Time-Lagged Prediction of Food Craving with Elastic Net Regression and BISCWIT:

Prediction Performance of Qualitative Distinct Predictor Types

Authors

Björn Butter, Tim Kaiser, Samuel Arzt, Björn Pannicke, Simon Ginzinger & Jens Blechert

Contacts

Björn Butter	bjoern.butter@stud.sbg.ac.at
Tim Kaiser	tim.kaiser@uni-greifswald.de
Samuel Arzt	samuel.arzt@fh-salzburg.ac.at
Björn Pannicke	bjoern.pannicke@sbg.ac.at
Simon Ginzinger	simon.ginzinger@fh-salzburg.ac.at
Jens Blechert	jens.blechert@sbg.ac.at

Abstract

Food craving (FC) peaks are highly context-dependent and variable. Accurate prediction of FC might help preventing disadvantageous eating behavior. Here, we examine whether data from two weeks of Ecological Momentary Assessment questionnaires on stress and emotions alongside smartphone sensor data would be able to predict food cravings approximately 2.5 hours into the future in $N = 46$ individuals. We compared two prediction approaches (logistic BISCWIT and Elastic Net Regression (ENR)). While overall prediction accuracy was low, passive sensing data alone was superior to predictions based on psychometric data and BISCWIT was superior to ENR for binary classification of FC peaks.

Key words: *Food cravings, time-lagged, idiographic models, Elastic Net regression, BISCWIT, Ecological Momentary Assessment, Passive Sensing.*

Introduction

Food craving (FC) is defined as an intense desire or urge to consume specific foods (Weingarten & Elston, 1991) that can also occur in the absence of hunger (Reichenberger, Richard et al., 2018). The high clinical relevance of FCs comes from their central role for binge eating in eating disorders (Moreno et al., 2009). FCs are also related to overeating in obesity (Verzija et al., 2018) and often underlie diet breaches in weight loss dieting (Meule et al., 2018; Fedoroff et al., 2003). FCs are highly contextualized behaviors, meaning that they are triggered in certain situations (confrontation with sights or smells of foods, others eating, hunger) more so than in others. General plans and intentions to eat healthily frequently fail in such situations. This has fueled the search for context-sensitive interventions that would intervene on these experiences at the right time. Grown from the tradition of ecological momentary interventions, so-called just in time adaptive interventions (JITAIs) have recently gained support (Wang & Miller, 2019). JITAIs are characterized by a data-driven approach to allow real-time and context-sensitive intervention (i.e. sending motivational tips to dieters when they experience hunger or during high craving situations such as grocery shopping) (Nahum-Shani et al., 2018).

Prediction of food craving, however, has proved quite difficult, when based on generalized models on the population level: influential factors include stress (Chao et al., 2015), negative emotions (Christensen, 2007) but also positive emotions (Moore & Konrath, 2015), circadian patterns (Reichenberger, Richard et al., 2018), and several more. Yet, the number of influential variables is high and their interactions are not fully clear. This limits the usefulness of nomothetic models for JITAIs.

In this context, the distinction between nomothetic research - determining global trends and heterogeneity *between* population groups - and idiographic research - modeling dynamic processes *within* single individuals - has proved useful. With the nomothetic assumption that randomized populations are homogenous, but only differ in the construct of interest, substantial variability within individuals is lost. Nomothetic research does not necessarily generalize to an individual level since person-specific features are not taken into account, and vice versa. (Adolf et al., 2014; Beltz et al., 2016; Fisher et al., 2018). However, both approaches may complement each other (Wright & Zimmermann, 2019; Beltz et al., 2016).

Yet, to model and intervene on problematic eating behaviors that result from craving, high-resolution data of intensive longitudinal data, that validly reflects person-specific internal and external states is required. This demand can be met with a rapidly growing data collection technique, known as ecological momentary assessment (EMA). EMA is described as the repeated measurement of real-time data in individuals' natural environments (Shiffman, 2014). The core principle of this method is that participants repeatedly respond to prompting signals to enter data on their mobile phones. The advantages of EMA sampling are: (1) Items are usually formalized concerning the individual's present state and context at the moment of entry, thus minimizing retrospective recall bias (Engel et al., 2016). (2) Repeated measurements of real-time states in real-world environments depict person-specific dynamics over time with concurrent internal and external contexts recorded. (3) EMA allows flexible sampling designs regarding the sampling period, sampling frequency, and timing (random, semi-random, or event-related sampling) as well as the scope of prompted items (Engel et al., 2016). (4) Besides actively self-reported data (*aEMA*), EMA designs have the potential to passively collect data (*pEMA*) on mobile phones, such as exact timestamps of data entries or mobile phone sensor data. From recorded timestamps, a multitude of temporal components can be derived, such as intraday rhythms or cycles and global trends across the sampling period. Fisher and Bosley

(2020) highlight that temporal components, especially cycles, are valuable predictors for out of sample prediction of idiographic processes. Also, with mobile phone sensors, a wide variety of parameters can be captured, such as app usage, accelerometer, GPS data, screen time, noise and light sensors, etc. These data may function as single predictors on their own (Bae et al., 2018) but can also be aggregated into categories or clusters that represent virtual situations (Beierle et al., 2018).

A distinction of active EMA data from passive EMA data

The precision of idiographic models predicting food cravings may crucially depend on the number and nature of utilized predictors. Importantly, which type of data is needed for an accurate prediction has a direct impact on participant issues such as burden and compliance. Thus, the present work highlights the distinction between aEMA data and pEMA data. We define aEMA as data where the participant's active engagement is required to answer prompted questionnaires. aEMA data provide insights into dynamic idiographic subjective-experiential processes that could represent direct targets of personalized JITAIs. pEMA is defined as data that contain both temporal facets and mobile phone sensor data, which can be tracked in the background with a much higher temporal resolution than aEMA data. Although temporal and sensor data differ regarding required preprocessing steps and aspects of data sampling, they are collectively classified as pEMA since participants are minimally involved in the sampling process. Importantly, pEMA data can determine the exact time of events and can capture some aspects of the external contexts in which a person currently is. By combining aEMA and pEMA data a full picture of internal as well as external states emerges which we refer to as full EMA (fEMA).

