns associated with each of them.

The current study therefore proposes to leverage a combination of passive sensing, machine learning, and data mining algorithms to identify patterns of behavior across the main spectra of adaptive and maladaptive personality traits. By filling in the methodological gaps of previous work, and introducing novel analytic approaches, we aim to generate new hypotheses about the everyday behavior patterns that maintain (or prevent) problems, as well as demonstrate the opportunities and value of these methods to enrich existing empirical models of personality pathology.

*Corresponding author

Email address: ry4jr@virginia.edu (Runze Yan)



2. Background and Related Work

2.1. Adaptive vs. Maladaptive Personality Traits

Traditional psychiatric classifications, as reflected in the American Psychiatric Association's Diagnostic and Statistical Manual for Mental Disorders [2] and the World Health Organization's International Classification of Disease (ICD), have conceptualized personality pathology categorically, under diagnoses such as borderline personality disorder, schizoid personality disorder, and narcissistic personality disorder. Each diagnosis describes a "type" that is based on meeting a certain number of criteria from a checklist of symptoms. However, categorical personality disorder diagnoses have critical weaknesses, including poor validity, low reliability, and limited clinical utility [60, 68]. Such issues have prompted a shift towards dimensional trait models of personality pathology that outperform categorical models psychometrically and may have greater clinical utility [36].

The dimensional approach is further supported by empirical and conceptual parallels between these maladaptive traits and the trait dimensions that have emerged from over a century of studying adaptive personality structure [40, 72]. Indeed, for each of the big five traits, personality's most prominent model, maladaptive traits have been identified that can be understood to cover the same behavioral content, albeit often keyed towards the opposite direction. See Figure 1 for elaboration of these traits and their descriptions. For example, whereas adaptive personality research finds Extraversion, which manifests in sociability, assertiveness, positive emotions, and energy, the maladaptive variant is Detachment which manifests in social withdrawal, passivity, lack of positive emotions, and lethargy. Correspondence between these sets of traits suggest that instead of maladaptive personality having discrete principles and properties that differentiate it from normal range personality (i.e., being a separate category), the two operate along shared underlying dimensions or spectra. In other words, while there is a continuum of functioning from adaptive to maladaptive, the two share the same fundamental traits. In recent years, variations on trait-based models of personality disorder classification and diagnosis have been included in the DSM-5 (provisionally, as an alternative approach in need of more study [67]) and the ICD-11 (officially [45]). In fact, it has been argued that maladaptive trait models can serve as useful structures for organizing all of psychopathology [35].

2.2. Assessing Personality Traits from Self Reports

What is thought to link an individual's personality to their level of psychosocial functioning and health are the dynamic and contextualized patterns of behavior they engage in. For example, a person who scores high on trait Detachment may be less motivated to socialize, so they may contact fewer people or go out in public less during the day than most people, which in turn contributes to poor relationships and low mood. Yet, most research on dimensional models has relied on cross-sectional, global self-report data, which are not well-suited to measure the dynamic moment-to-moment processes underlying personality and its pathology [26, 70]. Cross-sectional data is unable

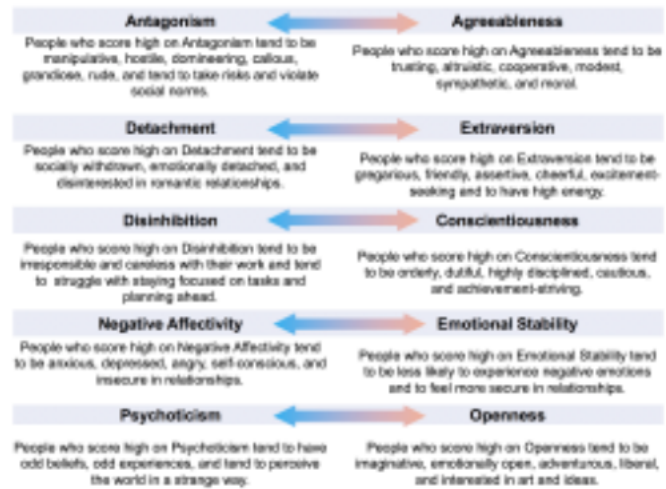


Figure 1: Descriptions of corresponding adaptive and maladaptive traits.

to capture the temporal aspect of maladaptive behaviors that unfold from moment-to-moment. To a large extent, issues with cross-sectional data can be remedied with intensive longitudinal study designs, such as ecological momentary assessment (EMA). EMA (sometimes referred to as experience sampling methodology or ambulatory assessment) can be used to assess people intensively and repeatedly in their naturalistic settings, thereby increasing ecological validity, reducing biases of retrospection, and capturing multiple points along an unfolding dynamic process. Each of these address the limitations of traditional global self-report scales. However, EMA typically uses self-report data which relies on the person being conscious of the behaviour and willing to report it—but many of the maladaptive patterns people engage in may be outside of awareness [11].

2.3. Assessing Personality Traits from Passively Sensed Behavior

Because self-report EMA study designs require participants to fill out multiple surveys per day or week, the burden to participants' in terms of time and effort limits the number of data points that can feasibly be collected throughout the day [61]. Passive sensing, or automatic data collection via a participant's smartphone or other device, is a methodological approach that has the potential to address these concerns [39]. It can provide continuous, contextualized, temporally sensitive, and direct measures of behavior (not reliant on participant report). Such an approach collects personality relevant information like frequency of texting and phone calls, average time spent in each location, and number of bluetooth devices scanned, which can be aggregated into higher order variables related to psychological constructs [22, 42, 66]. These nearly unbroken streams of high-resolution data on what people actually do during the day (not just what they are aware of) have the potential to offer new insights into maladaptive patterns linked to personality pathology.

One challenge associated with passive sensing, is that the type of data it produces, characterized by large numbers of vari-



ables, often overlapping, with unknown associations with behavioral outcomes, is not well suited to the statistical models traditionally applied in psychology research (i.e., mostly based on the general linear model). Such models often have a core assumption of relatively modest associations, can practically only handle a few variables, and assume a linear relationship between traits and behaviors that is often not met statistically or expected theoretically. In contrast machine learning has a number of tools available that can address these concerns. Decision-tree based regression algorithms such as XGBoost and random forest overcome the limitations of traditional analyses [9, 13]. Passive-sensing results in potentially dozens of highly correlated features. Because decision tree models do not make the same assumptions of independence, they are better suited to this type of question [9, 41]. Additionally the quantity of features derived from passive sensing cannot reasonably be included in traditional statistical analyses, especially since the number of features can often exceed the number of observations [57]. Decision trees can account for correlations among vast quantities of variables to identify predictive behaviors, and are also reported to be more stable than a typical step-wise approach used for variable selection in traditional analyses [41, 57]. Finally random forests are non-parametric and can be used to detect complex, non-linear associations [9, 41]. Machine learning can also be used to explore certain combinations of passive sensor features that are particularly predictive of certain trait levels. Characteristic combinations of daily behaviors are undetectable with covariance-based models in psychology or typical “black box” classification algorithms, but these combinations may reveal more nuanced patterns that contribute to a person’s health and well-being.

Prior research provides initial evidence that passive sensing can provide meaningful information about individual differences in adaptive and maladaptive functioning. Studies have shown that attributes and events related to categorical DSM diagnoses (e.g., depression, psychotic episodes [6, 10, 48], and adaptive personality traits [1, 5, 15, 28, 29, 43, 56, 52] can be predicted from smartphone sensor, although these associations have been modest in size. Some machine learning methods have been used in previous research to predict personality including support vector classifiers, regularized regression models, and decision tree algorithms, but our study is the first to our knowledge to apply association mining to identify feature combinations linked to personality traits. A few studies have investigated associations between heart rate measured by wearable devices and aspects of personality like emotional responses [23, 46, 17], but none have examined how personality traits relate to ambulatory heart rate. Given the transition towards conceptualizing personality pathology as dimensional variants of adaptive personality traits, linking smartphone sensor features to empirically-derived adaptive and maladaptive trait models has the potential to deepen our understanding of how personality shapes psychosocial functioning and important outcomes.

3. Methods

To explore the potential of passive sensing to reveal the dynamics of personality pathology, we designed and employed a series of analytical methods, including prediction, correlation, and association rule mining. These methods allow us to 1) identify and rank behavioral features related to each personality dimension and 2) measure the intensity of the behavioral features associated with those dimensions. The following sections first provide an overview of our data processing pipeline followed by a description of the analysis methods.

