Momentary Changes in Heart Rate Variability Can Detect Risk for Experiencing Emotional Eating Episodes

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Abstract

Objective: A range of evidence supports that emotion dysregulation contributes to maladaptive eating behaviors broadly and may function as a powerful antecedent to emotional eating, specifically. New passive sensing technology offers the prospect of detecting emotion regulation in real-time through measurement of heart rate variability (HRV), a transdiagnostic bio-signal for emotion regulation, which may in turn predict risk of a maladaptive eating behavior. In the current study, our primary aim was to test whether changes in momentary HRV can be used to detect risk of experiencing an emotional eating episode in an ecologically valid setting. Method: Participants were 21 adults with clinically significant emotional eating behaviors. The Empatica E4 wrist-sensor was worn to measure heart rate variability and emotional eating episodes were reported using ecological momentary assessment for four weeks. Time and frequency domain features of HRV were extracted in the 30-minute period preceding emotional eating episodes and control episodes. Machine learning models were implemented using time domain and frequency domain features. Results: We found that HRV domain features significantly differed in the minutes preceding emotional eating episodes as compared to controls, though no such differences were found in the corresponding time-domain features. Discussion: Future work should be conducted to improve existing ambulatory sensors for HRV to allow for the collection of more valid and complete HRV data, which would allow researchers to better explore the ways in which wearable sensor technology may replace current self-report measures of real-time emotional states and power just-in-time interventions targeting maladaptive eating behaviors.

Keywords: emotion regulation, heart rate variability, emotional eating, sensor technology, ecological momentary assessment

Word count: X

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Introduction

Emotion dysregulation (i.e., low levels of awareness, understanding, and acceptance of emotions, and the inability to engage in adaptive behaviors regardless of emotional state) is a broad, transdiagnostic risk and maintenance factor for numerous psychological disorders (e.g., substance abuse disorders, eating disorders, anxiety disorders) and is associated with high dropout from standard psychological treatments, poor compliance with treatment recommendations, and worse therapeutic outcomes. Maladaptive eating behaviors (e.g., disordered eating behaviors, eating behaviors that can facilitate weight gain) are one set of behaviors that are often strongly maintained by emotion dysregulation (e.g., Anderson et al., 2018; Crockett, Myhre, & Rokke, 2015; Dalrymple, Clark, Chelminski, & Zimmerman, 2018; Hunt, Forbush, Hagan, & Chapa, 2017; Leehr et al., 2015; Mallorquí-Bagué et al., 2018; Orihuela, Mrug, & Boggiano, 2017). A growing body of evidence suggests that individuals with eating disorders often experience elevated rates of emotion dysregulation, and disordered eating behaviors themselves can serve an emotion regulatory function (Mallorquí-Bagué et al., 2018; M Smyth et al., 2007). For example, several types of negative emotions, including fear, guilt, hostility, and sadness, have been shown to intensify prior to and be mitigated following binge eating and purging episodes (Berg et al., 2013), providing temporal evidence to suggest that these maladaptive eating behaviors can serve as external regulators of emotion. Emotion dysregulation can also maintain maladaptive eating behaviors outside of diagnosable eating disordered symptoms such as emotional eating (i.e., the tendency to eat in response to emotional experiences), a behavior strongly linked to weight gain and poor long-term health outcomes (Arnow, Kenardy, & Agras, 1995; Frayn & Knäuper, 2018; Masheb & Grilo, 2006; Ricca et al., 2009). Numerous theories have proposed a negative reinforcement-based function for emotion-driven eating (Heatherton & Baumeister, 1991) and studies utilizing ecological momentary assessment (EMA; Haedt-Matt & Keel, 2011), naturalistic recalls and diaries (Deaver, Miltenberger, Smyth, Meidinger, & Crosby, 2003; Johnson, Schlundt, Barclay, Carr-Nangle, & Engler, 1995; Lynch, Everingham, Dubitzky, Hartman, & Kasser, 2000), and laboratory-based studies (Cools, Schotte, & McNally, 1992; Tuschen-Caffier & Vögele, 1999) have all demonstrated that negative affect prospectively increases the likelihood of a variety of maladaptive eating episodes. Thus, a range of evidence supports that emotion dysregulation contributes to maladaptive eating behaviors broadly and may function as a powerful antecedent to emotional eating, specifically.

Given the clear evidence that emotion dysregulation can maintain maladaptive eating behaviors, it is perhaps unsurprising that improvement in emotion regulation is associated with treatment success for a range of maladaptive eating behaviors (e.g., Cancian, Souza, Liboni, Lara Machado, & Silva Oliveira, 2017; Compare, Calugi, Marchesini, Molinari, & Dalle Grave, 2013; Dolhanty & Greenberg, 2007, 2009; MacDonald, Trottier, & Olmsted, 2017; Peterson et al., 2017; Robinson, Dolhanty, & Greenberg, 2015). Accordingly, a range of emotion-focused treatment approaches have been developed for maladaptive eating behaviors (e.g., integrative cognitive-affective therapy for bulimia nervosa, emotion acceptance behavior therapy for anorexia nervosa, and dialectical behavior therapy for binge eating) (Chen et al., 2017; Clyne, Latner, Gleaves, & Blampied, 2010; Compare et al., 2013; Dolhanty & Greenberg, 2007, 2009; Robinson et al., 2015; Wnuk, Greenberg, & Dolhanty, 2015; Wonderlich et al., 2014), many of which have shown initial promise. However, to date, when emotion-focused treatment approaches are directly compared to existing cognitive and/or behavioral treatment (CBTs) approaches, the results largely fail to demonstrate any superiority of these treatment approaches (Chen et al., 2017; Linardon, Fairburn, Fitzsimmons-Craft, Wilfley, & Brennan, 2017; Wonderlich et al., 2014). Although relatively few RCTs have been conducted comparing CBTs to emotion-focused treatments for maladaptive eating behaviors and more research is sorely needed in this area, the existing data suggest that our current treatment approaches are failing to achieve optimal rates of efficacy.

One possible reason that emotion-focused treatments may be underperforming is that even after receiving a treatment designed to improve emotion dysregulation, many individuals continue to experience difficulty regulating emotions after treatment. While large average effect size improvements in emotion regulation are often observed in these studies (Cancian et al., 2017; MacDonald et al., 2017; Peterson et al., 2017), some studies have found that these improvements are similar to those observed in CBTs (Wonderlich et al., 2014) and that variability in response is common, with many patients continuing to experience difficulty regulating emotions by the end of treatment (Safer & Jo, 2010; Safer, Telch, & Agras, 2001). Identifying new methods to improve emotion regulation outside of conventional emotion-focused treatments may be needed to sufficiently engage this clinical target and adequately improve treatment outcomes.

Most emotion-focused treatments approaches that focus on maladaptive eating behavior try to improve emotion regulation through in-session provision of emotion regulatory skills and instructions to practice these skills at home and utilize the skills during times of distress. Although these skills can be effective when adequately employed, many patients fail to sufficiently utilize these skills in their daily life (Zendegui, West, & Zandberg, 2014), severely limiting the success of these traditionally-delivered interventions, as most if not all maladaptive eating episodes occur outside the therapy office. As such, there is a need to develop novel ways to intervene on behavior as it occurs in daily life. In fact, new technological advances are offering the opportunity to monitor risk factors, e.g., rising negative emotion, in individuals' natural environment, allowing for interventions to be delivered and received in real-time and in ecologically valid settings.

One methodological approach that has shown increasing popularity and promise in this regard is ecological momentary intervention (EMI), which gathers self-report data multiple times per day, often via smartphones, and delivers interventions when risk factors are reported. For example, an EMI aiming to prevent emotion-triggered maladaptive eating could assess emotion multiple times per day via a mobile survey and deliver in-the-moment emotion-focused interventions when strong negative emotions are endorsed, with the aim of thwarting a subsequent maladaptive eating episode. Nevertheless, despite its growing use and advantages, EMI has several important limitations. Notably, the efficacy of EMI is contingent on users' accurate and frequent self-reporting, which is time-consuming and inherently burdensome. Additionally, an individual may be unwilling (e.g., due to ambivalent motivation) or unable (e.g., due to poor emotional awareness) to accurately record the emotional experiences that are needed to accurately power an EMI system, especially when in an intense, negative emotional state.

Fortunately, the advent of new technology has offered other real-time, ecologically-valid methodologies that are not subject to these same limitations and thus offer discrete advantages over EMIs. Passive sensing systems, which are capable of objective, continuous or semi-continuous, real-time data collection that requires no user input, may be a more effective and acceptable methodology with which to detect in real-time risk of maladaptive eating behavior. Passive sensing systems not only reduce participant burden and eliminate self-report bias by circumventing user input, but they also allow for more frequent data collection (e.g., continuous or semi-continuous), which may result in better detection of risk factors and therefore more accurate and timelier interventions.

