

Methods & Results Section

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1 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 et al. 2007; Harthoorn and 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 and 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 (Shaffer and Ginsberg 2017; Rubin et al. 2016).

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 spectrograms 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, \dots, LF_6), the mean High Frequency signal (HF_1, HF_2, \dots, HF_6), and the mean Low Frequency-High Frequency Ratio ($LFHF_1, LFHF_2, \dots, LFHF_6$).

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 (Maindonald and Braun 2015; Good 2013). 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, and 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.

2 Results

2.1 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 summarise the completeness of data in the extracted time and frequency domain features.

MENTION HOW MANY CONTROLS AND EPISODES HERE (FOR SDNN we have n and for the remaining we have n range)

2.2 Comparison of Means

FILTER OUT HIGH STRESS CONTROLS AND REPORT PERMUTATION T

The mean values for each time-domain features is shown in Table 1 below:

Table 1: Summary of Time Domain Features

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	10.590042
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

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 2.

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

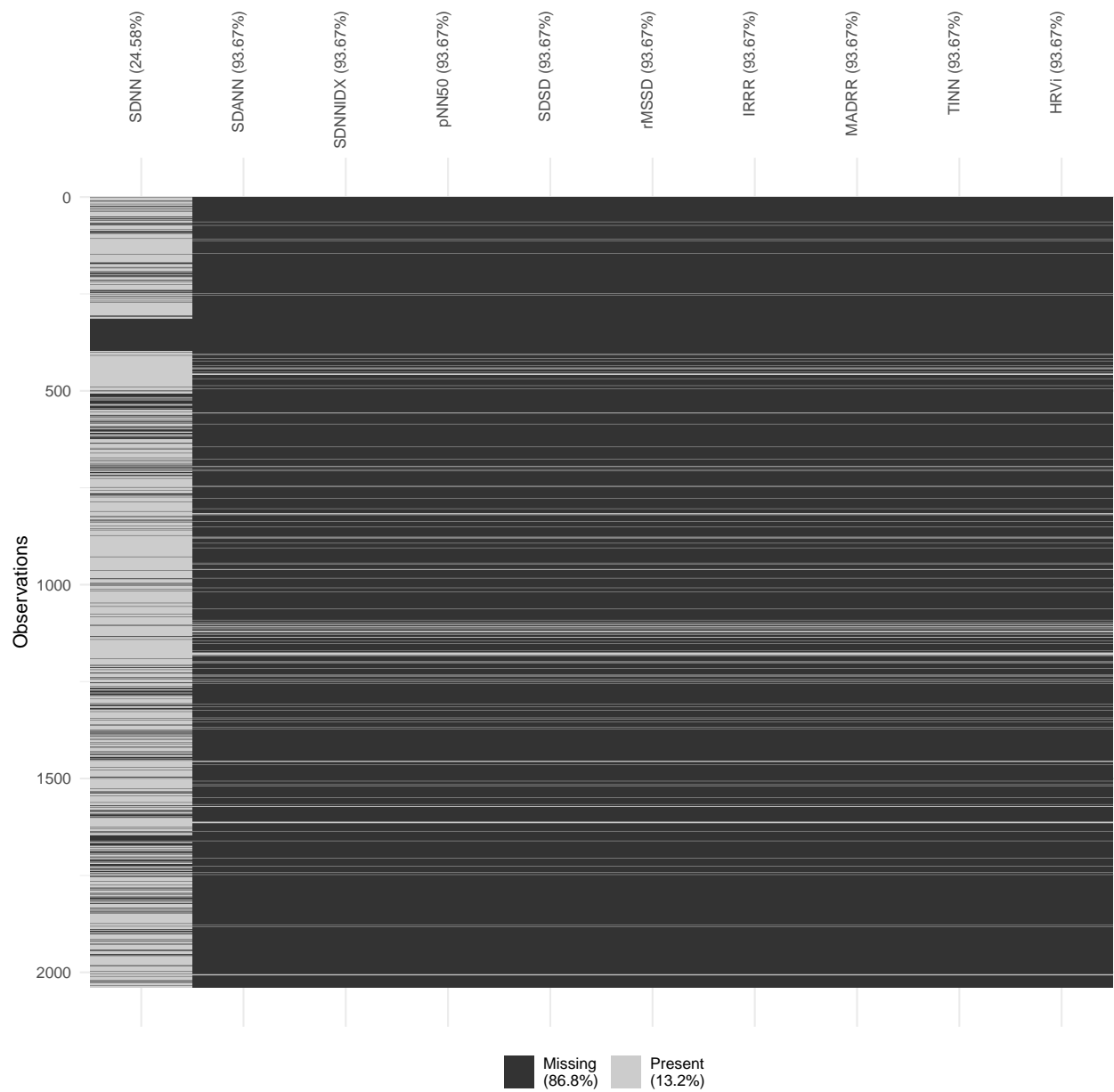


Figure 1: Completeness of Features in the Time Domain

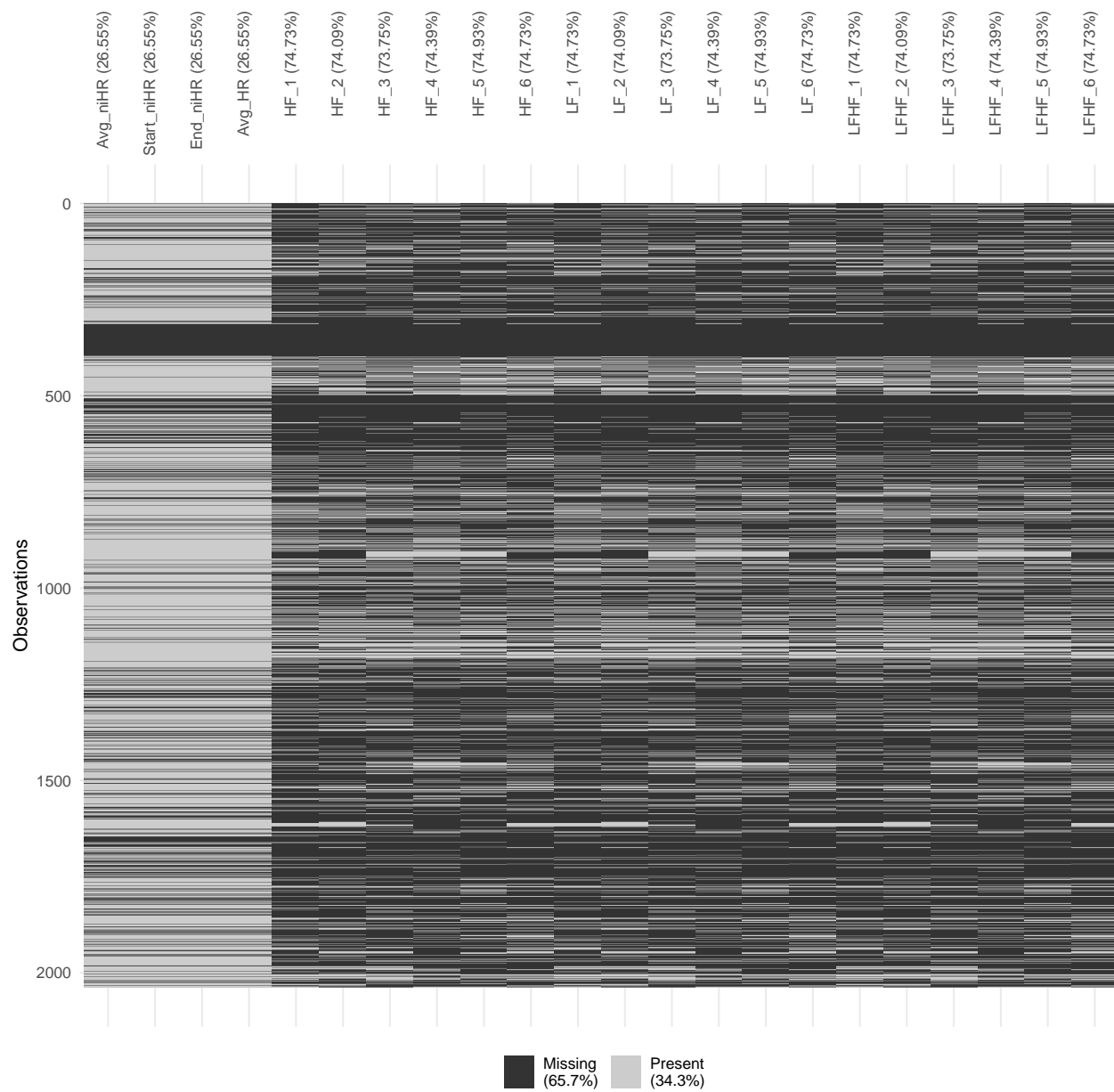


Figure 2: Completeness of Features in the Frequency Domain

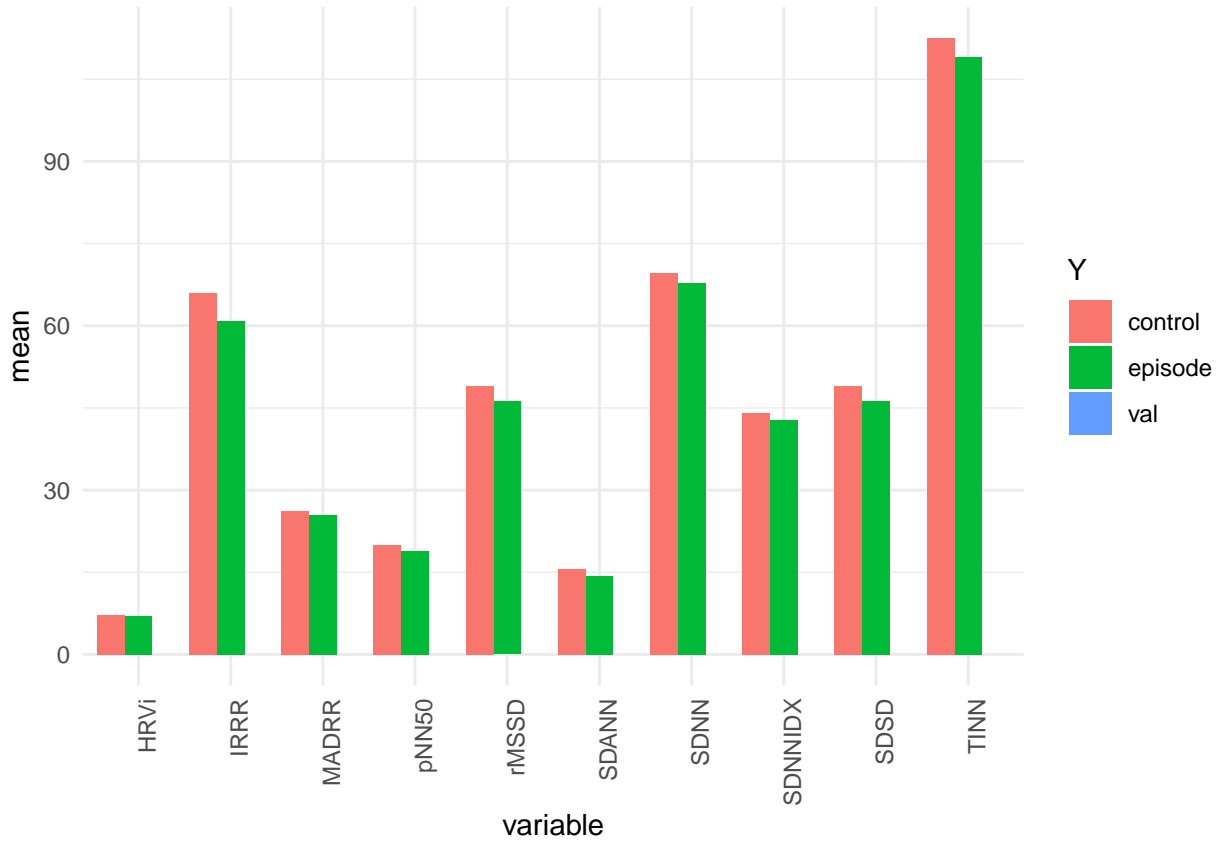


Figure 3: Between-Groups Permutation t -test of Time Domain Features

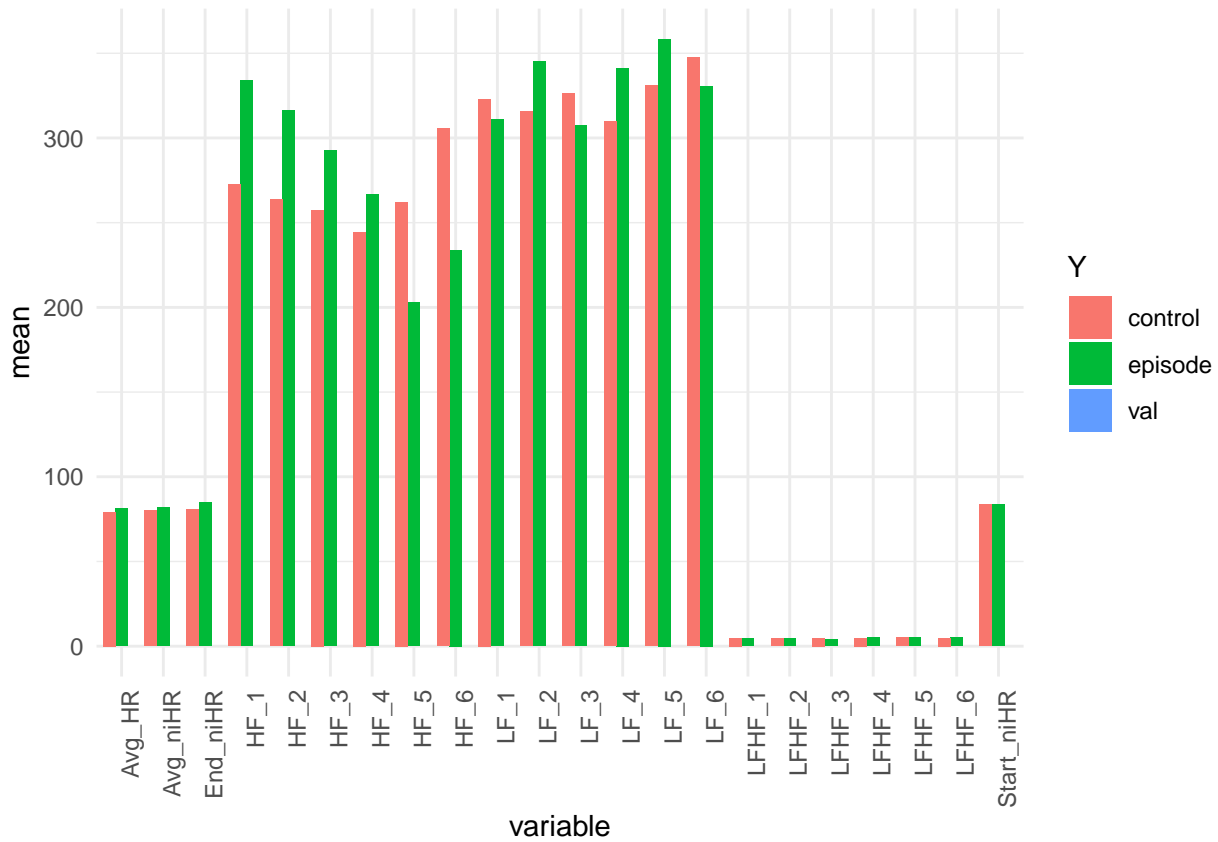
Table 2: Between-Groups Permutation t -test of Time Domain Features

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

variable	n	mean	sd
Avg_HR	1497	79.50	12.13
Avg_niHR	1497	80.26	12.20
End_niHR	1497	81.34	15.69
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
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
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
LFHF_6	515	4.85	3.42
Start_niHR	1497	83.58	17.76

Using the same Two- t permutation approach, we found significant 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.

variable	mean.control	mean.episode	n.control	n.episode	sd.control	sd.episode	p.val
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
End_niHR	80.77	84.71	1282	215	15.55	16.12	0.00
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
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
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
LFHF_6	4.80	5.14	444	71	3.43	3.35	0.44
Start_niHR	83.56	83.70	1282	215	18.21	14.85	0.92



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