3.1. Data Processing

3.1.1. Feature Extraction

To extract behavioral features from raw sensor data, we first divided each data stream into daily intervals. We aggregated the raw data and extracted different statistical measures such as minimum, maximum, mean, standard deviation as well as more complex behavioral features such as movement patterns and type, and duration of activities. We used RAPIDS, an open-source framework for extracting behavioral features from mobile and wearable devices [64]. Details of the extracted features are documented in [21].

3.1.2. Handling missing values

Datasets gathered from mobile sensor devices often suffer from a significant fraction of missing data due to issues such as poor communication, power depletion, and hardware failure. The missing rate across all features in the dataset we collected is 58.2%. To handle the missing data, we took a two-step approach. First, if all sensor data from a participant on a certain day was missing, we deleted the participant’s data for that day. Then, we deleted all participants with less than one week of data. We then removed features with more than 60% missing values. This percentage was chosen based on the average proportion of missing values among all feature columns. We used the Multiple Imputation by Chained Equations (MICE) to impute the rest of the missing values. MICE creates multiple imputations, as opposed to single imputations, thus accounting for the statistical uncertainty in the missing values. This reduces the imputation bias associated with large blocks of missing values [50]. In addition, the flexibility of the chained equations approach allows for handling multiple types of variables (e.g., continuous, binary, unordered, and ordered categorical data) simultaneously [53]. MICE can only work under the assumption that the data are missing at random (MAR) or the more stringent missing completely at random (MCAR). We believe that the MCAR assumption fits our data because sensor readings can fail randomly due to many different and non-systematic factors, including network error, sensor faulty, phone battery, etc [7]. We imputed the missing data multiple times using single imputation technologies, which resulted in multiple completed datasets. We then applied machine learning analysis on each completed dataset and pooled the final results by averaging the estimates of each model, computing the total variance over the repeated analyses and estimating the average error.



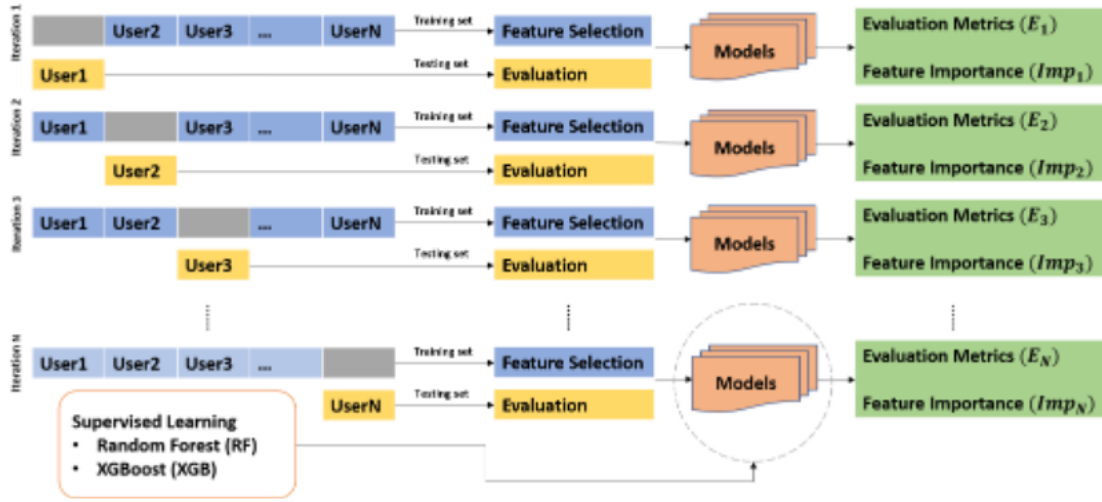


Figure 2: The leave-one-person-out cross-validation process to build machine learning models and select and rank features.

3.2. Analysis Pipeline

To investigate passive sensing capabilities in predicting adaptive and maladaptive traits, we developed an analysis pipeline including machine learning, feature ranking, and association rule mining.

3.2.1. Machine learning

We used adaptive and maladaptive trait measures from the self-reports as ground truth for performance analysis of the machine learning algorithms. We used the Random Forest (RF) and XGBoost (XGB) meta-algorithms because they are capable of handling the continuous personality trait values. Both methods use regression trees as base learners, but they have different strategies to prevent overfitting and performance improvement. Random Forest uses the Bagging (Bootstrap Aggregation) to reduce performance variance by first creating subsamples of the training set and then averaging the model performance resulted from each subsample [8, 54]. RF has a certain degree of randomness, which helps avoid overfitting and improves generalizability relative to a single tree model. XGboost, on the other hand, uses an iterative learning strategy called Boosting that weighs the samples based on the prediction results of the previous iteration [13]. The error is reduced in each iteration by correcting the misclassified samples from previous iterations. If the data set is small, over-fitting is prone to occur with XGBoost. We used these two complementary models to reduce prediction errors and to build models that support a stable hypothesis generation process for further analysis. Both methods output feature importance as part of the model building process. In a nested cross-validation process, we selected the highly ranked features in each iteration and used them to identify the final set of behavioral features that distinguish personality traits.

3.2.2. Feature selection

The large number of extracted features compared to the relatively small number of participants in our dataset required dimensionality reduction through feature selection. Our feature

selection proceeded in two steps. First, we identified redundant features by calculating the Pearson correlation between all feature pairs. If there is a high correlation between two features, the two features are more likely to be linearly dependent, and they will have nearly the same effect on the dependent variable. Because of this, in the second step, we kept the feature that correlated more strongly with the dependent variable (adaptive and maladaptive traits) and dropped the feature with the lower correlation.

3.2.3. Validation

We used leave-one-person-out cross-validation (LOOCV) on our dataset to evaluate the power of sensor features to predict personality traits [65]. LOOCV is a specific type of k-fold cross-validation, where the number of folds is equal to the number of participants on our dataset. In each iteration, data from $n-1$ participants is used for training, and the model is tested on the n th participant. LOOCV is a robust way to test the generalizability of a model that contains participant-level data. However, LOOCV is also the most computationally expensive, especially given that the data imputation and feature selection process is within the cycle of LOOCV [34].

3.2.4. Performance Measures

To measure the performance of the models, we used the mean squared error (MSE) and the mean absolute percentage error (MAPE), both of which calculate the average distance between the predicted and observed values in the data [62]. MSE is the average of the squared difference between the predicted value and the observed value, MAPE is the average of the absolute percentage between the predicted value and the observed value. However, MSE is scale-dependent, and MAPE is scale-independent. Although personality traits were rated on a scale from 0 to 4, the observed distribution of trait levels was not uniform across traits as shown in Figure 5. We, therefore, used both measures to give a more accurate picture of the prediction performance. While MSE represents the overall variance in the estimator's measures, MAPE shows the relative variance of the



estimator measures compared to data samples. To calculate the overall performance, we averaged the MSE and MAPE results from the LOOCV process.

3.2.5. Feature Ranking

Each iteration in the LOOCV process assigns an importance value to each feature in the training process. A higher importance value for a feature indicates a larger contribution to the prediction process. We logged these values during training and aggregated the overall ranks of each feature at the end of the process. Sensor features were ranked according to their frequency of being selected as well as their averaged importance across rounds in the LOOCV. For each training algorithm (RF or XGB), we considered features with frequency and importance greater than the median to be high ranked features selected by that algorithm. We then selected the features that are common across both algorithms. Those features were then ranked according to the following formulas:

$$f(Imp_i) = \begin{cases} 1 & \text{if } Imp_i > 0; \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

$$RS = \frac{\sum_{i=1}^N (Imp_{RF_i} \sum_{i=1}^N f(Imp_{RF_i}) + Imp_{XGB_i} \sum_{i=1}^N f(Imp_{XGB_i}))}{N} \quad (2)$$

where Imp is the importance value of the sensor feature, and N is the number of iteration in the LOOCV, which equals the number of participants.

3.2.6. Association Rules Mining

To take another approach to identify behavioral patterns associated with personality traits, we applied the Apriori, a well-known frequency-based method for analyzing transactional data and producing association rules that explain the frequency (support) and significance (confidence) of the observed patterns [30, 32]. In the association rules analysis, a collection of one or more items is called an itemset. If an itemset contains k items, it is called a k -itemset. Our analysis used the dataset containing participant's data and the frequently selected features in an iterative process to extract the 1 to k -itemsets. Since Apriori requires discrete data, we categorized the features and personality trait values into three ranges of low, moderate, and high. The sensor features were normalized into the 0 and 1 range and discretized into low (0 ~ 0.25), moderate (0.25 ~ 0.75), and high (0.75 ~ 1). Personality traits ranged from 0 to 4 and were discretized into low (0 ~ 1), moderate (1 ~ 3), and high (3 ~ 4). The distribution of participants in each group is shown in Figure 4. Each feature with its corresponding levels was then entered as items into the frequent item-set mining step of the Apriori algorithm. This step generates itemsets, including combinations of features and the relative frequency they occur together on the same day. For example, a 2-itemset can contain low location entropy and high frequent outgoing calls features that appear together 15 times (i.e., days) in the entire dataset. In the next step, Apriori generated a set of association rules from those frequent itemsets. An association between X and Y ($X \rightarrow$

Y) exists if items in X and Y frequently appear together. Support is the proportion of data samples that contain both X and Y , while confidence is the proportion of samples containing X that also contain Y [27]. A rule must achieve a minimum level of support and confidence to be considered significant. Figure 3 shows our approach in using Apriori to extract frequent behavior patterns from highly ranked features.