Moreover, increasing psychophysiological evidence indicates that negative affect, emotional reactivity, and emotion regulation can be passively sensed using physiological markers of autonomic nervous system activity (Appelhans & Luecken, 2006; Thayer & Sternberg, 2006). Heart rate variability (HRV), in particular, has been identified as a transdiagnostic bio-signal for self-regulation, and more specifically, emotion regulation

(Beauchaine & Thayer, 2015; Calvo & D'Mello, 2010). For example, higher levels of resting HRV have been found to be associated with increased trait-level emotion regulatory abilities, and lower levels of HRV with impairments in emotional coping and adaptive emotional response (Appelhans & Luecken, 2006; Spitoni et al., 2017; Thayer & Lane, 2009). In addition to providing trait-level information, HRV operates at the state level; for example, momentary increases in HRV correspond with effective emotion regulation across various laboratory tasks (Butler, Wilhelm, & Gross, 2006; Ingjaldsson, Laberg, & Thayer, 2003; Smith et al., 2011). As such, within-person variability of HRV allows researchers to investigate whether decreases in HRV correspond with momentary emotion dysregulation, and subsequently, whether these within-person changes in HRV could place individuals at risk for engagement in maladaptive behaviors to externally regulate emotion. For example, a recent study examining adolescent girls with disordered eating behavior found reductions in HRV preceded loss-of-control eating episodes, suggesting that HRV may serve as a biomarker for decreased emotion regulatory activity and consequently, susceptibility to loss-of-control eating (Ranzenhofer et al., 2016).

Nevertheless, most extant research studying the relation between HRV and emotion regulation has been conducted in laboratory settings, with HRV almost exclusively being measured by invasive or burdensome physiological sensors (e.g., medical-grade electrocardiogram monitors). The recent and rapid progression of wearable technology (e.g., wrist sensors) has opened a new wave of possibilities with which to acceptably and feasibly collect HRV data in ecologically-valid environments. One of the most promising current sensors is the commercially available Empatica E4 wristband, which has been validated for collecting momentary physiological data in real-world settings.(Cogan, Birjandtalab, Nourani, Harvey, & Nagaraddi, 2017; Vandecasteele et al., 2017) The Empatica E4 wrist sensor detects physiological signals using photoplethysmography (noninvasive optical measurement that can derive cardiovascular features from light absorption of the skin), skin conductance, and body temperature, and uploads data via a platform that can be viewable by study personnel for storage and analysis. Thus, given the newfound availability of validated wrist sensors like the Empatica E4, there is a critical need to translate primarily lab-based HRV findings into real-world environments using this more acceptable technology, which allows for real-time, ecologically-valid measurement and interventions.

In the current study, our primary aim was to test whether changes in momentary HRV can be used to detect risk of experiencing an emotional eating episode. Emotional eating was selected as an outcome variable for the following reasons: 1) it is highly prevalent in the population and it occurs at a high frequency (usually multiple times per week) among individuals with clinically significant emotional eating, thus increasingly the feasibility of an initial study of wearable HRV technology in detecting risk for a maladaptive eating behavior and 2) by definition, negative emotion occurs prior to and during the eating episode itself, thereby optimizing our ability to detect a relationship between within–person changes in HRV and subsequent engagement in a maladaptive eating episodes. As such, emotional eating represented the most fitting outcome variable for this initial test, though we anticipate the relationship between emotion dysregulation and maladaptive eating could be applicable to other maladaptive eating behaviors more broadly. A secondary aim of this study is to evaluate the feasibility and acceptability of using wrist-worn wearable sensors to detect HRV in this population to determine whether a wearable HRV sensor could be a viable augmentation to an EMI-system in future studies.

Methods

Data analyses were carried out in R version 3.5.0 (2018-04-23) and Python 2.7. In accordance with previous studies examining the relation between HRV and discrete eating episodes (Friesen, Lin, Schurman, Andre, & Callum, 2007; Harthoorn & Dransfield, 2007; Ranzenhofer et al., 2016), physiological data collected in the 30-minute period preceding the eating episode were examined. For each participant, the inter-beat interval (IBI) for each self-reported survey was selected, where surveys were either self-reported at the time of an eating episode, or pseudo-randomly triggered in the app. This resulted in an initial total of $n = 487$ emotional eating episodes and $n = 3155$ control episodes before cleaning the data.

Using the RHRV package (Rodriguez-Linares et al., 2017), IBI data streams were filtered, interpolated, and artifacts were removed, using thresholds and parameters in compliance with normative reported values for heart rate variability features (Shaffer & Ginsberg, 2017). Observations that did not meet normative criteria were removed. Consistent with existing research, features of heart rate variability were extracted from both the time and frequency domain to measure both the amount of variability and the amount of signal energy in the 30-minute period (Rubin, Abreu, Ahern, Eldardiry, & Bobrow, 2016; Shaffer & Ginsberg, 2017).

The following heart rate variability features were extracted from the IBI streams for each observation in the time domain: *SDNN* (Standard Deviation of all filtered inter-beat intervals); *SDANN* (Standard Deviation of inter-beat intervals between all successive heartbeats); *SDNNIX* (Mean of the standard deviations of all the filtered inter-beat intervals for each 5 min segment of the IBI stream); *pNN50* (Percentage of successive inter-beat intervals that differ by more than 50 ms); *SDSD* (Standard Deviation of Successive Differences of inter-beat intervals); *rMSSD* (Root Mean Square of Successive Differences); *IRRR* (length of the interval determined by the first and the third quantile of the inter-beat interval); *MADRR* (Median of the Absolute values of the successive Differences between the inter-beat intervals); *TINN* (Triangular Interpolation of inter-beat interval histogram); and *HRVi* (Heart Rate Variability index) (Rodriguez-Linares et al., 2017).

SDNN reflects the power of the components responsible for variability in heart rhythm, while *SDANN*, *SDNNIX*, *pNN50*, *SDSD*, *rMSSD*, *IRRR*, and *MADRR* reflect different statistical aspects of the high frequency variation in heart rhythm. Finally, *TINN* and *HRVi* represent geometric measures calculated from the density distribution of inter-beat intervals (Rodriguez-Linares et al., 2017).

In the frequency domain, features extracted included the mean non-interpolated heart rate (*mean niHR*), the mean interpolated Heart Rate (*mean HR*), and the heart rate values at the start and end of the 30 minute window (*Start HR*, *End HR*). Additional frequency domain features were extracted from the 30 minute streams by applying a Fourier transform to the heart rate signal, resulting in a spectrogram of the heart rate in the low and high frequency ranges. To extract a sufficient amount of information from these spectograms and increase the variance of our data, the spectrogram was split into 5 minute windows, as has been done previously in studies using heart rate variability to predict event-level behavior (Rubin et al., 2016). Mean features were extracted from each of these windows — the mean Low Frequency signal (LF_1, LF_2,... LF_6), the mean High Frequency signal (HF_1, HF_2,... HF_6), and the mean Low Frequency-High Frequency Ratio ($LFHF_1$, $LFHF_2$,... $LFHF_6$).

In order to examine any differences between means of the features, and address the issue of group imbalance affecting statistical power, we conducted between-groups permutation T-tests with each variable in the time and frequency domain (Good, 2013; Maindonald & Braun, 2015). Then, using the CARET package (Jed Wing et al., 2018), a Support Vector Machine with a polynomial kernel was implemented to predict episodes from controls. In order to address the group imbalance in this stage, all features were standardized, while controls were randomly downsampled and episodes were randomly upsampled using the ROSE package (Lunardon, Menardi, & Torelli, 2014). To evaluate model performance, models were tested using 4-fold cross validation, training models on 3/4 of the data and using the remaining data evaluate the model accuracy, specificity, and sensitivity.

Results

Missingness

After cleaning the dataset of erroneous surveys (e.g. no usable IBI data; overlapping survey responses; control observations with high self-reported stress), and filtering IBI streams that did not meet filtering quality criteria for preprocessing, the data consisted of $n = 285$ emotional eating episodes and $n = 1753$ controls. Of these clean observations, HRV features were extracted from the IBI streams, although even with filtering, many IBI streams were too sparse to compute HRV features. Figures 1 and 2 illustrate the completeness of data in the extracted time and frequency domain features, with table 1 showing the final number of observations used for analysis. Much of the data missing from the time domain is due to the fact that these features derived from SDNN and are dependent on having sufficient data in this feature.

Comparison of Means

The mean values for each time-domain features is shown in Table 2 below:

Using a Two t permutation test run between episodes and controls, none of the time-domain variables were found to be significantly different, shown in Table 3.

A similar approach was taken to analyze the frequency domain. Table 4 below outlines the mean values of features:

Using the same Two-t permutation approach, we found signficant differences in means for Average Heart Rate, Average non-interpolated Heart Rate, Ending non-interpolated Heart Rate, and the LF-HF ratio in the third window, shown in Table 5

Machine Learning

Machine learning models were implemented using time domain and frequency domain features separately. In order to run machine learning prediction of emotional eating episodes, only observations with complete data for all features in the time or frequency domain were used, data within each participant were scaled and centered, and observations were randomly upsampled (from episodes) or downsampled (from controls) to balance the number of observations and controls. SVM models were fit iteratively using 3/4's of the data, and evaluated on the remaining 1/4. Figure 6 show the mean accuracy, sensitivity, and specificity of the SVM across these four folds.