Within-person prediction of dynamically changing experiences and behaviors

The combination of state-of-the-art machine learning methods and comprehensive psychological models allow for the prediction of problematic behavior on a person-specific level. Such behavioral predictions constitute a promising approach for clinical prevention, treatment, and aftercare. Bae et al. (2018) were able to differentiate high-risk drinking windows from low-risk windows with an accuracy of 90.9% with solely temporal and mobile phone sensor data as predictors. The results of this and the work of (Fisher & Bosley, 2020) make clear, that cyclic components play a crucial role in modeling idiographic behaviors and states. The classification of low vs high-risk states from Bae et al. (2018) was attained 30min *after* drinking onset – thus leaving some time for setting an intervention before drinking gets worse. However, a classification *at*, or even *before* the onset of a problematic behavior would be clearly preferable for various other behaviors, where the behavior itself is rather short-lived and extra preventive measures need to be taken. A so called *time-lagged prediction* was implemented by Fisher & Soyster (2019) to predict the presence or absence of smoking events in the near future. Such time-lagged models could be the basis of reliable and effective JITAIs.

Aims of the study

The current study employed time-lagged predictions of FCs to evaluate the potential feasibility of a future JITAI approach. To do so we need to estimate the accuracy with which future FC states can be predicted, given a reasonably sized training data set. Technically, we predicted future FC values not only continuously but also in binary absence (low FC) versus presence (high FC) classes separated by an individual threshold because JITAIs need a binary trigger signal - ‘decision point’ in terminology suggested by (Nahum-Shani et al., 2018). Conceptually ‘high FC’ would indicate the need for a momentary intervention such as a tip. Additionally, we were interested in contrasting the predictive performance of 3 distinct predictor ensembles (aEMA, pEMA, fEMA). Further, we employed two statistical algorithms (Elastic Net Regression (ENR) and Best Item Scale that is Cross-Validated, Weighted, Informative and

Transparent (BISCWIT)) and contrasted their precision. We expected higher than chance prediction of food craving for both methods, although not at the AUC levels obtained in alcohol or smoking research as the contextual factors of food craving are potentially more complex and - because FC is an internal state and not a directly observable behavior – subject to potentially high measurement error. Lastly, since both EN and BISCWIT exert feature selection, where only a subset of available predictors is included to the model, we were interested in the frequency of selected predictors, reflecting the overall importance of single predictors.

Methods

Participants

Participants' time-series data were drawn from an EMA study on eating behaviors, stress and emotions. Participants were included in the study if they were motivated to pursue a conscious diet ($N = 184$). Participants were randomized to an intervention group receiving daily tips on eating behavior and a control group from which the present sample was drawn ($N = 83$) based on the use of an android device (enabling sensor data sampling) and sufficient data quantity of at least 50 % aEMA data ($N = 48$). Two participants were excluded due to missing variance of reported food cravings, leaving a total sample size of $N = 46$ for the present paper. Across the sampling period of 14 days, retained participants missed on average 14.7 ($SD = 11.6$) or 17.5% of all 84 signals (i.e. prompted questionnaires). Participants (82% female) had a mean age of 22.35 years ($SD = 2.67$) and a mean body-mass-index (BMI) of 23.22 ($SD = 3.02$).

Procedure

The study and all procedures were approved by the ethics committee of the University of Salzburg, Austria and all participants provided informed consent after receiving information on the purpose of the study in oral and written modality prior of data collection.

Active EMA data collection

EMA data collection was carried out using the Smarteater app, which was designed in collaboration with the department of MultiMedia Technology of the University of Applied Sciences Salzburg, Austria. Participants were prompted 6 times each day across 14 days with signals being separated by semi-random time-intervals of 150 (+15) minutes. Thus, a maximum of 84 data points was available for each participant. Participants could respond to the signal up to 60 minutes after signal onset and rated items either on a horizontal visual analog slider from 0 (*not at all*) to 100 (*very much*) or with *Yes / No* statements. In sum, 18 variables were collected as aEMA: 10 affect related items orientated on the Positive and Negative Affect Schedule (PANAS) scales (Watson & Clark, Lee, A, 1988), 3 stress and coping related items based on the Perceived Stress Scale (PSS; Cohen, Kamarck, & Mermelstein, 1983; German version by Büssing, 2001) and 5 food and craving related items. Full lists containing all items are provided in the supplemental materials.

Passive EMA data collection and preparation

PEMA data consisted of temporal variables and aggregated smartphone sensor data. Temporal components comprised *linear, quadratic, and cubic trends* computed both for the whole 14 day sampling periods and within days as well as *sinusoidal and cosinoidal ultradian and circadian cycles* (Fisher & Bosley, 2020). Additionally, binary *time of day* variables (e.g. morning, midday, etc.) were derived from signal numbering. The aggregation of mobile phone sensor data into distinct clusters or “virtual situations” was carried out as follows:

Sensor aggregation and clustering

The Smarteater application collected data from a variety of sensors including accelerometer (the average jerk of 5 minutes on the phone was calculated), audio volume (a recording of 10 seconds every 15 minutes; only the minimum, maximum and mean dB values were stored),

screen on/off time and notifications from other applications (only the time and app name were stored). In order to find reoccurring patterns in the collected data, the raw sensor values were first aggregated at regular time intervals, which matched the interval of the daily questionnaires presented to users.

Before the data of a one hour interval was aggregated, four sub-intervals of 15 minutes each were aggregated. Continuous data, such as the accelerometer, audio volume, or screen on/off time, were aggregated in the form of weighted averages, while discrete data, such as notifications, were counted. The resulting 4*4-dimensional feature space was then reduced to two dimensions using t-SNE (van der Maaten & Hinton, 2008) and clusters in the reduced data space were then automatically detected using spectral clustering (Luxburg, 2007) with a fixed k-value of 3 (see Arzt et al, in preparation). In summary, aEMA data contained 18 variables, pEMA data contained 19 variables (16 temporal and 3 cluster variables), and fEMA combining both predictor ensembles consisted of 37 variables.