4. Data collection

4.1. Participants and Procedures

Community members were recruited through posted flyers for a study of personality, daily stress, and social interactions. For inclusion, participants had to be between the ages of 18 and 40 and were not currently receiving treatment for psychosis or a psychotic disorder. Preliminary screening was used to recruit a gender-balanced sample and to ensure adequate representation of a range of personality pathology and interpersonal problems. The sample was also selected to balance individuals who had received recent mental health treatment within the past year with those who had not. Individuals were pre-screened using items from the Inventory of Interpersonal Problems - Personality Disorder Scales [44] and were recruited in an approximately 1-1-1 representation of low, moderate, and high levels of interpersonal difficulties within gender, treatment status, and the overall sample. For this study, we only analyzed a subset of participants that had smartphone sensor data.

The total sample size for our analyses was 128. Participants were mostly white (78%; 9% Asian; 9% Black/African-American), roughly balanced on gender (54% female), with an average age of 27.7 (SD = 6.6). Most participants had received mental health treatment in the past (23%) or were currently receiving treatment (37%).

Participation involved completing a battery of baseline assessments in an initial laboratory session followed by a 14-day ambulatory assessment (AA) protocol including self-reports and passive sensor data collection. Participants received \$50 for the baseline session. Those who answered 90% or greater of the surveys during the AA protocol earned an additional \$160. This amount was prorated by week for those who completed less than 90% of the surveys overall. Participation was also incentivized with random drawings for prizes, with chance of winning proportionally tied to rate of participation.

4.2. Self-Report Measures

Self-report measures of adaptive and maladaptive traits were completed during the initial laboratory session. During this session, participants were also provided instruction from a research assistant regarding the AA procedures and the required smartphone applications were installed on their personal Android or iOS smartphone. Smartphone sensor data was collected using an application called AWARE described in the next section. Because the focus of this study is on predicting adaptive traits from passive sensing, self-report AA surveys were not used in the current study.



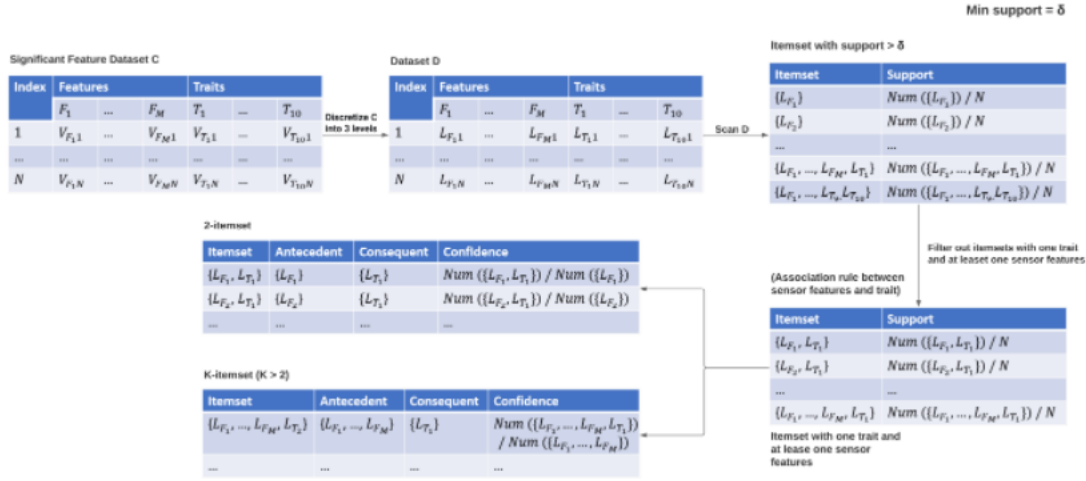


Figure 3: The process of mining association rules using the Apriori method. M is the number of highly ranked features we derived, V represents continuous values, and L represents the discrete levels.

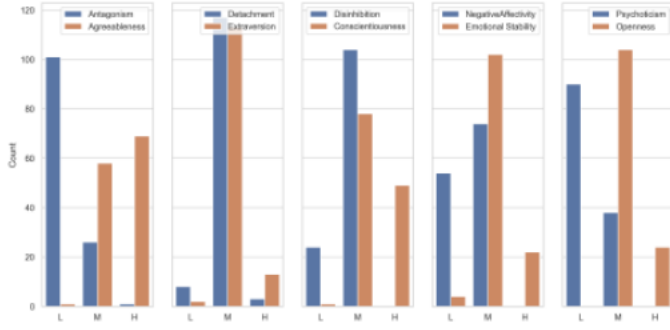


Figure 4: The number of participants in each group (low (L), moderate (M), and high (H) level) for each adaptive and maladaptive trait.

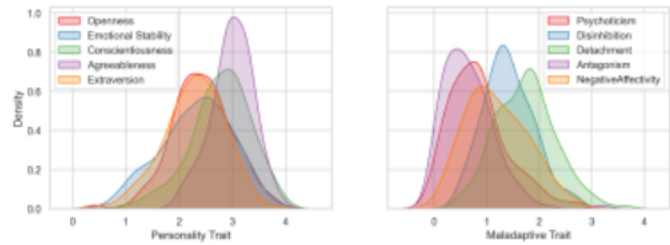


Figure 5: Density plot displays the distribution of the adaptive and maladaptive values of all participants. Each adaptive and maladaptive trait ranges from 0 to 4.

4.2.1. Personality traits

Personality traits were assessed using the self-report International Personality Item Pool - NEO-120 [33], which is a 120-item inventory designed to map onto the widely used NEO-Personality Inventory-Revised [16] traits in an abbreviated and open-source format. For each item, participants rated the extent to which a characteristic applies to them (e.g., “I am someone who is outgoing”) on a Likert scale from “Very Inaccurate” (0) to “Very Accurate” (4). The IPIP-NEO-120 was scored to provide a score of the five trait domains of Extraversion, Agree-

ableness, Conscientiousness, Emotional Stability, and Openness. Reliability for the trait scales in was high (mean McDonald’s Omega = .88; range = .84 ~ .91).

4.2.2. Maladaptive traits

Maladaptive traits were assessed using the Comprehensive Assessment of Traits Relevant to Personality Disorder (CAT-PD; [55]). The CAT-PD is a 216-item self-report inventory, which asks participants to describe themselves how they behave in general compared to others (e.g., “I get angry easily”). Items are rated on a Likert scale (0) “Very Untrue of Me” to (4) “Very True of Me.” The CAT-PD can be used to calculate the five higher-order maladaptive trait domains that map on to the big-five traits [72]). Specifically, these are Antagonism (maladaptive low Agreeableness), Detachment (maladaptive low Extraversion), Disinhibition (maladaptive low Conscientiousness), Negative Affectivity (maladaptive low Emotional Stability), and Psychoticism (maladaptive Openness). We calculated these higher-order domains by averaging lower-order facet scales associated with each domain. Reliability for the trait scales was good (mean McDonald’s Omega = .92; range = .90 ~ .95).

4.3. Descriptive Statistics

Density distributions of self-reported personality trait levels are shown in Figure 5. Overall, participants reported levels of adaptive traits above the midpoint of the scale ($M = 2.63$) and levels of maladaptive traits below the midpoint ($M = 1.25$). These distributions show that there was considerable variance between people representing a wide range of functioning.

Consistent with the broader literature showing the correspondence between adaptive and maladaptive traits, the strongest bivariate correlations were between the expected constructs (Figure 6). Agreeableness, Extraversion, Conscientiousness, and Emotional Stability were strongly negatively correlated with



their maladaptive counterparts of Antagonism, Detachment, Disinhibition, and Negative Affectivity respectively. Psychoticism and Openness were positively correlated in line with previous research suggesting these traits are not opposite poles on a continuum, but instead can be thought of as adaptive and maladaptive variants of the same pole [19, 58, 72].