To interpret the feature importance in each of these models, ROC curve analysis was conducted on each feature on the model as recommended by Khun Jed Wing et al. (2018), by systemmatically removing each variable from the model and comparing the achieved Area Under the Curve (AUC) against that of the full model. In order to assess whether or not these features discriminate well between episodes and controls, models were fitted on the original data and the fitted values were perturbed for each variable. The probabilities of predictions were extracted from each perturbed model and compared to the probabilities of the original model, to understand how increasing values of the features increased or decreased the likelihood of an eating episode. Figures 7 and 8 show the results of this analysis.

In the time domain, the most important feature by measure of scaled decrease in model AUC was *SDANN*, followed by *SDNN* and *MADRR*. Increasing values in *SDANN* by 1 unit tended to decrease the probability of observations being predicted as episode, suggesting that higher levels of *SDANN* decrease the likelihood of an eating episode. This same inference can be made of *MADRR*. In the case of *SDNN*, a 1 unit increase in values of this feature increased the probability of observations being predicted as episodes.

In the frequency domain, the most important features by measure of decrease in model AUC were the High Frequency windows HF_2, HF_6, and HF_3. Increasing values in HF_2 by one unit tended to decrease the probability of observations being predicted as episode, suggesting that stronger signals in the high frequency band at this time in the window decrease the likelihood of an eating episode. This inference is the opposite, however, for HF_6 and HF_3, which show that increasing these variables' values by one unit tends to increase the likelihood of an eating episode. Interestingly, while the heart rate variables *Avg_HR*, *Avg_niHR*, and *End_niHR* had significantly different means, their affect on the achieved AUC was relatively minimal, indicating they had very small feature importance for this model.

To better interpret how the signal in the high frequency band of heart rate varies through the 30-minute window, we plot these values in Figure 9 below:

The visualisation shows that at the second window, HF_2, there is an inverse relationship between the trajectories of episodes and controls, which may represent the high variable importance of HF_2. HF_6 shows a similar inverse trend, as increasing values of this variable are associated with episodes while decreasing values are associated with controls.

RAW DATA OF ML MODEL NO COLOUR CODE ON LOLLIPOP PLOTS

Discussion

A major hurdle to producing interpretable results is the sanity of data obtained from the devices. Despite best efforts, figures 1 and 2 illustrate how sparse the data can be and how this affects its overall usefulness in running analyses.The causes for this data sparsity are unclear, and could include reasons such as improper usage or low signal while recording data. The result of this challenge is that derived features are incalculable; for example, time domain feature calculations are strongly dependent on a sliding window that must have within it at least some number of consecutive heart beats, or completeness and consecutiveness of *SDNN*; frequency domain variables are dependent on Fourier transforms which are sensitive to small and variations in wave frequencies. Nevertheless, by following proper data sanity checks and procedures provided in analyses packages and in the literature, it's still possible to extract useful information from these data.

Although no features in the time domain were significantly different between episode and control observations when tested, it's worth mentioning that the machine learning model was still able to achieve decent classification accuracy, sensitivity, and specificity using these features. The most impactful features in this model were *rMSSD* (Root Mean Square of Successive Differences); *SDSD* (Standard Deviation of Successive Differences of inter-beat intervals); and *MADRR* (Median of the Absolute values of the successive Differences between the inter-beat intervals). However, the frequency domain achieved superior classification accuracy in comparison to the time domain, with mean accuracy of 78%, sensitivity of 78.80%, and specificity of 75%. For this model, the greatest variable importance was for HF_1, LF_5, LF_6, LF_1, and LF_2. This may reflect a tendency of heart rate to change most noticeably in the low frequency power band, in the moments leading up to an eating episode.

Discussion

References

Anderson, L. K., Claudat, K., Cusack, A., Brown, T. A., Trim, J., Rockwell, R., … Kaye, W. H. (2018). Differences in emotion regulation difficulties among adults and adolescents across eating disorder diagnoses. *Journal of Clinical Psychology*. Journal Article.

Appelhans, B. M., & Luecken, L. J. (2006). Heart rate variability as an index of regulated emotional responding. *Review of General Psychology*, *10*(3), 229. Journal Article.

Arnow, B., Kenardy, J., & Agras, W. S. (1995). The emotional eating scale: The development of a measure to assess coping with negative affect by eating. *International Journal of Eating Disorders*, *18*(1), 79–90.

Beauchaine, T. P., & Thayer, J. F. (2015). Heart rate variability as a transdiagnostic biomarker of psychopathology. *International Journal of Psychophysiology*, *98*(2), 338–350. Journal Article. doi:http://dx.doi.org/10.1016/j.ijpsycho.2015.08.004

Berg, K. C., Crosby, R. D., Cao, L., Peterson, C. B., Engel, S. G., Mitchell, J. E., & Wonderlich, S. A. (2013). Facets of negative affect prior to and following binge-only, purge-only, and binge/purge events in women with bulimia nervosa. *Journal of Abnormal Psychology*. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3646562/

Butler, E. A., Wilhelm, F. H., & Gross, J. J. (2006). Respiratory sinus arrhythmia, emotion, and emotion regulation during social interaction. *Psychophysiology*, *43*(6), 612–622. Journal Article.

Calvo, R. A., & D’Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, *1*(1), 18–37. Journal Article. doi:10.1109/T-AFFC.2010.1

Cancian, A. C. M., Souza, L. A. S. de, Liboni, R. P. A., Lara Machado, W. de, & Silva Oliveira, M. da. (2017). Effects of a dialectical behavior therapy-based skills group intervention for obese individuals: A brazilian pilot study. *Eating and Weight Disorders-Studies on Anorexia, Bulimia and Obesity*, 1–13. Journal Article.

Chen, E., Cacioppo, J., Fettich, K., Gallop, R., McCloskey, M., Olino, T., & Zeffiro, T. (2017). An adaptive randomized trial of dialectical behavior therapy and cognitive behavior therapy for binge-eating. *Psychological Medicine*, *47*(4), 703–717. Journal Article.

Clyne, C., Latner, J. D., Gleaves, D. H., & Blampied, N. M. (2010). Treatment of emotional dysregulation in full syndrome and subthreshold binge eating disorder. *Eating Disorders*, *18*(5), 408–424. Journal Article.

Cogan, D., Birjandtalab, J., Nourani, M., Harvey, J., & Nagaraddi, V. (2017). Multi-biosignal analysis for epileptic seizure monitoring. *International Journal of Neural Systems*, *27*(01), 1650031. Journal Article.

Compare, A., Calugi, S., Marchesini, G., Molinari, E., & Dalle Grave, R. (2013). Emotion-focused therapy and dietary counseling for obese patients with binge eating disorder: A propensity score-adjusted study. *Psychotherapy and Psychosomatics*, *82*(3), 193–194. Journal Article.

Cools, J., Schotte, D. E., & McNally, R. J. (1992). Emotional arousal and overeating in restrained eaters. *Journal of Abnormal Psychology*, *101*(2), 348.

Crockett, A. C., Myhre, S. K., & Rokke, P. D. (2015). Boredom proneness and emotion regulation predict emotional eating. *Journal of Health Psychology*, *20*(5), 670–680. Journal Article.

Dalrymple, K. L., Clark, H., Chelminski, I., & Zimmerman, M. (2018). The interaction between mindfulness, emotion regulation, and social anxiety and its association with emotional eating in bariatric surgery candidates. *Mindfulness*, 1–14. Journal Article.

Deaver, C. M., Miltenberger, R. G., Smyth, J., Meidinger, A., & Crosby, R. (2003). An evaluation of affect and binge eating. *Behavior Modification*, *27*(4), 578–599.

Dolhanty, J., & Greenberg, L. S. (2007). Emotion-focused therapy in the treatment of eating disorders. *European Psychotherapy*, *7*(1), 97–116. Journal Article.

Dolhanty, J., & Greenberg, L. S. (2009). Emotion-focused therapy in a case of anorexia nervosa. *Clinical Psychology & Psychotherapy*, *16*(4), 336–382. Journal Article.

Frayn, M., & Knäuper, B. (2018). Emotional eating and weight in adults: A review. *Current Psychology*, *37*(4), 924–933.

Friesen, C. A., Lin, Z., Schurman, J. V., Andre, L., & Callum, R. W. M. (2007). Autonomic nervous system response to a solid meal and water loading in healthy children: Its relation to gastric myoelectrical activity. *Neurogastroenterology & Motility*, *19*(5), 376–382. doi:10.1111/j.1365-2982.2007.00906.x

Good, P. (2013). *Permutation tests: A practical guide to resampling methods for testing hypotheses*. Springer Science & Business Media.

Haedt-Matt, A. A., & Keel, P. K. (2011). Revisiting the affect regulation model of binge eating: A meta-analysis of studies using ecological momentary assessment. *Psychological Bulletin*, *137*(4), 660.