Data preprocessing

Preprocessing with R version 3.6.1 (R Core Team, 2019) in R Studio (RStudio Team, 2016) involved missing data imputation for aEMA values using a Kalman filter (Tusell, 2011), linear interpolation for respective time differences, z-transformation of predictors and lagging the FC variable backward for one measurement entry. Thus, and vital for time-lagged models, predictors were not associated with concurrent FCs, but with FCs one signal ahead. For classification models, FCs were dichotomized individually based on the individual mean (obtained from training data) into classes of high FC and classes of low FC. By determining the threshold individually, person-specific response tendencies are taken into account (Batchelor & Miao, 2016).

Idiographic models with Elastic Net Regression and BISCWIT

The current work compared two statistical methods: Elastic Net Regression (ENR) (Friedman et al., 2010) and BISCWIT (Revelle, 2019). Essentially, ENR Regression augments OLS regression with a combination of L1 (lasso) and L2 (ridge) regularization. Both regularizations were developed to counteract overfitting and increase out-of-sample generalizability by penalizing coefficients, but with only L1 regularization being able to shrink coefficients exactly to zero. Shrinking coefficients to zero provides feature selection which results in sparse and more interpretable models. EN regression was performed with the *cva.glmnet* function from the *glmnet* package (Friedman et al., 2010) with a 10-fold cross-validation. Hyperparameters (alpha and lambda) were tuned on the cross-validated mean absolute error (MAE).

The Best Items Scale that is Cross-validated, Unit-weighted, Informative and Transparent (BISCUIT; Revelle, 2019) is a simple correlation-based machine learning technique. Pairwise correlations between a set of predictors and one or more criterion variables are calculated. The correlations are cross-validated and predictors with the highest average correlation are retained. Retained predictors are unit-weighted and combined to a sum score. A modification of BISCUIT is BISCWIT. Here, the items are weighted by their correlation with the criterion instead of unit-weighted. Such simple alternatives to more sophisticated machine learning approaches often perform comparable to and sometimes even better especially when sample sizes and effects are small while measurement error is high (Dana & Dawes, 2004; Dawes, 1979; Lichtenberg & Simsek, 2016; Elleman et al., 2020). In this study, BISCWIT was used instead of BISCUIT because correlation-weighted models were more extensively studied and showed more favorable performance in more recent simulation studies (Waller & Jones, 2010; Finch & Holden, 2010). Models were computed using the *bestScales* function, again with 10-fold cross-validation and correlation-weighted scale scores were obtained by *scoreWtd* from the *psych* package (Revelle, 2019). The minimum number of selected variables was set to 1 and the maximum number was set to the total number of variables available for each model.

Models were built on training data (first 75% of time series data, i.e. 63 signals, representing 10.5 days) and were assessed upon test data (last 25% of time series data, i.e. 21 signals, representing 3.5 days). Models were established with (1) aEMA, (2) pEMA, and (3) fEMA variables as predictors, predicting (a) continuous as well as (b) binary classes of FC. Thus 6 models were calculated for (a) ENR regression and (b) BISCWIT, resulting in a total of 12 models per participant. To maximize the reproducibility of our analyses, we set a seed at the beginning of the analysis script. Note that due to cross-validation, which both methods apply, results of single models may differ.

Evaluation of model performance.

Considering a JITAI approach large errors should be weighted more since large errors are more likely to either increase the false positive or false negative rate. Therefore, the root mean square error (RMSE) assessed numeric prediction accuracy, which gives weight to large errors. Also, the mean absolute error (MAE) between estimated and actual values was computed, representing the average error of prediction. A baseline model constantly predicted the individual mean of food craving retrieved from the training data and thus contains no information from the regression equation.

For binary class predictions, the area under the receiver operating characteristic curve (ROC curve or AUC) was calculated, representing a well-established measure derived from sensitivity and specificity scores across possible cutoff thresholds. Yet, certain aspects of the AUC score can be misleading such as the unit weighting of omission and commission errors as well as the evaluation of test performance in extreme ROC regions (Lobo et al., 2008). Thus, we also provide the Brier Score, representing the accuracy of probabilistic predictions. While an AUC value of 0.5 was considered as reference, a baseline model for the Brier Score constantly predicted the class with the highest occurrence in the training data.

Results

Food Craving

Across the two-week sampling period the 46 participants exhibited numeric food cravings with a mean of 23.08 ($SD = 26.98$) ranging from 0 to 100. Individual thresholds (i.e. food craving mean) ranging from 3.11 to 64.3 across the sample, were calculated from participant's training data and was used to categorize both training and test data into classes of 'low' and 'high' food craving.

Time-lagged Prediction of Continuous Food Craving Values

For each participant both EN and BISCUIT models predicted continuous food craving values approximately 2.5 hours into the future by separately utilizing the 3 distinct predictor ensembles (aEMA, pEMA, fEMA). Elastic net models with aEMA data outperformed the baseline model in 21 participants (i.e. 46%), models with pEMA data in 24 cases (i.e. 52%) and models using fEMA data in 19 cases (i.e. 41%). BISCUIT models outperformed the baseline model with aEMA data in 10 cases (i.e. 22%), with pEMA data in 16 cases (i.e. 35%) and with fEMA data in 15 cases (i.e. 33%). The RMSE statistic yielded similar results but is not explained in detail here (see Tables 13 & 14 in the supplemental materials). Table 1 presents the overall prediction accuracy (MAE) across predictor ensembles across all 46 participants.

Table 1. *Mean absolute error (MAE) of predictor ensembles and statistical methods in predicting continuous food cravings*

Method	Predictor Type	MAE Mean	MAE Range
Baseline		16.31 ($SD = 7.17$)	5.16 – 40.68
ENR	aEMA	16.43 ($SD = 7.74$)	4.80 – 42.33
	pEMA	18.13 ($SD = 11.92$)	5.16 – 76.99
	fEMA	16.55 ($SD = 8.00$)	5.16 – 45.25
	aEMA	17.33 ($SD = 7.50$)	5.24 – 44.77

BISCWIT	pEMA	16.73 (<i>SD</i> = 6.90)	4.72 – 36.78
	fEMA	17.34 (<i>SD</i> = 7.26)	4.81 – 41.99

Note: ENR = Elastic net Regression, BISCWIT = Best Items Scale that is Cross-validated, Weighted, Informative and Transparent, MAE = mean absolute error. The table presents average MAE across 46 idiographic prediction models with time-lagged continuous food cravings as the criterion.