	Antagonism	Detachment	Disinhibition	Negative Affectivity	Psychoticism
Agreeableness	-.71	-.08	-.06	-.20	-.20
Extraversion	.07	-.71	-.27	-.46	-.12
Conscientiousness	-.27	-.12	-.76	-.35	-.37
Emotional Stability	-.13	-.35	-.49	-.86	-.42
Openness	.06	-.27	.15	.03	.28

Figure 6: Bivariate correlations between maladaptive and adaptive traits. Values on the diagonal are correlations between corresponding adaptive and maladaptive variants of the same trait.

4.4. Passive Sensing

Data from participant’s smartphone sensors was collected via the AWARE application [24]. AWARE runs in the background on both iOS and Android platforms and continuously collects data from phone channels. For this study, we used battery data, phone call logs, GPS, microphone sensors, and phone screen lock/unlock data. Collection of battery, call logs, and screen status sensors were event-based, such that a data sample or observation is created in the database when a change (event) is detected (e.g., a phone call is made). GPS and microphone sensors were sampled at regular intervals. Specifically, GPS sensors were sampled every 180 seconds and the microphone sensors recorded audio for one minute with three minutes of pause in between samplings. Participants were also provided with a Fitbit Blaze smartwatch to collect physiological measures related to heart rate, steps, and sleep via AWARE. Heart rate and movement data were sampled in one minute intervals. Sleep features were estimated from a combination of movement and heart-rate patterns. Seventy-three participants used an iOS equipped smartphone and 55 used an Android smartphone. On average, 12 days of sensor data were collected from every participant (SD = 1.5).

5. Results

5.1. adaptive and Maladaptive Trait Prediction

As shown in Figure 7, the error range of RF and XGB were very close when predicting each trait, with RF performing slightly better. Agreeableness had the lowest average prediction error, while Emotional Stability and Openness had the highest average error. We also found that the pairs of corresponding maladaptive and adaptive traits tended to have comparable prediction errors. For example, the values of MSE for both Psychoticism and Openness are relatively high, and the values of MSE for both Conscientiousness and Disinhibition are relatively low. A potential hypothesis is that the more distinct behavioral features are between the adaptive and maladaptive pairs, the lower the prediction error will be.

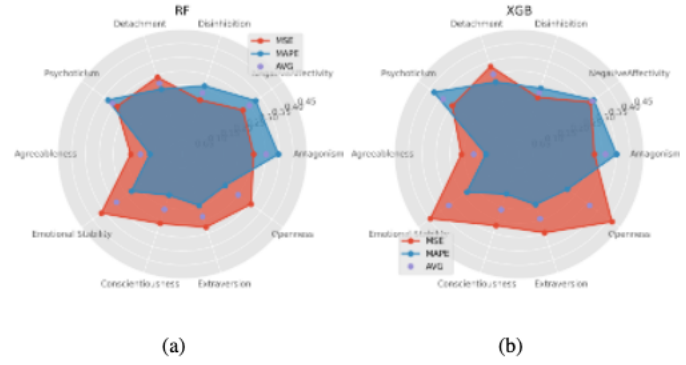


Figure 7: The radar plots visualize the MSE and MAPE of machine learning models when predicting each adaptive and maladaptive trait.

Sensor	Sensor feature code and description
Heart Rate	HR1: The median of the heart rate in one day
	HR2: The number of minutes the heart rate fell within the fat burn zone in one day
	HR3: The mean of the resting heart rate in one day
Sleep	SL1: The average length of the segment the participant was asleep in one day
	SL2: The sum of time the participant stayed in bed after waking up for nap in one day
	SL3: The sum of time the participant was awake but still in bed in one day
Step	ST1: The number of active segments in one day
	ST2: The number of sedentary segments in one day
Activity	ACT1: The total duration of on foot, running, and on bicycle activities
Battery	Bat1: The total duration of all discharging segments
	Bat2: The total duration of all charging segments
Call	Call1: The estimate of Shannon entropy for the duration of all incoming calls in one day
	Call2: The estimate of Shannon entropy for the duration of all outgoing calls in one day
Audio	Aud1: The standard deviation of the level of noise in one day
	Aud2: The ratio between noise and whole conversation (silence, noise, voice, unknown)
	Aud3: The minimum of the level of voice in one day
Location	Loc1: The maximum distance from home in meters.
	Loc2: The number of significant locations visited in one day.
	Loc3: The standard deviation of the length of all movements
	Loc4: The estimate of Shannon entropy for the significant locations visited in one day.
	Loc5: The shortest time the user staying at a significant location
	Loc6: The ratio between the time of moving status and static status
Screen	SR1: The number of all unlock segments
	SR2: The hours since midnight of the first unlock in one day
	SR3: The length of the shortest unlock segment

Table 1: List of highly ranked sensor features selected by the machine models..

5.2. Frequently selected behavioral features and their relationship to adaptive and maladaptive traits

The machine learning and feature selection as part of the LOOCV approach provided a list of 25 features (out of 177, 14%) with highest ranking scores calculated using Formula 2 (see Table 1). Recall that the high ranking scores indicates that the behavioral feature had both a high overall feature importance and was frequently selected during the iterative training process. Table 1 provides a description for each sensor feature. For presentation clarity, we use abbreviations to represent each feature, which will be used throughout the section. We report feature ranking scores and correlations between each sensor feature and personality traits in Figure 3. The x-axis lists the important and frequently selected features in pairs with ranking score followed by the correlation of that feature.

We organized the features roughly into those related to physiology (e.g., heart rate, sleep) and context-independent physical activities (e.g., battery use, level of activity) on the left side of Figure 8 and features related to social interactions (e.g., calls) and contextualized activities (e.g., time spent in particular locations) on the right side. Although the line is not clear cut, the figure shows that maladaptive traits were generally bet-



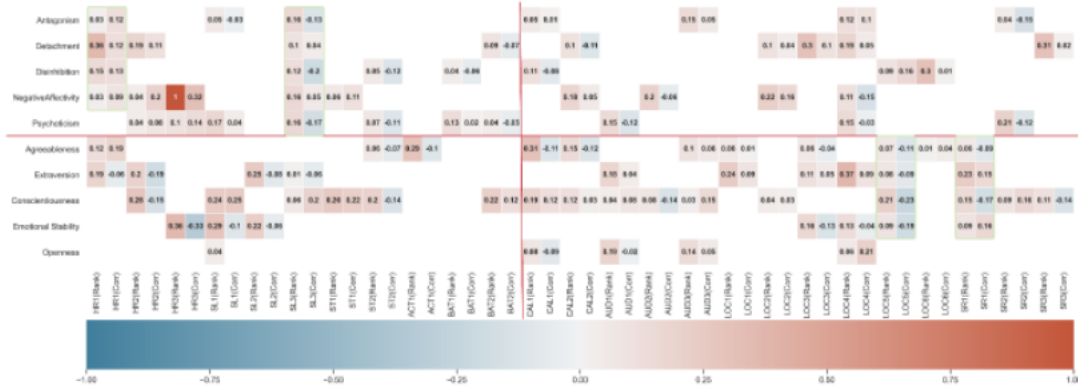


Figure 8: The heatmap shows high ranked features and their correlation with adaptive and maladaptive traits.

		(NegativeAffectivity) / (Emotional Stability)	(Detachment) / (Extraversion)					(Antagonism) / (Agreeableness)			(Disinhibition) / (Conscientiousness)				(Psychoticism) / (Openness)			
		HR3	HR1	HR2	SL3	LOC3	LOC4	HR1	CAL1	CON3	SL3	ST2	CAL1	LOC5	SL1	AUD1	LOC4	
Correlation		0.32 / -0.33	0.12 / -0.06	0.11 / -0.19	0.04 / -0.06	0.1 / 0.05	0.05 / 0.09	0.12 / 0.19	0.01 / -0.11	0.05 / 0.06	-0.2 / 0.2	-0.12 / 0.22	-0.08 / 0.12	0.16 / -0.23	0.04 / -0.15	-0.12 / -0.02	-0.03 / 0.15	
Frequency	RF	108 / 91	120 / 73	120 / 102	115 / 67	105 / 123	120 / 123	88 / 126	87 / 121	88 / 126	119 / 76	97 / 126	111 / 125	120 / 117	78 / 120	86 / 127	96 / 76	
	XGB	82 / 120	111 / 122	120 / 123	111 / 91	120 / 76	120 / 122	80 / 127	91 / 117	92 / 127	120 / 119	101 / 126	116 / 125	119 / 124	96 / 127	92 / 118	89 / 125	
Importance	RF	0.33 / 0.78	0.61 / 0.28	0.55 / 0.81	0.3 / 0.28	0.94 / 0.53	0.51 / 0.57	0.28 / 0.28	0.38 / 0.3	0.6 / 0.32	0.42 / 0.28	0.32 / 0.59	0.29 / 0.37	0.32 / 0.31	1.0 / 0.28	0.35 / 0.43	0.36 / 0.3	
	XGB	0.25 / 0.87	0.91 / 0.72	0.4 / 0.31	0.4 / 0.28	0.48 / 0.27	0.44 / 0.9	0.35 / 0.39	0.3 / 1.0	0.51 / 0.31	0.32 / 0.36	0.27 / 0.35	0.42 / 0.53	0.31 / 0.65	0.33 / 0.31	0.73 / 0.49	0.68 / 0.29	