Harthoorn, L. F., & Dransfield, E. (2007). Periprandial changes of the sympathetic–parasympathetic balance related to perceived satiety in humans. *European Journal of Applied Physiology*, *102*(5), 601–608.

doi:10.1007/s00421-007-0622-5

Heatherton, T. F., & Baumeister, R. F. (1991). Binge eating as escape from self-awareness. *Psychological Bulletin*, *110*(1), 86.

Hunt, T. K., Forbush, K. T., Hagan, K. E., & Chapa, D. A. (2017). Do emotion regulation difficulties when upset influence the association between dietary restraint and weight gain among college students? *Appetite*, *114*, 101–109. Journal Article.

Ingjaldsson, J. T., Laberg, J. C., & Thayer, J. F. (2003). Reduced heart rate variability in chronic alcohol abuse: Relationship with negative mood, chronic thought suppression, and compulsive drinking. *Biological Psychiatry*, *54*(12), 1427–1436. Journal Article.

Jed Wing, M. K. C. from, Weston, S., Williams, A., Keefer, C., Engelhardt, A., Cooper, T., … Hunt., T. (2018). *Caret: Classification and regression training*. Retrieved from https://CRAN.R-project.org/package=caret

Johnson, W. G., Schlundt, D. G., Barclay, D. R., Carr-Nangle, R. E., & Engler, L. B. (1995). A naturalistic functional analysis of binge eating. *Behavior Therapy*, *26*(1), 101–118.

Leehr, E. J., Krohmer, K., Schag, K., Dresler, T., Zipfel, S., & Giel, K. E. (2015). Emotion regulation model in binge eating disorder and obesity-a systematic review. *Neuroscience & Biobehavioral Reviews*, *49*, 125–134. Journal Article.

Linardon, J., Fairburn, C. G., Fitzsimmons-Craft, E. E., Wilfley, D. E., & Brennan, L. (2017). The empirical status of the third-wave behaviour therapies for the treatment of eating disorders: A systematic review. *Clinical Psychology Review*. Journal Article.

Lunardon, N., Menardi, G., & Torelli, N. (2014). *ROSE: Random over-sampling examples.* Retrieved from https://CRAN.R-project.org/package=ROSE

Lynch, W. C., Everingham, A., Dubitzky, J., Hartman, M., & Kasser, T. (2000). Does binge eating play a role in the self-regulation of moods? *Integrative Physiological and Behavioral Science*, *35*(4), 298–313.

MacDonald, D. E., Trottier, K., & Olmsted, M. P. (2017). Rapid improvements in emotion regulation predict intensive treatment outcome for patients with bulimia nervosa and purging disorder. *International Journal of Eating Disorders*, *50*(10), 1152–1161. Journal Article.

Maindonald, J. H., & Braun, W. J. (2015). *DAAG: Data analysis and graphics data and functions*. Retrieved from https://CRAN.R-project.org/package=DAAG

Mallorquí-Bagué, N., Vintró-Alcaraz, C., Sánchez, I., Riesco, N., Agüera, Z., Granero, R., … Fernández-Aranda, F. (2018). Emotion regulation as a transdiagnostic feature among eating disorders: Cross-sectional and longitudinal approach. *European Eating Disorders Review*, *26*(1), 53–61. Journal Article.

Masheb, R. M., & Grilo, C. M. (2006). Emotional overeating and its associations with eating disorder psychopathology among overweight patients with binge eating disorder. *International Journal of Eating Disorders*, *39*(2), 141–146.

M Smyth, J., A Wonderlich, S., Heron, K., J Sliwinski, M., D Crosby, R., Mitchell, J., & G Engel, S. (2007). Daily and momentary mood and stress are associated with binge eating and vomiting in bulimia nervosa patients in the natural environment. *Journal of Consulting and Clinical Psychology*, *75*, 629–38. doi:10.1037/0022-006X.75.4.629

Orihuela, C. A., Mrug, S., & Boggiano, M. M. (2017). Reciprocal relationships between emotion regulation and motives for eating palatable foods in african american adolescents. *Appetite*, *117*, 303–309. Journal Article.

Peterson, C. B., Berg, K. C., Crosby, R. D., Lavender, J. M., Accurso, E. C., Ciao, A. C., … Crow, S. J. (2017). The effects of psychotherapy treatment on outcome in bulimia nervosa: Examining indirect effects through emotion regulation, self-directed behavior, and self-discrepancy within the mediation model. *International Journal of Eating Disorders*, *50*(6), 636–647. Journal Article.

Ranzenhofer, L. M., Engel, S. G., Crosby, R. D., Haigney, M., Anderson, M., McCaffery, J. M., & Tanofsky-Kraff, M. (2016). Real-time assessment of heart rate variability and loss of control eating in adolescent girls: A pilot study. *International Journal of Eating Disorders*, *49*(2), 197–201.

Ricca, V., Castellini, G., Sauro, C. L., Ravaldi, C., Lapi, F., Mannucci, E., … Faravelli, C. (2009). Correlations between binge eating and emotional eating in a sample of overweight subjects. *Appetite*, *53*(3), 418–421.

Robinson, A. L., Dolhanty, J., & Greenberg, L. (2015). Emotion-focused family therapy for eating disorders in children and adolescents. *Clinical Psychology & Psychotherapy*, *22*(1), 75–82. Journal Article.

Rodriguez-Linares, L., Vila, X., Lado, M. J., Mendez, A., Otero, A., & Garcia, C. A. (2017). *RHRV: Heart rate variability analysis of ecg data*. Retrieved from https://CRAN.R-project.org/package=RHRV

Rubin, J., Abreu, R., Ahern, S., Eldardiry, H., & Bobrow, D. G. (2016). Time, frequency & complexity analysis for recognizing panic states from physiologic time-series. In *Proceedings of the 10th eai international conference on pervasive computing technologies for healthcare* (pp. 81–88). ICST, Brussels, Belgium, Belgium: ICST (Institute for Computer Sciences, Social-Informatics; Telecommunications

Engineering). Retrieved from http://dl.acm.org/citation.cfm?id=3021319.3021332

Safer, D. L., & Jo, B. (2010). Outcome from a randomized controlled trial of group therapy for binge eating disorder: Comparing dialectical behavior therapy adapted for binge eating to an active comparison group therapy. *Behavior Therapy*, *41*(1), 106–120. Journal Article.

Safer, D. L., Telch, C. F., & Agras, W. S. (2001). Dialectical behavior therapy for bulimia nervosa. *American Journal of Psychiatry*, *158*(4), 632–634. Journal Article.

Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. *Frontiers in Public Health*, *5*. doi:10.3389/fpubh.2017.00258

Smith, T. D., Cribbet, M. R., Nealey-Moore, J. B., Uchino, B. N., Williams, P. G., Mackenzie, J., & Thayer, J. F. (2011). Matters of the variable heart: Respiratory sinus arrhythmia response to marital interaction and associations with marital quality. *Journal of Personality and Social Psychology*, *100 1*, 103–19.

Spitoni, G. F., Ottaviani, C., Petta, A. M., Zingaretti, P., Aragona, M., Sarnicola, A., & Antonucci, G. (2017). Obesity is associated with lack of inhibitory control and impaired heart rate variability reactivity and recovery in response to food stimuli. *International Journal of Psychophysiology*, *116*, 77–84. Journal Article.

Thayer, J. F., & Lane, R. D. (2009). Claude bernard and the heart–brain connection: Further elaboration of a model of neurovisceral integration. *Neuroscience & Biobehavioral Reviews*, *33*(2), 81–88. Journal Article.

Thayer, J. F., & Sternberg, E. (2006). Beyond heart rate variability. *Annals of the New York Academy of Sciences*, *1088*(1), 361–372. Journal Article.

Tuschen-Caffier, B., & Vögele, C. (1999). Psychological and physiological reactivity to stress: An experimental study on bulimic patients, restrained eaters and controls. *Psychotherapy and Psychosomatics*, *68*(6), 333–340.

Vandecasteele, K., De Cooman, T., Gu, Y., Cleeren, E., Claes, K., Paesschen, W. V., … Hunyadi, B. (2017). Automated epileptic seizure detection based on wearable ecg and ppg in a hospital environment. *Sensors*, *17*(10), 2338. Journal Article.

Wnuk, S. M., Greenberg, L., & Dolhanty, J. (2015). Emotion-focused group therapy for women with symptoms of bulimia nervosa. *Eating Disorders*, *23*(3), 253–261. Journal Article.

Wonderlich, S. A., Peterson, C. B., Crosby, R. D., Smith, T. L., Klein, M. H., Mitchell, J. E., & Crow, S. J. (2014). A randomized controlled comparison of integrative cognitive-affective therapy (icat) and enhanced cognitive-behavioral therapy (cbt-e) for bulimia nervosa. *Psychological Medicine*, *44*(3), 543–553. Journal Article.