Time-lagged Prediction of Binary Food Craving Classes

Similar to numeric predictions, both logistic EN and BISCWIT models predicted food craving classes roughly 2.5 hours into the future using each of the 3 distinct predictor ensembles. For each participant, the AUC and the Brier Score were calculated as measures of classification accuracy. EN models outperformed the AUC baseline by aEMA models in 26 cases (i.e. 57%), by pEMA models in 33 cases (i.e. 72%), and by fEMA models in 34 cases (i.e. 74%). BISCWIT models outperformed the baseline model with aEMA data in 41 cases (i.e. 89%), with pEMA data in 40 cases (i.e. 87%) and with fEMA data in 39 cases (i.e. 85%). The Brier score yielded similar results but is not discussed in further detail (see Tables 15 & 16 in the supplemental materials). To assess the overall prediction accuracy of methods and predictor types, Table 2 presents overall prediction accuracy (AUC) across predictor ensembles across all 46 participants.

Table 2. *Accuracy of predictor ensembles and statistical methods in predicting food craving classes*

Method	Predictor Type	AUC Mean	AUC range
Baseline		0.50	0.50 – 0.50
ENR	aEMA	0.58 (<i>SD</i> = 0.10)	0.40 – 0.90
	pEMA	0.59 (<i>SD</i> = 0.12)	0.44 – 0.95
	fEMA	0.60 (<i>SD</i> = 0.11)	0.44 – 0.95
BISCWIT	aEMA	0.65 (<i>SD</i> = 0.13)	0.36 – 0.95
	pEMA	0.63 (<i>SD</i> = 0.13)	0.41 – 0.90
	fEMA	0.63 (<i>SD</i> = 0.14)	0.44 – 1.00

Note: ENR = Elastic net Regression, BISCWIT = Best Items Scale that is Cross-validated, Weighted, Informative and Transparent, AUC = area under the ROC curve. The table presents average accuracy measures across 46 idiographic prediction models with time-lagged dichotomous food craving classes as the criteria. Food cravings were split by the individual food craving mean.

Further, variability within participants was found in which predictor ensemble classifies best. Consequently, such variability of which predictor type is preferred for classification is also found at a aggregated level, across all participants. Figure 2 depicts this variability showing exemplary results from 5 participants.

Figure 1

Note. Exemplary AUC results obtained from BISCWIT models of 5 participants. The figure shows the within and between-participant variance that predictor ensembles revealed.

Feature Selection of Elastic Net and BISCWIT Methods

Both methods (ENR & BISCWIT) employ feature selection: ENR with lasso regularization and BISCWIT by selecting the best predictors based on cross-validated raw correlations. The Tables 1-12 in the supplemental materials demonstrate the frequency a specific variable was selected as a predictor for each model across all participants. For all 6 ENR models, each variable was selected within a range of 13 to 30 times and across all BISCWIT models, each variable was selected within a range of 2 to 31 times. Within each predictor ensemble, none of the variables was overrepresented, meaning that models were highly individual for each participant. Overall, BISCWIT models were more parsimonious than ENR models (see Table 3).

Table 3. *The average number of selected predictors for logistic EN and BISCWIT models across 46 participants*

Method	Predictor Ensemble	Average number of selected predictors
ENR	aEMA	9.09 (SD = 7.72)
	pEMA	8.72 (SD = 7.92)
	fEMA	8.72 (SD = 15.09)
BISCWIT	aEMA	6.50 (SD = 2.31)
	pEMA	6.96 (SD = 2.08)
	fEMA	7.28 (SD = 1.63)

Note. Average numbers of selected predictors for continuous prediction models can be found in the supplemental materials.

Discussion

Although food cravings (FC) play a key role in enhancing problematic eating behaviors (Verzijl et al., 2018), the present study is the first to establish idiographic time-lagged models to test whether their prediction into the future is feasible and acceptably accurate. To remedy that, time series data of 46 healthy participants motivated for weight loss were drawn from an EMA study

on eating behaviors, stress and emotions. For each participant, 12 prediction models were established, resulting from a model grid of (a) three predictor ensembles (aEMA, pEMA, fEMA), (b) two applied prediction algorithms (Elastic net regularization and BISCWIT), and (c) two codings of the criterion variable (continuous and binary). Importantly, all established models were time-lagged, meaning that each model estimate referred to the upcoming signal (roughly 150 minutes into the future). Further, models were built on training data and out-of-sample generalizability was assessed on test data. It was hypothesized, that food craving states of upcoming signals can accurately be predicted and that predictor ensembles differ in precision.

Prediction Accuracy of Predictor Ensembles (aEMA, pEMA, fEMA)

We found that overall results of numeric as well as binary predictions show that independently from the statistical method neither aEMA, pEMA nor fEMA data differ in their precision. This may lead to the conclusion that all ensembles perform equally well in predicting FC. That may be true on the nomothetic level (i.e. across participants) as indicated by Table 1 & 2 and corresponds with existing findings that FC is associated with internal psychological states as well as certain contextual factors and follows temporal patterns (Reichenberger et al., 2018). On an idiographic level, however, it can make crucial differences in which ensemble is used for FC prediction (as indicated by Figure 2). This represents an unexpected variability regarding what ensemble is preferred within each participant and highlights that the problem of group-to-individual generalizability persists for wide-ranging predictor ensembles (Fisher et al., 2018). Further research is needed to detect differences on the nomothetic level for whom aEMA and for whom pEMA predicts FCs best. Note that also in other research areas such as substance use, differences regarding the prediction performance of aEMA and pEMA are to date unexplored.

Regarding aEMA, future studies could further improve the prediction of food cravings by examining a broader set of predictors, validating and expanding them by involving

stakeholders (Soyster & Fisher, 2019). Additionally, pEMA predictor sets could also be expanded by including a wider variety of sensor data, possibly adding physiological measures like heart rate or skin conductance response. By using techniques like the Lombard-Scargle periodogram, more individualized cyclic temporal predictors could be extracted directly from psychometric time-series.