Table 2: Common high ranked features shared by the pair of adaptive and maladaptive traits. The table also shows the results of correlation between sensor features and traits, how often each sensor feature is selected and the average importance of each sensor feature across leave one participant out cross-validation.

ter predicted by physiological and context-independent features whereas adaptive traits were better predicted by social and contextualized features. For example, the total time spent in bed after waking up (SL3) predicted all five maladaptive traits, shorter amounts of time staying in at significant locations (e.g., home or work; LOC5) and less screen unlocks (SR1) predicted higher levels of most adaptive traits. Out of 14 social contextual features, seven collectively predicted at least three of the adaptive traits (50%) whereas this number was 9% (1 out of 11) for the physiological/context-independent features.

Some features were strongly predictive of specific traits. For example, average resting heart rate (HR3) showed the highest ranking score (1) for predicting Negative Affectivity. Resting heart rate is the number of heart beats per minute while the person is at rest. Lower resting heart rate has been shown to associate with better heart function, whereas higher rate may indicate stress and anxiety [12, 4]. Consistent with this interpretation of heart rate, people who scored higher on Negative Affectivity tended to have a higher resting heart rate and people who scored higher on Emotional Stability (the adaptive counterpart of Negative Affectivity) tended to have a lower heart rate. For Detachment, median heart rate (HR1), variation in movement patterns (LOC3), and the unlock patterns of the phone (SR2) were highly ranked and positively correlated with the trait. Extraversion (the adaptive trait counterpart of Detachment) was negatively correlated with those same features, in line with the idea that reflects opposite behavioral tendencies. As expected, social and contextualized activity features were also predictive of Extraversion, particularly location (LOC1 and LOC4) and phone usage (SR1). The positive correlation with these features indicated more movement and more frequent phone usage predicted higher Extraversion.

High Agreeableness was predicted by low variation in the

duration of incoming and outgoing calls (CAL1, CAL2) and low daily activity level (ACT1). Although feature rankings for Psychoticism (maladaptive) and Openness (adaptive) traits were relatively low compared to other traits, we found that Psychoticism was largely predicted by physiological and context-independent features while Openness was predicted by social and contextualized activity features.

Unlike the other traits, Conscientiousness was predicted by a more balanced mix of physiological, social, and contextualized activity features. In particular, the average length of sleep (SL1), the number of active segments in one day (ST1), and the number of minutes the heart rate fell within the fat burn zone in one day (HR2) were most predictive of Conscientiousness. The positive correlation of SL1 and ST1 with Conscientiousness may suggest that people who score high Conscientiousness can better regulate their sleep at night and keep active during the day. While heart rate features predicted the majority of maladaptive traits, HR2 seems to be predictive of both adaptive and maladaptive traits. Among features related to heart rate zones, i.e., Fat Burn Zone (114 to 134 bpm), Cardio Zone (135 to 159 bpm), and Peak Zone (160+ bpm), only the fat burn zone feature (HR2) was selected highly ranked by the machine learning process [25]. We found that maladaptive traits tended to be correlated with more time per day in the Fat Burn Zone and adaptive traits were correlated with less time. Table 2 shows the common highly ranked sensor features shared by each pair of adaptive and maladaptive traits. For many cases shown in the table, the same sensor feature had opposite associations with the adaptive and maladaptive variants. These results suggest that these traits manifest in opposite extremes of behavior in everyday life.



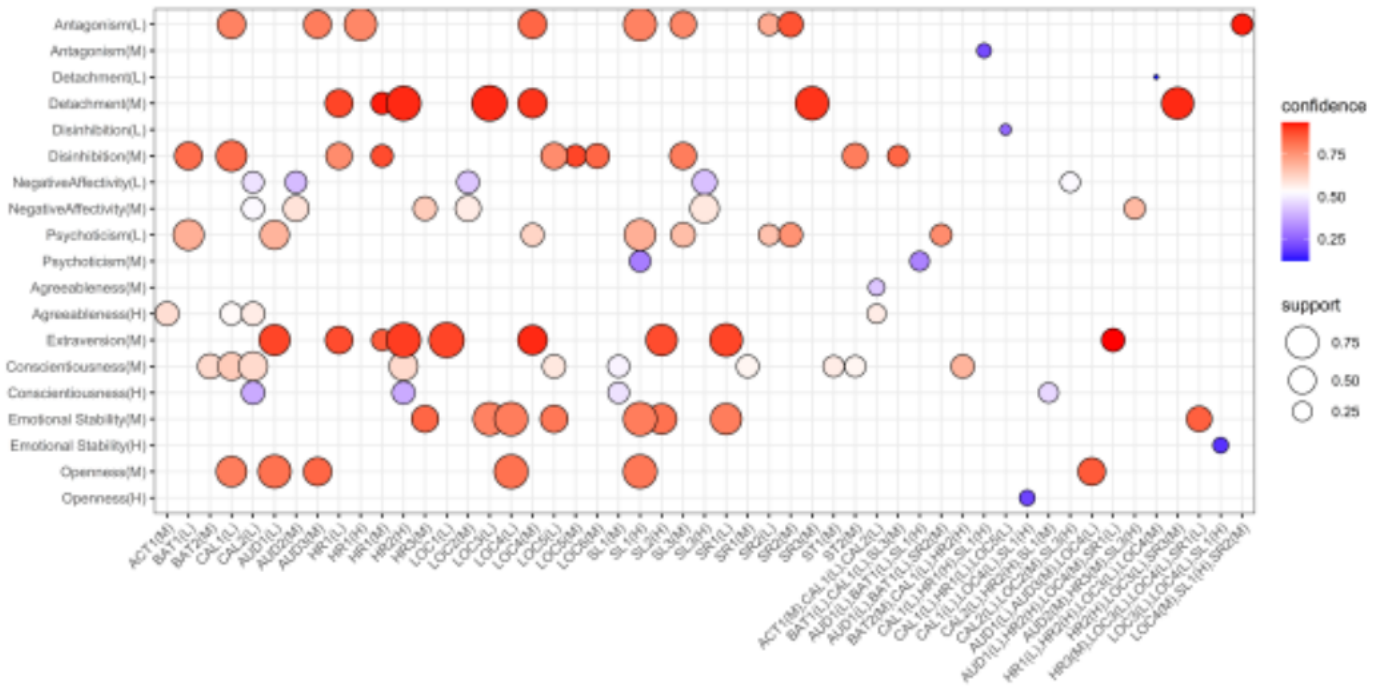


Figure 9: The figure visualizes the associations between behavioral features and traits.

5.3. Mining collective behavioral patterns associated with adaptive and maladaptive traits

While the machine learning analysis and feature ranking showed the predictive power of different features, mining association rules described associations between traits and characteristic combinations of sensor features that tended to co-occur within a day. The feature combinations shown in Figures 9 and 10 are consistent with the results of machine learning and correlation analysis described in the previous section, i.e., the itemsets with the highest confidence for a specific trait tended to include highly ranked features identified by the machine learning models. For example, HR3 had the highest ranking score in models predicting Negative Affectivity, and the association rule of the moderate level of HR3 and Negative Affectivity had the highest confidence among all single sensor feature rules related to the trait. However, unlike the machine learning models, the mined patterns (Figure 9) show associations between distinct levels of features and traits, which offers unique information about how personality is expressed in everyday life that is undetectable with decision-tree analyses. For example, while Figure 8 showed few social and contextualized activity features predicted Openness, Figure 9 reveals that low to moderate levels of those features are highly associated with a moderate level of Openness (average support = 67.5% and average confidence = 82%). A similar pattern was observed for Antagonism, where high levels of HR1 and SL1 are associated with a low level of Antagonism (average support = 76% and average confidence = 78.5%). Among the most pronounced patterns with highest support and confidence were high level of heart rate in fat burn zone (HR2), low movement variation (LOC3), and moderate frequency of phone usage (SR3) being associated

with moderate levels Detachment; and low ambient noise variation (AUD1), high HR2, moderate variation in places visited (LOC4), and low frequency of phone usage (SR1) being collectively associated with moderate Extraversion (the adaptive trait counterpart of Detachment). The alignment between corresponding traits in terms of combined behavioral patterns is depicted in Figure 10.