Zendegui, E. A., West, J. A., & Zandberg, L. J. (2014). Binge eating frequency and regular eating adherence: The role of eating pattern in cognitive behavioral guided self-help. *Eating Behaviors*, *15*(2), 241–243. Journal Article.

Table 1

Number of Observations Extracted for Each Feature

Variable	Control	Episode
Heart Rate Variability		
SDNN	1318	219
SDANN	110	19
SDNNIDX	110	19
pNN50	110	19
SDSD	110	19
rMSSD	110	19
IRRR	110	19
MADRR	110	19
TINN	110	19
HRVi	110	19
Heart Rate		
Avg_niHR	1282	215
Start_niHR	1282	215
End_niHR	1282	215
Avg_HR	1282	215
High Frequency		
HF_1	433	82
HF_2	451	77
HF_3	456	79
HF_4	440	82
HF_5	445	66
HF_6	444	71
Low Frequency		
LF_1	433	82

Table 2

Summary of Features in the Time Domain

variable	n	mean	sd
HRVi	129	7.171186	1.992292
IRRR	129	65.288888	28.536286
MADRR	129	26.043073	10.932954
pNN50	129	19.830466	10.590041
rMSSD	129	48.539227	13.137957
SDANN	129	15.440406	15.451301
SDNN	1537	69.429465	24.835250
SDNNIDX	129	43.869882	12.781756
SDSD	129	48.557984	13.143443
TINN	129	112.049788	31.129567

Table 3

Between-Groups Permutation t-test of Time Domain Features

variable	mean.control	mean.episode	n.control	n.episode	sd.control	sd.episode	p.val
HRVi	7.20	6.98	110	19	2.12	1.04	0.66
IRRR	66.05	60.86	110	19	30.50	11.52	0.47
MADRR	26.14	25.49	110	19	11.22	9.33	0.73
pNN50	19.99	18.93	110	19	10.93	8.54	0.69
rMSSD	48.95	46.17	110	19	13.61	9.95	0.39
SDANN	15.62	14.40	110	19	16.33	9.02	0.74
SDNN	69.69	67.87	1318	219	25.23	22.32	0.31
SDNNIDX	44.04	42.86	110	19	13.45	8.05	0.70
SDSD	48.97	46.19	110	19	13.61	9.96	0.39
TINN	112.55	109.14	110	19	33.06	16.20	0.66

Table 4

Summary of Features in the Frequency Domain

variable	n	mean	sd
Heart Rate			
Avg_HR	1497	79.50	12.13
Avg_niHR	1497	80.26	12.20
Start_niHR	1497	83.58	17.76
End_niHR	1497	81.34	15.69
High Frequency			
HF_1	515	282.34	382.80
HF_2	528	271.35	351.14
HF_3	535	262.68	291.35
HF_4	522	248.05	289.56
HF_5	511	254.59	317.44
HF_6	515	295.68	432.77
Low Frequency			
LF_1	515	320.98	254.62
LF_2	528	319.81	246.48
LF_3	535	323.36	247.22
LF_4	522	314.75	238.92
LF_5	511	334.37	253.86
LF_6	515	345.29	269.47
LF-HF Ratio			
LFHF_1	515	4.69	3.42
LFHF_2	528	4.68	3.53
LFHF_3	535	4.59	3.46
LFHF_4	522	4.83	3.55
LFHF_5	511	4.98	3.55

Table 5

Between-Groups Permutation t-test of Frequency Domain Features

variable	mean.control	mean.episode	n.control	n.episode	sd.control	sd.episode	p.val
Heart Rate							
Avg_HR	79.22	81.20	1282	215	12.25	11.30	0.03
Avg_niHR	80.01	81.76	1282	215	12.31	11.41	0.05
Start_niHR	83.56	83.70	1282	215	18.21	14.85	0.92
End_niHR	80.77	84.71	1282	215	15.55	16.12	0.00
High Frequency							
HF_1	272.59	333.79	433	82	329.02	591.06	0.18
HF_2	263.68	316.23	451	77	305.91	546.34	0.22
HF_3	257.48	292.74	456	79	257.94	438.11	0.31
HF_4	244.61	266.51	440	82	259.52	416.97	0.55
HF_5	262.25	202.95	445	66	335.09	143.31	0.14
HF_6	305.57	233.80	444	71	460.86	163.01	0.18
Low Frequency							
LF_1	322.90	310.85	433	82	255.19	252.93	0.70
LF_2	315.46	345.28	451	77	245.66	251.30	0.33
LF_3	326.12	307.45	456	79	253.17	210.27	0.53
LF_4	309.79	341.38	440	82	235.44	256.66	0.27
LF_5	330.80	358.43	445	66	252.93	260.77	0.41
LF_6	347.62	330.70	444	71	273.40	244.74	0.63
LF-HF Ratio							
LFHF_1	4.72	4.57	433	82	3.46	3.20	0.71
LFHF_2	4.68	4.67	451	77	3.50	3.72	0.97
LFHF_3	4.72	3.86	456	79	3.49	3.19	0.04
LFHF_4	4.78	5.09	440	82	3.54	3.60	0.46
LFHF_5	4.98	5.02	445	66	3.52	3.74	0.94