Prediction Accuracy and Feature Selection of Prediction Algorithms (EN regularization & BISCWIT)

We applied two prediction algorithms: ENR (Friedman et al., 2010) and BISCWIT (Elleman et al., 2020). BISCWIT originates from nomothetic personality research and is used - to the authors' best knowledge - for the first time for idiographic model building. We found that prediction algorithms did not differ in their overall precision (see Table 1) in predicting continuous FCs from a Gaussian model and did not outperform the baseline model.

However, BISCWIT performed better in differentiation between FC classes, with overall AUC values surpassing the baseline for one standard deviation for aEMA and pEMA models. The fact that BISCWIT performs equally in numeric predictions and outperforms ENR in distinguishing 'low FCs' from 'high FCs', supports findings of Lichtenberg and Simsek (2016) that simpler models can outperform more sophisticated methods when data sets are small and measurement errors are high. Note, however, that the Brier statistic did not indicate this difference. The difference between continuous and dichotomous predictions could be explained by the extreme rarity of food cravings in most participants. Instead, dichotomization into "food craving presence" / "absence" might be a more appropriate way to describe food cravings in non-clinical populations.

Since both procedures exert feature selection, we can take a deeper look at the variables selected by the models as contributing non-redundant information to the prediction. On average,

BISCWIT selected considerably fewer predictors than ENR, thus resulting in more parsimonious models. The fact that the frequency at which each variable was selected seemed evenly distributed within each model with almost no outliers (see Tables 1-12 in the supplemental materials), suggests that each participant has its own unique set of variables predicting FC. Therefore, it was not possible to identify key predictors among all 37 available variables. As a consequence, a personalized real-world JITAI application targeting FC should arrange interventions addressing each possible variable. Scientifically, this is noteworthy: it actually suggests that there is no generalizable pattern in variable importance but prediction models are fully idiosyncratic. The constellation of variables being important for craving prediction of participant 1 allows no extrapolation to the potential constellation in participant 2. It is also noteworthy that the presence or absence of a specific virtual cluster from mobile phone sensor data did also contribute to predicting FCs. Thus, high-dimensional mobile phone sensor data can be aggregated to meaningful, virtual clusters that are associated with internal subjective states and behaviors (Beierle et al., 2018; Arzt et al, in preparation). This comes with the clear advantage of gathering predictive variables in the background, without increasing participant burden. Additionally, it is worth mentioning, that global trend variables were frequently considered as predictors. This indicates non-stationarity in some time-series data and could reflect one reason why estimates for out-of-sample data were rather imprecise (Fisher & Bosley, 2020).

Practical Implications and limitations of the study

Although models for some participants exhibited almost perfect classification scores (AUC scores of 0.8 - 1.0), the overall above chance information within predictions remains low relative to other behaviors, and maybe too low for a real-world JITAI application. More accurate predictions could be obtained by predicting multiple aspects of FC instead of one single item. Similar to the prediction of mood profiles (Fisher & Bosley, 2020), FC profiles

could be generated by employing established instruments such as the Food Craving Questionnaire (Nijs et al., 2007). Also, a sampling period exceeding 14 days would provide more data for prediction algorithms to make better estimates of future FCs, but would, of course, increase burden.

The present study separated classes of FCs using the individual mean, which accounts for personalization and individual differences in response behavior. However, and since we analyzed healthy participants, we can not claim that such a threshold can differentiate between the absence and presence of a clinical risk state as, e.g., uncontrolled binge eating. The definition of a threshold that indicates the need for a personalized intervention has to be empirically validated especially for clinical participants. The results of this work suggest, that no predictor ensemble outperforms the other in overall prediction accuracy of FC. As a consequence, researchers may decide whether aEMA or pEMA data should be sampled depending on whether participant burden should be minimized or other technical requirements and data processing steps. Pragmatically, the present results suggest that pEMA would be sufficient for acceptable predictions in just about half of the participants.

Conclusion

Results of the present work demonstrate that a time-lagged prediction of FC classes in general is feasible. We found that aEMA does not provide any additional accuracy over pEMA data and that simple models such as BISCWIT should be considered even for high-dimensional data. Further research is needed to determine individually and *a priori* which type of data might produce the highest prediction accuracy and for whom a time-lagged prediction in general works. A challenge for future research would be combining individual prediction models with theory based, between person predictors such as age, gender, BMI or trait level emotional eating scores or food craving as done in multi-level based prediction models (Reichenberger et al., 2020; Reichenberger, Kuppens et al., 2018).

References

- Adolf, J., Schuurman, N. K., Borkenau, P., Borsboom, D., & Dolan, C. V. (2014). Measurement invariance within and between individuals: A distinct problem in testing the equivalence of intra- and inter-individual model structures. *Frontiers in Psychology*, 5, 883. <https://doi.org/10.3389/fpsyg.2014.00883>
- Arzt, S., Blechert, J., Arend, A. K., Kaiser, T., Pannicke, B., & Ginzinger, S. (2020). *Fine-grained Routine Detection in Smartphone Usage and Sensor Data to Improve Prediction of Subjective Psychological Scales: Algorithm Development and Validation*. Manuscript in preparation.
- Bae, S., Chung, T., Ferreira, D., Dey, A. K., & Suffoletto, B. (2018). Mobile phone sensors and supervised machine learning to identify alcohol use events in young adults: Implications for just-in-time adaptive interventions. *Addictive Behaviors*, 83, 42–47. <https://doi.org/10.1016/j.addbeh.2017.11.039>
- Batchelor, J. H., & Miao, C. (2016). Extreme Response Style: A Meta-Analysis. *Journal of Organizational Psychology*, 16(2). <https://doi.org/10.33423/jop.v16i2.1790>
- Beierle, F., Tran, V. T., Allemand, M., Neff, P., Schlee, W., Probst, T., Pryss, R., & Zimmermann, J. (2018). Context Data Categories and Privacy Model for Mobile Data Collection Apps. *Procedia Computer Science*, 134, 18–25. <https://doi.org/10.1016/j.procs.2018.07.139>
- Beltz, A. M., Wright, A. G. C., Sprague, B. N., & Molenaar, P. C. M. (2016). Bridging the Nomothetic and Idiographic Approaches to the Analysis of Clinical Data. *Assessment*, 23(4), 447–458. <https://doi.org/10.1177/1073191116648209>
- Chao, A., Grilo, C. M., White, M. A., & Sinha, R. (2015). Food cravings mediate the relationship between chronic stress and body mass index. *Journal of Health Psychology*, 20(6), 721–729. <https://doi.org/10.1177/1359105315573448>
- Christensen, L. (2007). Craving for sweet carbohydrate and fat-rich foods ? possible triggers and impact on nutritional intake. *Nutrition Bulletin*, 32(s1), 43–51. <https://doi.org/10.1111/j.1467-3010.2007.00615.x>
- Dana, J., & Dawes, R. M. (2004). The Superiority of Simple Alternatives to Regression for Social Science Predictions. *Journal of Educational and Behavioral Statistics*, 29(3), 317–331. <https://doi.org/10.3102/10769986029003317>
- Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist*, 34(7), 571–582. <https://doi.org/10.1037/0003-066X.34.7.571>