Figure 10: The figure shows the association rules between the combination of multiple sensor features and personality traits. Each sensor feature and trait have been discretized into three categories: low (L), moderate (M), and high (H). The combination with the highest confidence is shown in the figure for each level of adaptive and maladaptive trait. For some categories of traits, the values of supports are all very low, so the names of sensor features are not listed.



6. Discussion

There is growing evidence for conceptualizing personality pathology using dimensional traits in a unified model with adaptive personality, but there is a need to better understand the everyday manifestations of these traits that contribute to functioning and dysfunction. Towards this end, we applied multiple machine learning methods to sensor data collected from mobile and wearable devices and found that (1) maladaptive traits can be predicted from smartphone sensor data and (2) there are behavior patterns that link adaptive and maladaptive variants consistent with contemporary models of personality pathology.

This study adds to the literature showing smartphone sensor data captures personality-relevant patterns of behavior. We extended previous research by showing maladaptive traits can also be predicted from this type of data, providing initial evidence for the utility of passive sensing to study pathological personality. In addition to using correlational and decision tree models applied in previous work, we used association mining methods to show that specific combinations of features are associated with personality traits. We offer tentative interpretations of our results for hypothesis generating purposes, but emphasize that more work is needed to test these hypotheses.

6.1. Traits vary in how well they can be predicted from sensors

Our results indicate that some features are generally more (or less) predictive of personality—only 13% of the 177 features we extracted met our selection criteria. All features from certain sensors, such as WiFi and Bluetooth detection, had negligible correlations with traits and were omitted from analyses suggesting they may be less useful for studying personality. Heart rate, sleep, and location-based metrics, on the other hand, tended to be important for predicting adaptive and maladaptive personality across the different machine learning models. In particular, maladaptive traits were generally predicted by physiological features whereas adaptive traits were predicted most by social and contextualized activity features. Nearly all maladaptive traits were associated with higher heart rate throughout the day, amount of time spent awake in bed, and the consistency of time spent at different locations. Adaptive traits, on the other hand, were associated with frequency of screen unlocks, consistency of call lengths, and time spent at regularly-visited locations. Taken together, the feature selection results and specific associations between features and traits suggest typical physiological responses may be an especially important indicator of maladaptive functioning and engagement with other people and the environment may be especially related to adaptive functioning.

However, the direction of these feature's correlations with (mal)adaptiveness was not consistent, indicating that their role in functioning is not straight-forward. For example, some maladaptive traits were associated with more time awake in bed and others with less. People who scored higher on Detachment or Negative Affectivity tended to stay in bed while awake longer, which may reflect social withdrawal, low mood, passive rumination, and lack of energy that is common to these traits. In contrast, people scoring high on Disinhibition, Antagonism, or

Psychoticism tended to stay awake in bed less, perhaps because these trait's shared aspects of behavioral and/or cognitive activation prevent people from relaxing or remaining sedentary in bed.

We also showed that some traits are generally more (or less) predictable from passively sensed behavior. In the machine learning models, the most predictable trait pairs were Detachment / Extraversion, Disinhibition / Conscientiousness, and Antagonism / Agreeableness. One reason certain traits were better predicted is the nature of what can be detected by smartphone and FitBit sensors; namely, social behavior and movement. Because Detachment and Extraversion reflect individual differences in sociability and energy, it makes sense that these traits would be more easily predicted from this data. Previous research using passive sensing has also found that Extraversion is the most predictable adaptive trait (e.g., [43, 66]), but our study demonstrates further that its maladaptive variant, Detachment, is similarly predictable. Disinhibition and Conscientiousness reflect individual differences in impulse control and goal-directedness, which may be tracked well with features indexing behavioral (in)consistency (e.g., entropy/variability of calls or movement) and indicators of distractibility (e.g., phone unlocks). The predictability of Antagonism and Agreeableness was less expected because these traits are generally defined by social intentions that are internally experienced rather than observable, detectable behaviors. Our results suggest that there may be behavioral manifestations of the tendency to be at odds with others (Antagonism) or to cooperate (Agreeableness) that may not have been considered in prior theorizing and research.

6.2. Evidence for behavioral indicators that span adaptive and maladaptive trait dimensions

Our results bring a new perspective to the continuity between adaptive and pathological personality by identifying behavioral content that characterizes the full range of functioning in different trait dimensions. The corresponding adaptive and maladaptive traits were strongly correlated with one another as expected, and the machine learning models selected several important features in common for most trait pairs. Overlap between features extracted across adaptive and maladaptive models suggest these behaviors are especially strong indicators of the underlying trait. These indicators, in turn, can help us understand what people do in everyday life that accounts for the link between personality and life outcomes.

For example, Negative Affectivity is a robust risk factor for cardiovascular disease (and Emotional Stability a protective factor), but it is unclear how exactly these traits influence cardiovascular health [37, 51, 59]. Because this trait dimension reflects how easily stressed and emotionally reactive a person tends to be, one hypothesis is that people who score high on Negative Affectivity overuse their stress response system, which over time takes a toll on cardiovascular health [3, 38]. There has been mixed support for this hypothesis, and most research investigating the association between stress responses and Negative Affectivity/Emotional Stability has been conducted in laboratory settings [14, 63]. Instead of sampling heart rate in



a few experiments, we sampled heart rate continuously in everyday life, which may give a more representative picture of people's typical stress response patterns. Our results are consistent with the stress response hypothesis as we found both poles of this trait were strongly associated with heart rate, but in opposite directions: people who scored high on Negative Affectivity had a higher resting heart rate and people who scored high on Emotional Stability had a lower resting heart rate.

To take another example, several features were important indicators of the trait continuum from Disinhibition to Conscientiousness. These traits encompass individual differences in the motivation and ability to maintain focus on long-term goals and are strongly associated with academic and work success. It is thought that people who score high on Disinhibition do poorly in school and work because they struggle to complete tasks and tend to act impulsively whereas people who score high on Conscientiousness generally have better outcomes because they are able to focus on tasks and control their impulses. We found that people who scored high on Disinhibition tended to spend less time awake in bed, have shorter periods of being sedentary, and make calls of inconsistent durations, which may reflect difficulty staying still and engaging in more erratic social behavior. In contrast, people scoring high on Conscientiousness showed the opposite patterns, in line with more controlled and routine behavior. These results suggest that passive sensing may be used to detect consequential behavior patterns that potentially explain how this trait dimension helps (or hinders) functioning.

In addition to the machine learning models, we used Apriori association mining models to explore what configurations of behaviors on a given day are characteristic of traits. Supporting the potential of this method for studying personality, we found that some levels of every trait could be predicted from feature combinations. Because the same behavior can relate to multiple traits for different reasons (e.g., longer sedentary durations may reflect the ability to focus for long periods of time or it may represent lack of energy and low mood), this method has the potential to disambiguate associations between traits and passive sensor features. For instance, people with high scores on Conscientiousness had more days with consistent call lengths, moderate sleep durations, and high levels of physical activity whereas people who scored high on Agreeableness also had more days with consistent call lengths but in combination with moderate levels of activity. Thus, although Agreeableness and Conscientiousness are both traits associated with more adaptive functioning, and both relate to consistent social behavior, they can be differentiated by co-occurring behaviors. Both behavior sets seem to reflect balanced activity patterns, but perhaps being achievement-striving and disciplined is tied to well-regulated sleep and exercising more, whereas being more agreeable is primarily related to routine social interactions.

6.3. Limitations and future directions

The major advantage of using passive sensing and machine learning to study personality pathology is that they allow us to assess aspects of behavior that cannot be measured with any other methods and with potentially much greater precision. At

the same time, because passive sensing is a relatively new technology, the psychometrics of the method have not been comprehensively evaluated yet. Before passive sensing research can be translated into theory or clinical applications, more work is needed to establish the reliability and validity of features and feature combinations. In terms of construct validity, some sensor features are human-interpretable (e.g., more phone calls usually indicate more social activity), but others are more ambiguous and less readily interpreted. By examining associations with personality traits that have well-established psychometrics, our study provides some insight into how to interpret passive sensor features. Future research can build on this foundation by examining associations with contemporaneous participant reports; for example, to determine whether days with longer durations of being sedentary typically reflect high motivation and concentrated studying or lack of motivation and low mood, the passive sensor data could be correlated with participant reports of the activity they are engaging in.