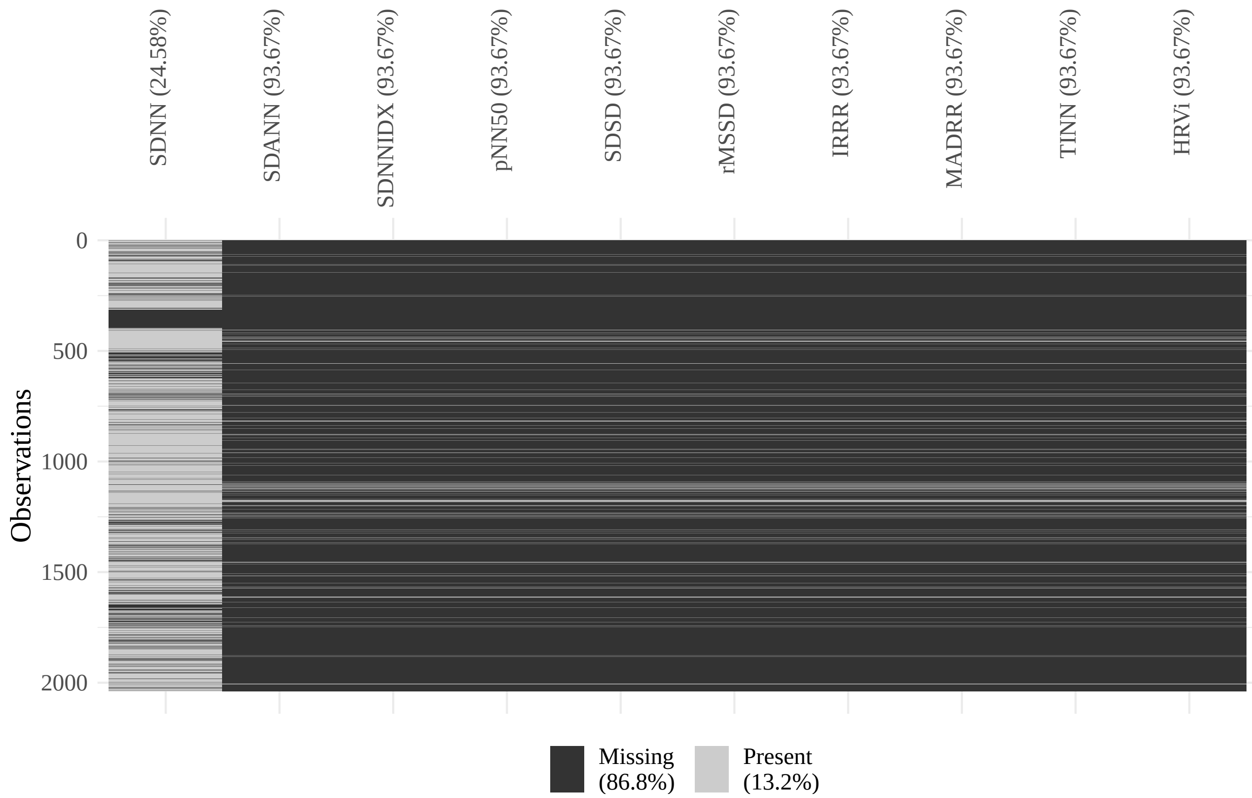

Figure 1. Completeness of Features in the Time Domain

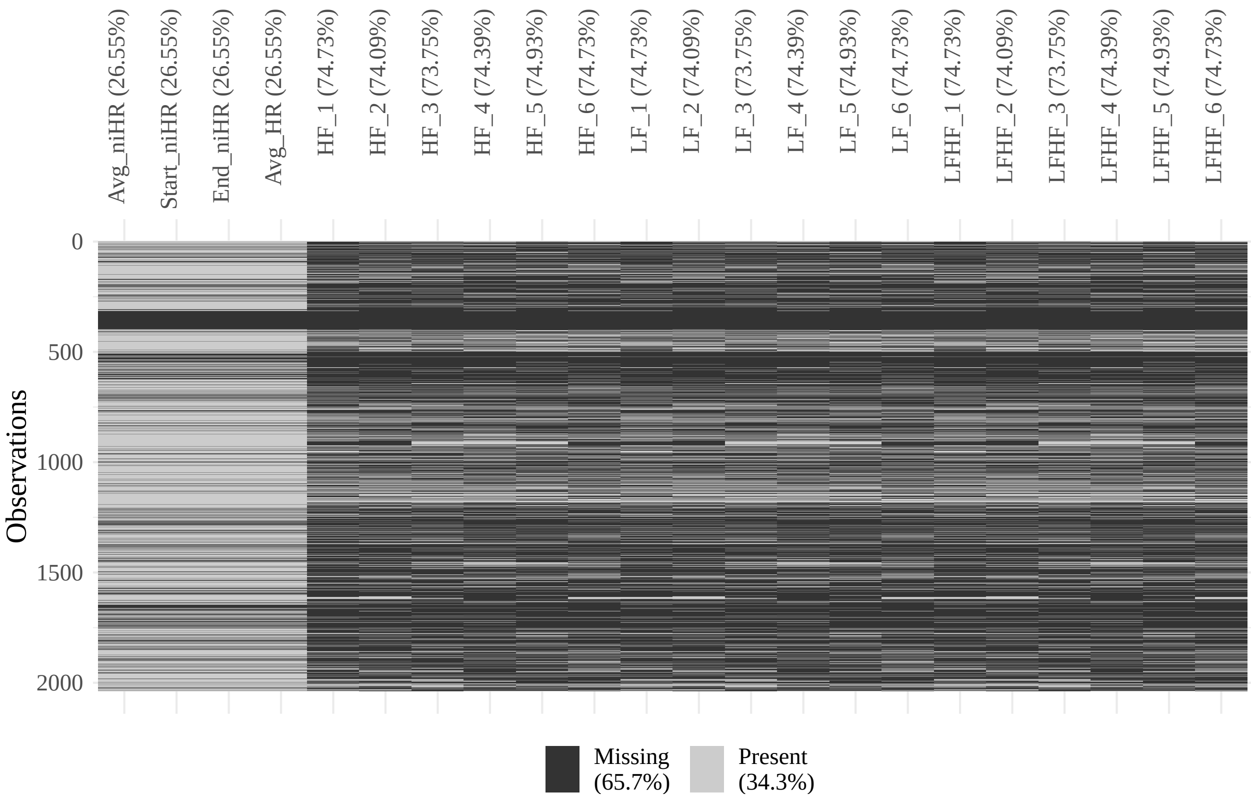

Figure 2. Completeness of Features in the Frequency Domain

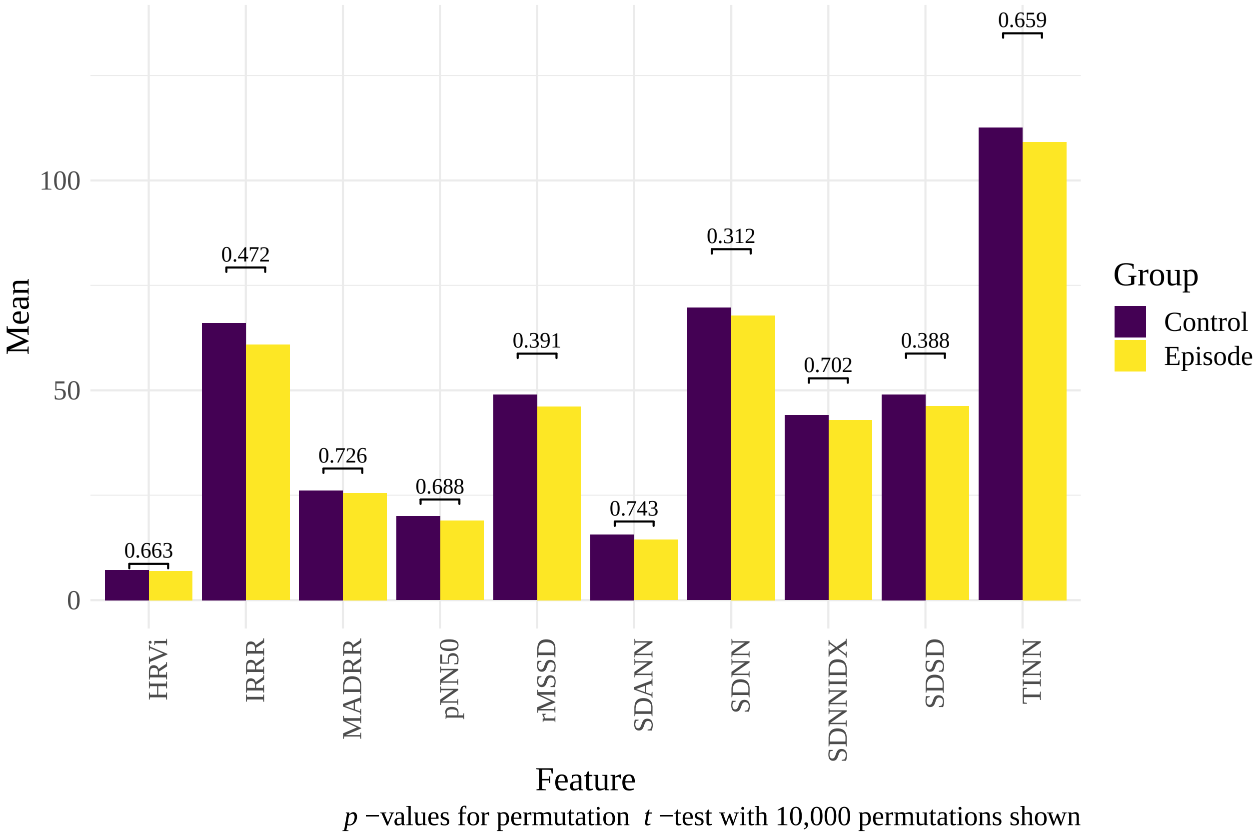

Figure 3. Between-Groups Permutation t-test of Time Domain Features

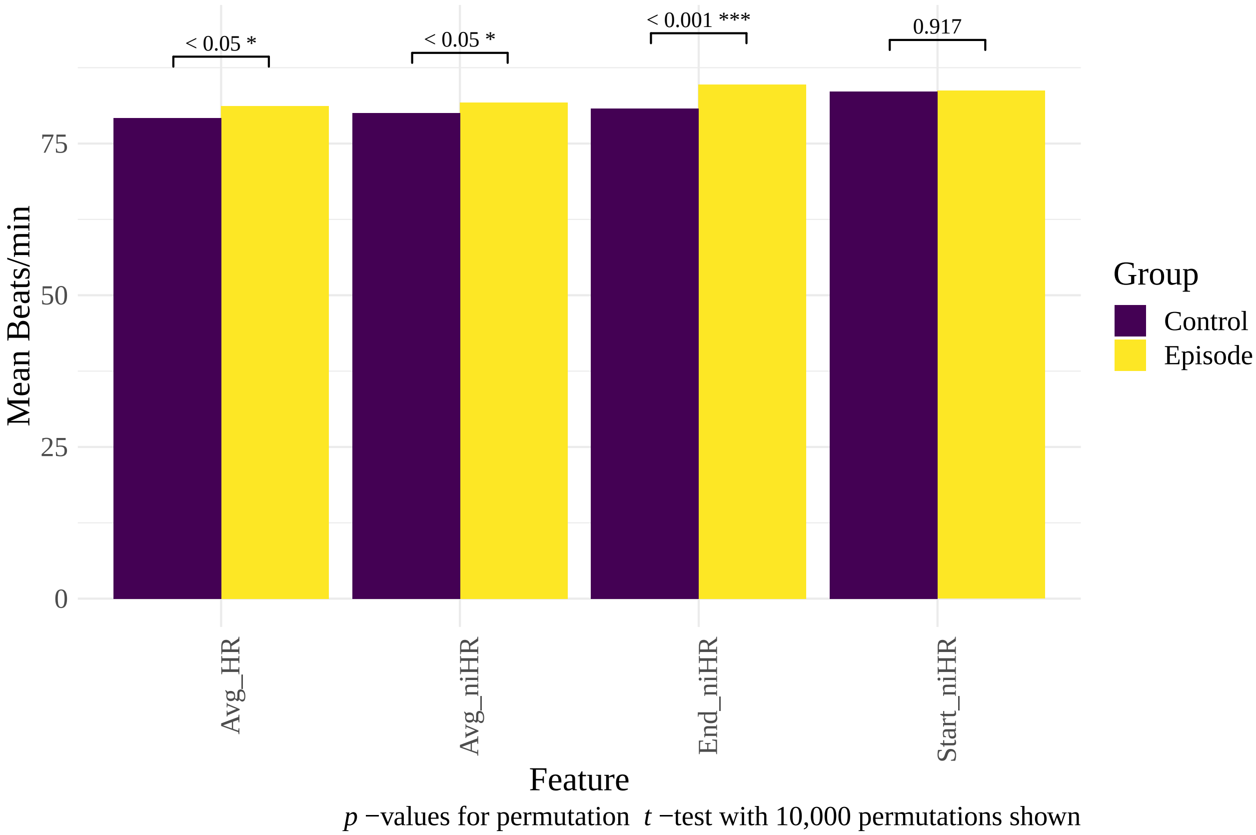

Figure 4. Between-Groups Permutation t-test of Frequency Domain Heart Rate Features