- Elleman, L. G., McDougald, S. K., Condon, D. M., & Revelle, W. (2020). *That takes the BISCUIT: A comparative study of predictive accuracy and parsimony of four statistical learning techniques in personality data, with data missingness conditions*. <https://doi.org/10.31234/osf.io/tuqap>
- Engel, S. G., Crosby, R. D., Thomas, G., Bond, D., Lavender, J. M., Mason Tyler, Steffen, K. J., Green, D. D., & Wonderlich, S. A. (2016). Ecological Momentary Assessment in Eating Disorder and Obesity Research: A Review of the Recent Literature. *Current Psychiatry Reports*, 18(4), 1–9. <https://doi.org/10.1007/s11920-016-0672-7>
- Fedoroff, I., Polivy, J., & Peter Herman, C. (2003). The specificity of restrained versus unrestrained eaters' responses to food cues: general desire to eat, or craving for the cued food? *Appetite*, 41(1), 7–13. [https://doi.org/10.1016/S0195-6663\(03\)00026-6](https://doi.org/10.1016/S0195-6663(03)00026-6)
- Fisher, A. J., & Bosley, H. G. (2020). Identifying the presence and timing of discrete mood states prior to therapy. *Behaviour Research and Therapy*, 128, 103596. <https://doi.org/10.1016/j.brat.2020.103596>
- Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences of the United States of America*, 115(27), E6106-E6115. <https://doi.org/10.1073/pnas.1711978115>
- Fisher, A. J., & Soyster, P. D. (2019). *Generating Accurate Personalized Predictions of Future Behavior: A Smoking Exemplar*. <https://doi.org/10.31234/osf.io/e24v6>
- Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, 33(1), 1–22.
- Lichtenberg, J. M., & Simsek, Ö. (2016). Simple Regression Models. *Proceedings of Machine Learning Research*, 58, 13–25.
- Lobo, J. M., Jiménez-Valverde, A., & Real, R. (2008). AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography*, 17(2), 145–151. <https://doi.org/10.1111/j.1466-8238.2007.00358.x>
- Luxburg, U. von (2007). A tutorial on spectral clustering. *Statistics and Computing*, 17(4), 395–416. <https://doi.org/10.1007/s11222-007-9033-z>
- Meule, A., Küppers, C., Harms, L., Friederich, H.-C., Schmidt, U., Blechert, J., & Brockmeyer, T. (2018). Food cue-induced craving in individuals with bulimia nervosa and binge-eating disorder. *PLoS ONE*, 13(9). <https://doi.org/10.1371/journal.pone.0204151>
- Moore, D. J., & Konrath, S. (2015). “I can almost taste it:” Why people with strong positive emotions experience higher levels of food craving, salivation and eating intentions. *Journal of Consumer Psychology*, 25(1), 42–59. <https://doi.org/10.1016/j.jcps.2014.07.001>
- Moreno, S., Warren, C. S., Rodríguez, S., Fernández, M. C., & Cepeda-Benito, A. (2009). Food cravings discriminate between anorexia and bulimia nervosa. Implications for

- "success" versus "failure" in dietary restriction. *Appetite*, 52(3), 588–594.
<https://doi.org/10.1016/j.appet.2009.01.011>
- Nijs, I. M. T., Franken, I. H. A., & Muris, P. (2007). The modified Trait and State Food-Cravings Questionnaires: Development and validation of a general index of food craving. *Appetite*, 49(1), 38–46. <https://doi.org/10.1016/j.appet.2006.11.001>
- Reichenberger, J., Kuppens, P., Liedlgruber, M., Wilhelm, F. H., Tiefengrabner, M., Ginzinger, S., & Blechert, J. (2018). No haste, more taste: An EMA study of the effects of stress, negative and positive emotions on eating behavior. *Biological Psychology*, 131, 54–62. <https://doi.org/10.1016/j.biopsycho.2016.09.002>
- Reichenberger, J., Pannicke, B., Arend, A.-K., Petrowski, K., & Blechert, J. (2020). Does stress eat away at you or make you eat? Ema measures of stress predict day to day food craving and perceived food intake as a function of trait stress-eating. *Psychology & Health*, 1–19. <https://doi.org/10.1080/08870446.2020.1781122>
- Reichenberger, J., Richard, A., Smyth, J. M., Fischer, D., Pollatos, O., & Blechert, J. (2018). It's craving time: Time of day effects on momentary hunger and food craving in daily life. *Nutrition (Burbank, Los Angeles County, Calif.)*, 55-56, 15–20.
<https://doi.org/10.1016/j.nut.2018.03.048>
- Shiffman, S. (2014). Conceptualizing analyses of ecological momentary assessment data. *Nicotine & Tobacco Research : Official Journal of the Society for Research on Nicotine and Tobacco*, 16 Suppl 2, S76-87. <https://doi.org/10.1093/ntr/ntt195>
- Soyster, P. D., & Fisher, A. J. (2019). Involving stakeholders in the design of ecological momentary assessment research: An example from smoking cessation. *PLoS ONE*, 14(5), e0217150. <https://doi.org/10.1371/journal.pone.0217150>
- Tusell, F. (2011). Kalman Filtering in R. *Journal of Statistical Software*, 39(2).
- van der Maaten, L., & Hinton, G. (2008). Visualizing Data using t-SNE. *Journal of Machine Learning Research*, 9, 2579–2605.
- Verzijl, C. L., Ahlich, E., Schlauch, R. C., & Rancourt, D. (2018). The role of craving in emotional and uncontrolled eating. *Appetite*, 123, 146–151.
<https://doi.org/10.1016/j.appet.2017.12.014>
- Waller, N. G., & Jones, J. A. (2010). Correlation Weights in Multiple Regression. *Psychometrika*, 75(1), 58–69. <https://doi.org/10.1007/s11336-009-9127-y>
- Wang, L., & Miller, L. C. (2019). Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. *Health Communication*, 1–14.
<https://doi.org/10.1080/10410236.2019.1652388>
- Watson, D., & Clark, Lee, A (1988). Development and Validation of Brief Measures of Positive and Negative Affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063–1070.