Related to the unknown psychometrics of passive sensing methods, the technology is still in early stages of development and potentially prone to errors throughout the data collection process. There are currently no empirical criteria for determining valid data captured by sensor streams, meaning investigators have to apply ad hoc heuristics for assessing validity. Because of the exploratory nature of our study, we only removed observations with values outside of plausible ranges (e.g., negative value for distance travelled in a day). This liberal approach allowed us to maximize the amount of data analyzed, but it is possible that some of the data included errors (e.g., distance travelled that was calculated from inaccurately encoded raw GPS data). Alongside continued refinement of data collection technologies, it will be important to establish empirical criteria for determining valid data with more focused research efforts moving forward.

Another limitation of our study is that we were unable to identify combinations of features correlated with very high levels of personality pathology using the Apriori method. Because this approach is based on the frequency with which certain trait values appear in a dataset, there was less confidence and support for feature combinations related to high levels of maladaptive traits (or low levels of adaptive traits) that were less common in our sample. To maximize association mining methods to understand maladaptive personality, future research will need to collect data from samples selected for very high pathology (e.g., psychiatric patients with specific diagnoses).

7. Conclusion

As clinical psychology and psychiatry increasingly adopt dimensional models of classifying personality pathology, understanding what the specific patterns of behavior people engage in are that connect personality to poor psychosocial and physical health outcomes are key remaining questions. Our study highlights the opportunities and challenges of using machine learning and passive sensor data to address these questions. We showed that maladaptive traits are predictable from



passive sensor features and feature combinations, and the results provoke new hypotheses about day-to-day processes underlying personality traits and open fresh directions of inquiry.

8. Acknowledgements

Support for this research was provided by the National Institutes of Health (NIH) (R01 AA026879; L30 MH101760), the National Science Foundation (NSF-IIS-1816687), the University of Pittsburgh's Clinical and Translational Science Institute, which is funded by the NIH Clinical and Translational Science Award (CTSA) program (UL1 TR001857), and grants from the University of Pittsburgh Central Research Development Fund and a Steven D. Manners Faculty Development Award from the University of Pittsburgh University Center for Social and Urban Research.

References

- [1] Ai, P., Liu, Y., Zhao, X., 2019. Big five personality traits predict daily spatial behavior: Evidence from smartphone data. *Personality and Individual Differences* 147, 285–291.
- [2] American Psychiatric Association, A., Association, A.P., et al., 2013. Diagnostic and statistical manual of mental disorders: Dsm-5.
- [3] Barlow, D.H., Ellard, K.K., Sauer-Zavala, S., Bullis, J.R., Carl, J.R., 2014. The origins of neuroticism. *Perspectives on Psychological Science* 9, 481–496.
- [4] Batsel , E., Stefaniak, N., Fantini-Hauwel, C., 2019. Resting heart rate variability moderates the relationship between trait emotional competencies and depression. *Personality and Individual Differences* 138, 69–74.
- [5] Beierle, F., Probst, T., Allemann, M., Zimmermann, J., Pryss, R., Neff, P., Schlee, W., Stieger, S., Budimir, S., 2020. Frequency and duration of daily smartphone usage in relation to personality traits. *Digital Psychology* 1, 20–28.
- [6] Ben-Zeev, D., Brian, R., Wang, R., Wang, W., Campbell, A.T., Aung, M.S., Merrill, M., Tseng, V.W., Choudhury, T., Hauser, M., et al., 2017. Crosscheck: Integrating self-report, behavioral sensing, and smartphone use to identify digital indicators of psychotic relapse. *Psychiatric rehabilitation journal* 40, 266.
- [7] Bennett, D.A., 2001. How can i deal with missing data in my study? *Australian and New Zealand journal of public health* 25, 464–469.
- [8] Biau, G., Scornet, E., 2016. A random forest guided tour. *Test* 25, 197–227.
- [9] Breiman, L., 2001. Random forests. *Machine learning* 45, 5–32.
- [10] Canzian, L., Musolesi, M., 2015. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis, in: *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pp. 1293–1304.
- [11] Carlson, E.N., Vazire, S., Oltmanns, T.F., 2013. Self-other knowledge asymmetries in personality pathology. *Journal of Personality* 81, 155–170.
- [12] Carnevali, L., Sgoifo, A., 2014. Vagal modulation of resting heart rate in rats: the role of stress, psychosocial factors, and physical exercise. *Frontiers in physiology* 5, 118.
- [13] Chen, T., He, T., Benesty, M., Khotilovich, V., Tang, Y., Cho, H., et al., 2015. Xgboost: extreme gradient boosting. *R package version 0.4-2* 1.
- [14] Chida, Y., Hamer, M., 2008. Chronic psychosocial factors and acute physiological responses to laboratory-induced stress in healthy populations: a quantitative review of 30 years of investigations. *Psychological bulletin* 134, 829.
- [15] Chittaranjan, G., Blom, J., Gatica-Perez, D., 2013. Mining large-scale smartphone data for personality studies. *Personal and Ubiquitous Computing* 17, 433–450.
- [16] Costa, P.T., McCrae, R.R., 1992. Normal personality assessment in clinical practice: The neo personality inventory. *Psychological assessment* 4, 5.
- [17] Daly, M., Delaney, L., Doran, P.P., Harmon, C., MacLachlan, M., 2010. Naturalistic monitoring of the affect-heart rate relationship: a day reconstruction study. *Health Psychology* 29, 186.
- [18] DeYoung, C.G., 2015. Cybernetic big five theory. *Journal of research in personality* 56, 33–58.
- [19] DeYoung, C.G., Grazioplene, R.G., Peterson, J.B., 2012. From madness to genius: The openness/intellect trait domain as a paradoxical simplex. *Journal of Research in Personality* 46, 63–78.
- [20] Dixon-Gordon, K.L., Whalen, D.J., Layden, B.K., Chapman, A.L., 2015. A systematic review of personality disorders and health outcomes. *Canadian Psychology/Psychologie Canadienne* 56, 168.
- [21] Doryab, A., Chikarsel, P., Liu, X., Dey, A.K., 2018. Extraction of behavioral features from smartphone and wearable data. *arXiv preprint arXiv:1812.10394*.
- [22] Doryab, A., Villalba, D.K., Chikarsel, P., Dutcher, J.M., Tumminia, M., Liu, X., Cohen, S., Creswell, K., Mankoff, J., Creswell, J.D., et al., 2019. Identifying behavioral phenotypes of loneliness and social isolation with passive sensing: statistical analysis, data mining and machine learning of smartphone and fitbit data. *JMIR mHealth and uHealth* 7, e13209.
- [23] Ebner-Priemer, U.W., Kuo, J., Schlotz, W., Kleindienst, N., Rosenthal, M.Z., Detterer, L., Linehan, M.M., Bohus, M., 2008. Distress and affective dysregulation in patients with borderline personality disorder: A psychophysiological ambulatory monitoring study. *The Journal of nervous and mental disease* 196, 314–320.
- [24] Ferreira, D., Kostakos, V., Dey, A.K., 2015. Aware: mobile context instrumentation framework. *Frontiers in ICT* 2, 6.
- [25] Fitbit, 2021. How do i track heart rate with my fitbit device? URL: https://help.fitbit.com/articles/en_US/Help_article/1565.html.
- [26] Hamaker, E.L., Wichers, M., 2017. No time like the present: Discovering the hidden dynamics in intensive longitudinal data. *Current Directions in Psychological Science* 26, 10–15.
- [27] Han, J., Kamber, M., Pei, J., 2011. Data mining concepts and techniques third edition. *The Morgan Kaufmann Series in Data Management Systems* 5, 83–124.
- [28] Harari, G.M., M ller, S.R., Stachl, C., Wang, R., Wang, W., B hner, M., Rentfrow, P.J., Campbell, A.T., Gosling, S.D., 2019. Sensing sociability: Individual differences in young adults' conversation, calling, texting, and app use behaviors in daily life. *Journal of personality and social psychology*.
- [29] Harari, G.M., Vaid, S.S., M ller, S.R., Stachl, C., Marrero, Z., Schoedel, R., B hner, M., Gosling, S.D., 2020. Personality sensing for theory development and assessment in the digital age. *European Journal of Personality* 34, 649–669.
- [30] Hegland, M., 2007. The apriori algorithm—a tutorial. *Mathematics and computation in imaging science and information processing*, 209–262.
- [31] Hengartner, M.P., Zimmermann, J., Wright, A.G., 2018. Personality pathology.
- [32] Ilayaraja, M., Meyyappan, T., 2013. Mining medical data to identify frequent diseases using apriori algorithm, in: *2013 International Conference on Pattern Recognition, Informatics and Mobile Engineering, IEEE*. pp. 194–199.
- [33] Johnson, J.A., 2014. Measuring thirty facets of the five factor model with a 120-item public domain inventory: Development of the ipip-neo-120. *Journal of Research in Personality* 51, 78–89.
- [34] Kearns, M., Ron, D., 1999. Algorithmic stability and sanity-check bounds for leave-one-out cross-validation. *Neural computation* 11, 1427–1453.
- [35] Kotov, R., Krueger, R.F., Watson, D., Cicero, D.C., Conway, C.C., DeYoung, C.G., Eaton, N.R., Forbes, M.K., Hallquist, M.N., Latzman, R.D., et al., 2021. The hierarchical taxonomy of psychopathology (hitop): A quantitative nosology based on consensus of evidence. *Annual review of clinical psychology* 17.
- [36] Krueger, R.F., Eaton, N.R., 2010. Personality traits and the classification of mental disorders: Toward a more complete integration in dsm-5 and an empirical model of psychopathology. *Personality Disorders: Theory, Research, and Treatment* 1, 97.
- [37] Kubzansky, L.D., Kawachi, I., 2000. Going to the heart of the matter: do negative emotions cause coronary heart disease? *Journal of psychosomatic research* 48, 323–337.
- [38] Lahey, B.B., 2009. Public health significance of neuroticism. *American Psychologist* 64, 241.
- [39] Lane, N.D., Miluzzo, E., Lu, H., Peebles, D., Choudhury, T., Campbell,