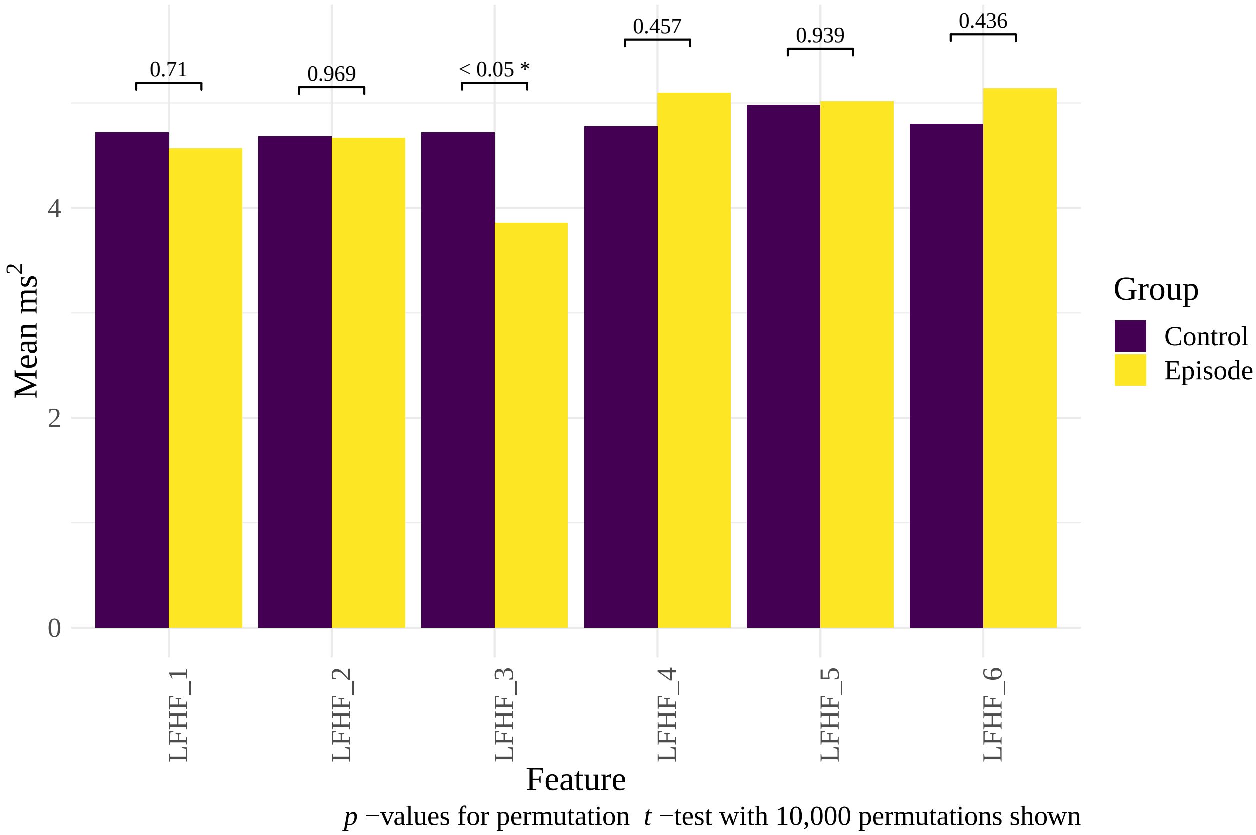

Figure 5. Between-Groups Permutation t-test of Low Frequency-High Frequency Ratio Features