Weingarten, H. P., & Elston, D. (1991). Food Cravings in a College Population. *Appetite*(17), 167–175.

Wright, A. G. C., & Zimmermann, J. (2019). Applied ambulatory assessment: Integrating idiographic and nomothetic principles of measurement. *Psychological Assessment*, 31(12), 1467–1480. <https://doi.org/10.1037/pas0000685>

SUPPLEMENTAL MATERIALS

Tables 1-12 present for each prediction model the frequency across all 46 participants a specific variable was selected as a predictor of food craving.

Table 1

Logistic Elastic Net (aEMA)		
Category/ Instrument	Item	Frequency of feature selection
PANAS	How happy are you right now?	25
	How enthusiastic are you right now?	25
	How relaxed are you right now?	24
	How calm are you right now?	27
	How tense are you right now?	25
	How worried are you right now?	20
	How depressed are you right now?	23
	How bored are you right now?	22
	How nervous or stressed are you right now?	25
	How active are you right now?	22
PSS	Do you feel that you are on top of things?	22
	Do you feel that you can cope with all upcoming things that you will have to do?	23
	Did you experience an unpleasant stressful event since your last entry?	20
Consumed Food	Have you consumed some food since your last entry?	21
Consumed Food Amount	How much food have you consumed since your last entry?	21
Hunger	How hungry are you at the moment?	23
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	26
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	24

Table 2

Logistic Elastic Net (pEMA)		
Category	Item	Frequency of feature selection
Time of day pings	Morning	25
	Midday	21
	Early afternoon	24
	Late afternoon	23
	Evening	23
	Night	23
Cycles	Linear Cycle (linear trend within 1 day)	22
	Quadratic Cycle (quadratic trend within 1 day)	22
	Cubic Cycle (cubic trend within 1 day)	20
	Cos (1 day)	20
	Sin (1 day)	18
	Cos (2 days)	24
	Sin (2 days)	18
Global Trends	Linear Trend (linear trend across 14 days)	23
	Quadratic Trend (quadratic trend across 14 days)	24
	Cubic Trend (cubic trend across 14 days)	18
Clusters	Cluster1	21
	Cluster2	15
	Cluster3	17

Table 3

Logistic Elastic Net (fEMA)		
Category/ Instrument	Item	Frequency of selection
PANAS	How happy are you right now?	21
	How enthusiastic are you right now?	24
	How relaxed are you right now?	19
	How calm are you right now?	20
	How tense are you right now?	22
	How worried are you right now?	20
	How depressed are you right now?	22
	How bored are you right now?	21
	How nervous or stressed are you right now?	21
	How active are you right now?	21
PSS	Do you feel that you are on top of things?	22
	Do you feel that you can cope with all upcoming things that you will have to do?	22

	Did you experience an unpleasant stressful event since your last entry?	19
Consumed Food	Have you consumed some food since your last entry?	18
Consumed Food Amount	How much food have you consumed since your last entry?	19
Hunger	How hungry are you at the moment?	18
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	23
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	22
Time of day pings	Morning	19
	Midday	21
	Early afternoon	24
	Late afternoon	27
	Evening	20
	Night	18
Cycles	Linear Cycle (linear trend within 1 day)	19
	Quadratic Cycle (quadratic trend within 1 day)	21
	Cubic Cycle (cubic trend within 1 day)	20
	Cos (1 day)	19
	Sin (1 day)	20
	Cos (2 days)	21
	Sin (2 days)	19
Global Trends	Linear Trend (linear trend across 14 days)	21
	Quadratic Trend (quadratic trend across 14 days)	23
	Cubic Trend (cubic trend across 14 days)	18
Clusters	Cluster1	22
	Cluster2	17
	Cluster3	13

Table 4

Numeric Elastic Net (aEMA)		
Category/ Instrument	Item	Frequency of feature selection
PANAS	How happy are you right now?	17
	How enthusiastic are you right now?	17
	How relaxed are you right now?	17
	How calm are you right now?	17
	How tense are you right now?	20
	How worried are you right now?	13
	How depressed are you right now?	17

	How bored are you right now?	20
	How nervous or stressed are you right now?	21
	How active are you right now?	18
PSS	Do you feel that you are on top of things?	16
	Do you feel that you can cope with all upcoming things that you will have to do?	18
	Did you experience an unpleasant stressful event since your last entry?	20
Consumed Food	Have you consumed some food since your last entry?	19
Consumed Food Amount	How much food have you consumed since your last entry?	15
Hunger	How hungry are you at the moment?	15
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	19
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	16

Table 5

Numeric Elastic Net (pEMA)		
Category	Item	Frequency of feature selection
Time of day pings	Morning	29
	Midday	25
	Early afternoon	26
	Late afternoon	26
	Evening	30
	Night	27
Cycles	Linear Cycle (linear trend within 1 day)	20
	Quadratic Cycle (quadratic trend within 1 day)	22
	Cubic Cycle (cubic trend within 1 day)	24
	Cos (1 day)	25
	Sin (1 day)	23
	Cos (2 days)	26
	Sin (2 days)	22
Global Trends	Linear Trend (linear trend across 14 days)	28
	Quadratic Trend (quadratic trend across 14 days)	27
	Cubic Trend (cubic trend across 14 days)	18
Clusters	Cluster1	19
	Cluster2	20
	Cluster3	19