- A.T., 2010. A survey of mobile phone sensing. *IEEE Communications magazine* 48, 140–150.
- [40] Markon, K.E., Krueger, R.F., Watson, D., 2005. Delineating the structure of normal and abnormal personality: an integrative hierarchical approach. *Journal of personality and social psychology* 88, 139.
- [41] Matsuki, K., Kuperman, V., Van Dyke, J.A., 2016. The random forests statistical technique: An examination of its value for the study of reading. *Scientific Studies of Reading* 20, 20–33.
- [42] Mohr, D.C., Zhang, M., Schueller, S.M., 2017. Personal sensing: understanding mental health using ubiquitous sensors and machine learning. *Annual review of clinical psychology* 13, 23–47.
- [43] Mønsted, B., Mollgaard, A., Mathiesen, J., 2018. Phone-based metric as a predictor for basic personality traits. *Journal of Research in Personality* 74, 16–22.
- [44] Morse, J.Q., Pilkonis, P.A., 2007. Screening for personality disorders. *Journal of personality disorders* 21, 179–198.
- [45] Organization, W.H., et al., 2018. International classification of diseases for mortality and morbidity statistics (11th revision).
- [46] Pieper, S., Brosschot, J.F., van der Leeden, R., Thayer, J.F., 2007. Cardiac effects of momentary assessed worry episodes and stressful events. *Psychosomatic medicine* 69, 901–909.
- [47] Powers, A.D., Oltmanns, T.F., 2013. Borderline personality pathology and chronic health problems in later adulthood: The mediating role of obesity. *Personality Disorders: Theory, Research, and Treatment* 4, 152.
- [48] Renn, B.N., Pratap, A., Atkins, D.C., Mooney, S.D., Areán, P.A., 2018. Smartphone-based passive assessment of mobility in depression: Challenges and opportunities. *Mental health and physical activity* 14, 136–139.
- [49] Ringwald, W.R., Woods, W.C., Edershile, E.A., Sharpe, B.M., Wright, A.G., 2021. Psychopathology and personality functioning, in: *The Handbook of Personality Dynamics and Processes*. Elsevier, pp. 273–293.
- [50] Royston, P., White, I.R., et al., 2011. Multiple imputation by chained equations (mice): implementation in stata. *J Stat Softw* 45, 1–20.
- [51] Rugulies, R., 2002. Depression as a predictor for coronary heart disease: a review and meta-analysis. *American journal of preventive medicine* 23, 51–61.
- [52] Schoedel, R., Pargent, F., Au, Q., Völkel, S.T., Schuwerk, T., Bühner, M., Stachl, C., 2020. To challenge the morning lark and the night owl: Using smartphone sensing data to investigate day–night behaviour patterns. *European Journal of Personality* 34, 733–752.
- [53] Shah, A.D., Bartlett, J.W., Carpenter, J., Nicholas, O., Hemingway, H., 2014. Comparison of random forest and parametric imputation models for imputing missing data using mice: a caliber study. *American journal of epidemiology* 179, 764–774.
- [54] Shi, T., Horvath, S., 2006. Unsupervised learning with random forest predictors. *Journal of Computational and Graphical Statistics* 15, 118–138.
- [55] Simms, L.J., Goldberg, L.R., Roberts, J.E., Watson, D., Welte, J., Rotterman, J.H., 2011. Computerized adaptive assessment of personality disorder: Introducing the cat–pd project. *Journal of personality assessment* 93, 380–389.
- [56] Stachl, C., Au, Q., Schoedel, R., Gosling, S.D., Harari, G.M., Buschek, D., Völkel, S.T., Schuwerk, T., Oldemeier, M., Ullmann, T., et al., 2020. Predicting personality from patterns of behavior collected with smartphones. *Proceedings of the National Academy of Sciences* 117, 17680–17687.
- [57] Strobl, C., Malley, J., Tutz, G., 2009. An introduction to recursive partitioning: rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological methods* 14, 323.
- [58] Thomas, K.M., Yalch, M.M., Krueger, R.F., Wright, A.G., Markon, K.E., Hopwood, C.J., 2013. The convergent structure of dsm-5 personality trait facets and five-factor model trait domains. *Assessment* 20, 308–311.
- [59] Thurston, R.C., Rewak, M., Kubzansky, L.D., 2013. An anxious heart: anxiety and the onset of cardiovascular diseases. *Progress in cardiovascular diseases* 55, 524–537.
- [60] Trull, T.J., Durrett, C.A., 2005. Categorical and dimensional models of personality disorder. *Annu. Rev. Clin. Psychol.* 1, 355–380.
- [61] Trull, T.J., Ebner-Priemer, U., 2013. Ambulatory assessment. *Annual review of clinical psychology* 9, 151–176.
- [62] Tuli, S., Tuli, S., Tuli, R., Gill, S.S., 2020. Predicting the growth and trend of covid-19 pandemic using machine learning and cloud computing. *Internet of Things* 11, 100222.
- [63] Turner, A.I., Smyth, N., Hall, S.J., Torres, S.J., Hussein, M., Jayasinghe, S.U., Ball, K., Clow, A.J., 2020. Psychological stress reactivity and future health and disease outcomes: A systematic review of prospective evidence. *Psychoneuroendocrinology* 114, 104599.
- [64] Vega, J., 2021. Rapids (reproducible analysis pipeline for data) streams. URL: <https://rapidspitt.readthedocs.io/en/latest/index.htm>.
- [65] Vehtari, A., Gelman, A., Gabry, J., 2017. Practical bayesian model evaluation using leave-one-out cross-validation and waic. *Statistics and computing* 27, 1413–1432.
- [66] Wang, W., Harari, G.M., Wang, R., Müller, S.R., Mirjafari, S., Masaba, K., Campbell, A.T., 2018. Sensing behavioral change over time: Using within-person variability features from mobile sensing to predict personality traits. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1–21.
- [67] Waugh, M.H., Hopwood, C.J., Krueger, R.F., Morey, L.C., Pincus, A.L., Wright, A.G., 2017. Psychological assessment with the dsm-5 alternative model for personality disorders: Tradition and innovation. *Professional Psychology: Research and Practice* 48, 79.
- [68] Widiger, T.A., Samuel, D.B., 2005. Diagnostic categories or dimensions? a question for the diagnostic and statistical manual of mental disorders-. *Journal of abnormal psychology* 114, 494.
- [69] Wright, A.G., Calabrese, W.R., Rudick, M.M., Yam, W.H., Zelazny, K., Williams, T.F., Rotterman, J.H., Simms, L.J., 2015. Stability of the dsm-5 section iii pathological personality traits and their longitudinal associations with psychosocial functioning in personality disordered individuals. *Journal of Abnormal Psychology* 124, 199.
- [70] Wright, A.G., Hopwood, C.J., 2016. Advancing the assessment of dynamic psychological processes. *Assessment* 23, 399–403.
- [71] Wright, A.G., Pincus, A., Hopwood, C., 2020. Contemporary integrative interpersonal theory: Integrating structure, dynamics, temporal scale, and levels of analysis .
- [72] Wright, A.G., Simms, L.J., 2014. On the structure of personality disorder traits: conjoint analyses of the cat-pd, pid-5, and neo-pi-3 trait models. *Personality Disorders: Theory, Research, and Treatment* 5, 43.