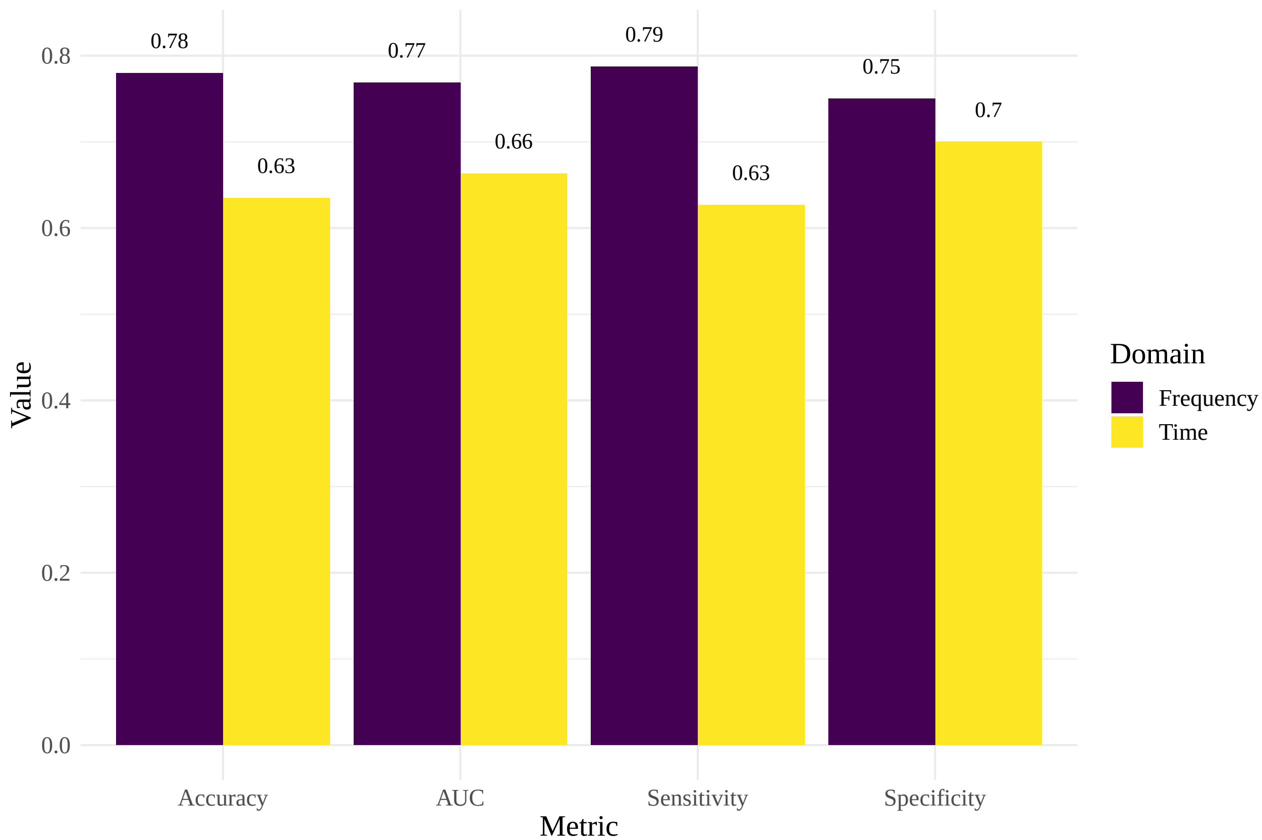

Figure 6. Machine Learning Evaluation Metrics

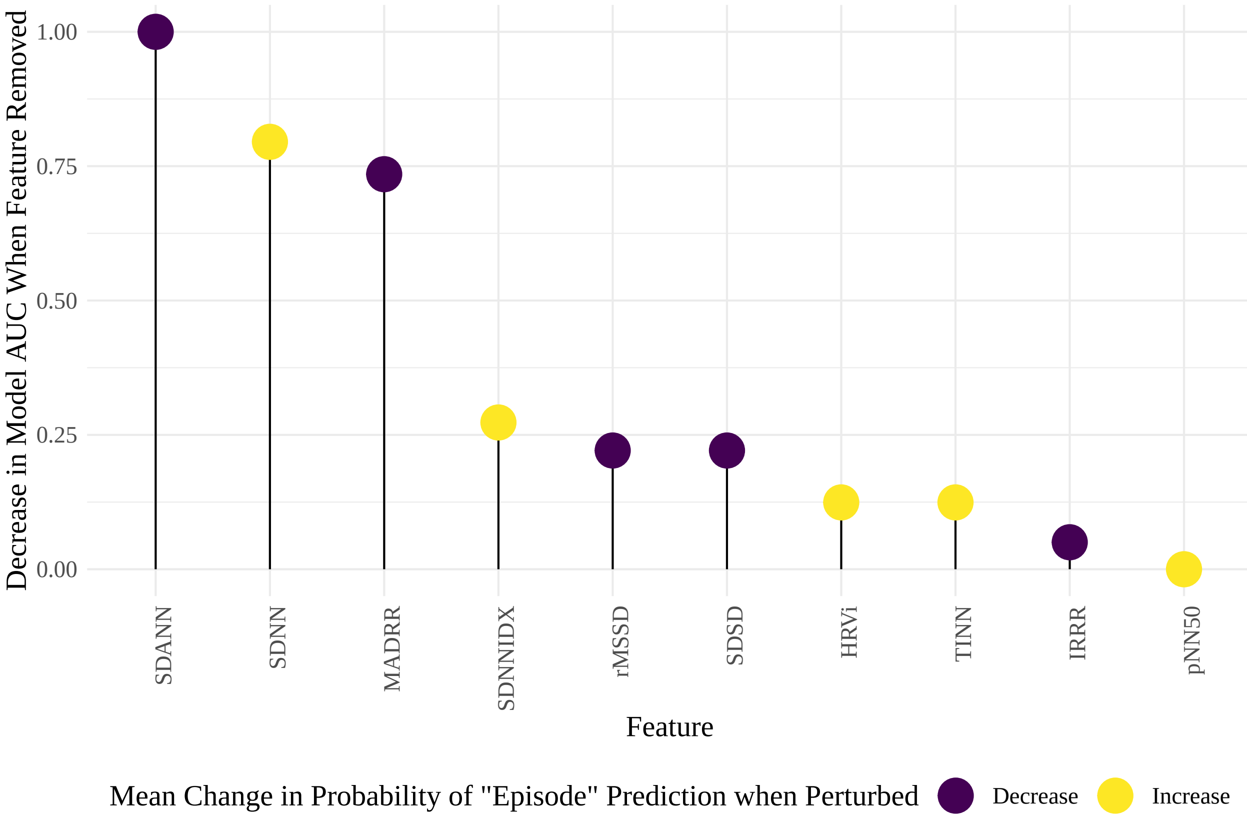

Figure 7. Pseudo-Feature Importance by Removing & Perturbing Each Feature: Time Domain

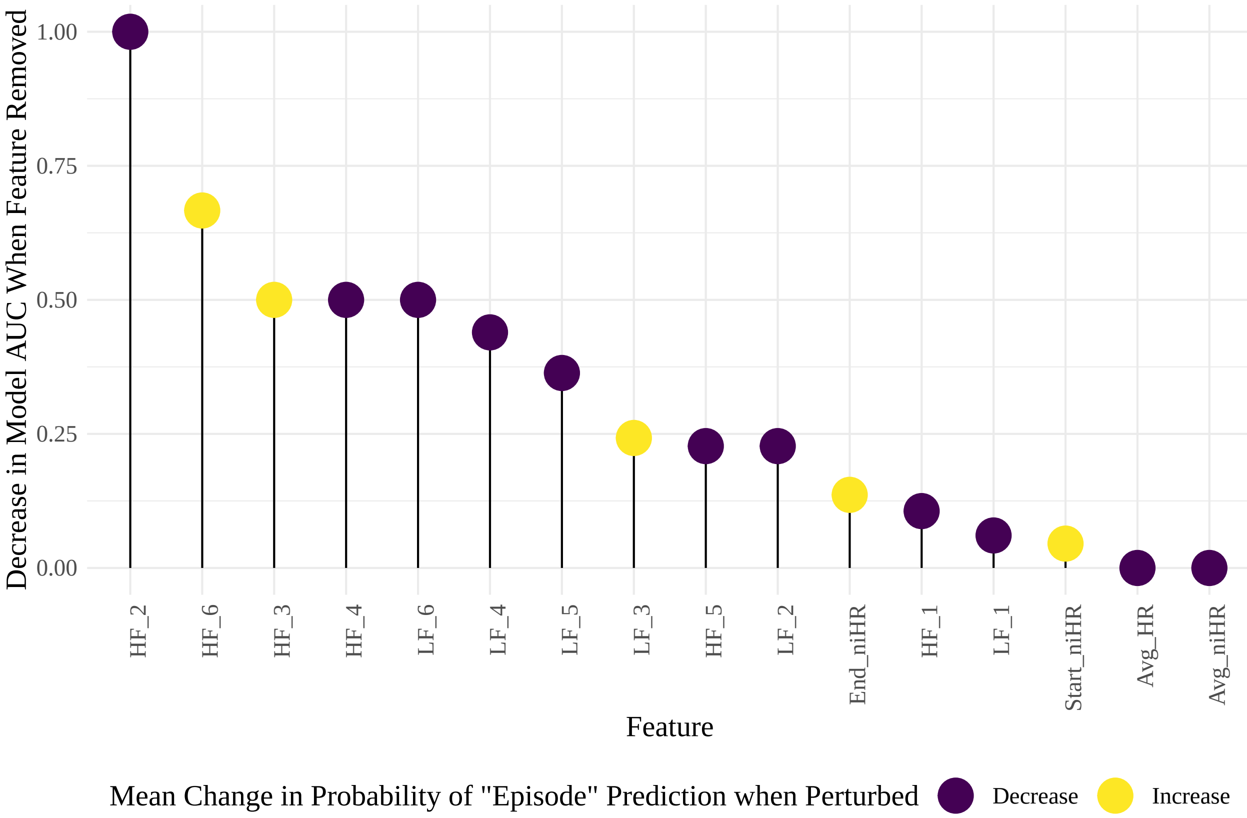

Figure 8. Pseudo-Feature Importance by Removing & Perturbing Each Feature: Frequency Domain

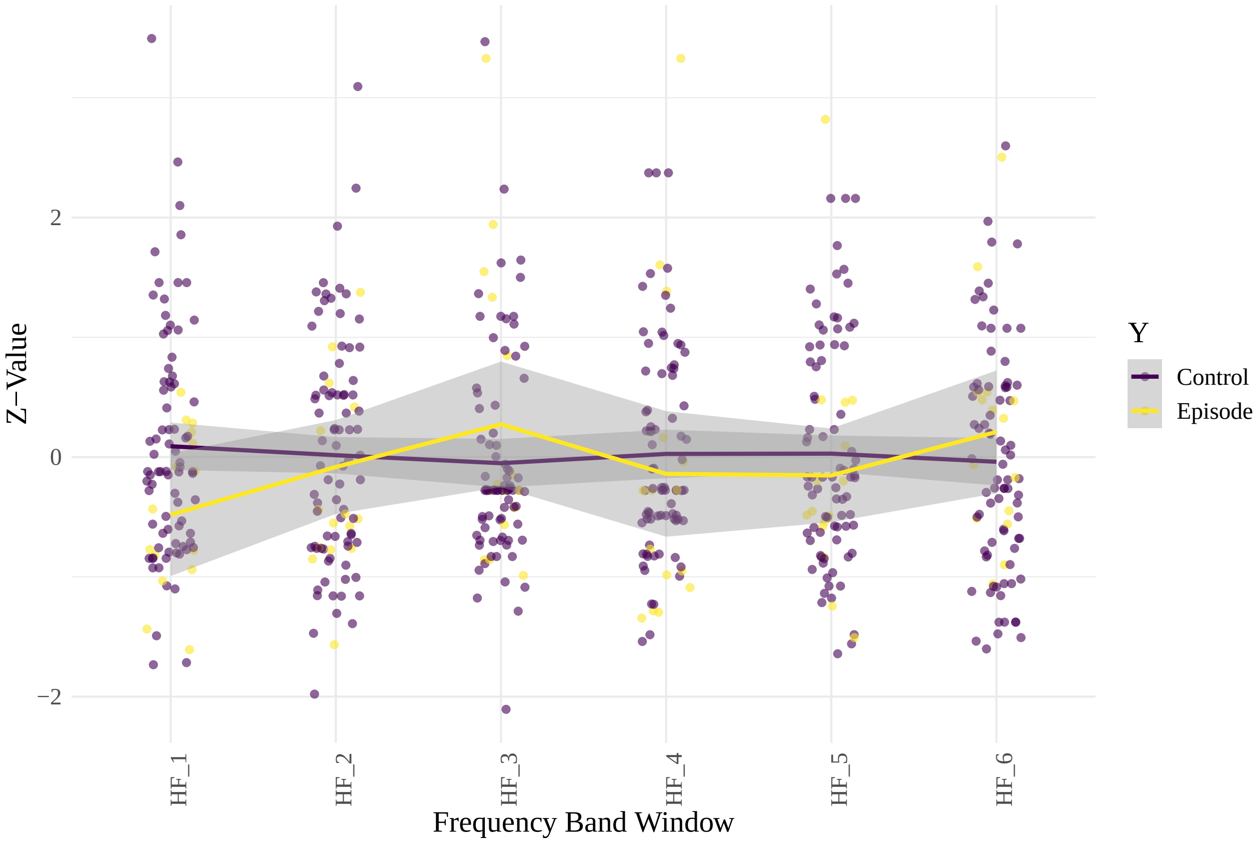

Figure 9. Time Series of High Frequency Band