Table 6

Numeric Elastic Net (fEMA)		
Category/ Instrument	Item	Frequency of selection
PANAS	How happy are you right now?	16
	How enthusiastic are you right now?	18
	How relaxed are you right now?	18
	How calm are you right now?	18
	How tense are you right now?	18
	How worried are you right now?	16
	How depressed are you right now?	20
	How bored are you right now?	20
	How nervous or stressed are you right now?	19
	How active are you right now?	17
PSS	Do you feel that you are on top of things?	14
	Do you feel that you can cope with all upcoming things that you will have to do?	15
	Did you experience an unpleasant stressful event since your last entry?	20
Consumed Food	Have you consumed some food since your last entry?	20
Consumed Food Amount	How much food have you consumed since your last entry?	17
Hunger	How hungry are you at the moment?	18
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	21
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	16
Time of day pings	Morning	24
	Midday	21
	Early afternoon	25
	Late afternoon	18
	Evening	24
	Night	19
Cycles	Linear Cycle (linear trend within 1 day)	18
	Quadratic Cycle (quadratic trend within 1 day)	18
	Cubic Cycle (cubic trend within 1 day)	19
	Cos (1 day)	17
	Sin (1 day)	19
	Cos (2 days)	21

	Sin (2 days)	20
Global Trends	Linear Trend (linear trend across 14 days)	20
	Quadratic Trend (quadratic trend across 14 days)	20
	Cubic Trend (cubic trend across 14 days)	15
Clusters	Cluster1	15
	Cluster2	17
	Cluster3	16

Table 7

Logistic BISCWIT (aEMA)		
Category/ Instrument	Item	Frequency of feature selection
PANAS	How happy are you right now?	15
	How enthusiastic are you right now?	16
	How relaxed are you right now?	20
	How calm are you right now?	20
	How tense are you right now?	19
	How worried are you right now?	20
	How depressed are you right now?	19
	How bored are you right now?	13
	How nervous or stressed are you right now?	19
	How active are you right now?	16
PSS	Do you feel that you are on top of things?	24
	Do you feel that you can cope with all upcoming things that you will have to do?	18
	Did you experience an unpleasant stressful event since your last entry?	15
Consumed Food	Have you consumed some food since your last entry?	11
Consumed Food Amount	How much food have you consumed since your last entry?	13
Hunger	How hungry are you at the moment?	10
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	13
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	18

Table 8

Logistic BISCWIT (pEMA)		
-------------------------	--	--

Category	Item	Frequency of feature selection
Time of day pings	Morning	16
	Midday	14
	Early afternoon	21
	Late afternoon	20
	Evening	13
	Night	18
Cycles	Linear Cycle (linear trend within 1 day)	14
	Quadratic Cycle (quadratic trend within 1 day)	16
	Cubic Cycle (cubic trend within 1 day)	17
	Cos (1 day)	10
	Sin (1 day)	11
	Cos (2 days)	17
	Sin (2 days)	10
Global Trends	Linear Trend (linear trend across 14 days)	31
	Quadratic Trend (quadratic trend across 14 days)	31
	Cubic Trend (cubic trend across 14 days)	28
Clusters	Cluster1	11
	Cluster2	12
	Cluster3	10

Table 9

Logistic BISCWIT (fEMA)		
Category/ Instrument	Item	Frequency of selection
PANAS	How happy are you right now?	9
	How enthusiastic are you right now?	10
	How relaxed are you right now?	10
	How calm are you right now?	9
	How tense are you right now?	7
	How worried are you right now?	8
	How depressed are you right now?	9
	How bored are you right now?	7
	How nervous or stressed are you right now?	14
	How active are you right now?	6
PSS	Do you feel that you are on top of things?	15
	Do you feel that you can cope with all upcoming things that you will have to do?	11
	Did you experience an unpleasant stressful event since your last entry?	8

Consumed Food	Have you consumed some food since your last entry?	4
Consumed Food Amount	How much food have you consumed since your last entry?	5
Hunger	How hungry are you at the moment?	2
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	6
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	10
Time of day pings	Morning	5
	Midday	9
	Early afternoon	13
	Late afternoon	6
	Evening	9
	Night	11
Cycles	Linear Cycle (linear trend within 1 day)	5
	Quadratic Cycle (quadratic trend within 1 day)	9
	Cubic Cycle (cubic trend within 1 day)	6
	Cos (1 day)	7
	Sin (1 day)	6
	Cos (2 days)	9
	Sin (2 days)	7
Global Trends	Linear Trend (linear trend across 14 days)	27
	Quadratic Trend (quadratic trend across 14 days)	19
	Cubic Trend (cubic trend across 14 days)	20
Clusters	Cluster1	5
	Cluster2	7
	Cluster3	5

Table 10

Numeric BISCWIT (aEMA)		
Category/ Instrument	Item	Frequency of feature selection
PANAS	How happy are you right now?	15
	How enthusiastic are you right now?	15
	How relaxed are you right now?	20
	How calm are you right now?	16
	How tense are you right now?	18
	How worried are you right now?	12
	How depressed are you right now?	15
	How bored are you right now?	18

	How nervous or stressed are you right now?	16
	How active are you right now?	17
PSS	Do you feel that you are on top of things?	17
	Do you feel that you can cope with all upcoming things that you will have to do?	20
	Did you experience an unpleasant stressful event since your last entry?	13
Consumed Food	Have you consumed some food since your last entry?	14
Consumed Food Amount	How much food have you consumed since your last entry?	10
Hunger	How hungry are you at the moment?	9
Retrospective Craving	How strong was your urge for specific, palatable food since your last entry?	17
Momentary Craving	How strong is your urge for specific, palatable food at the moment?	16

Table 11

Numeric BISCWIT (pEMA)		
Category	Item	Frequency of feature selection
Time of day pings	Morning	19
	Midday	18
	Early afternoon	22
	Late afternoon	17
	Evening	19
	Night	18
Cycles	Linear Cycle (linear trend within 1 day)	14
	Quadratic Cycle (quadratic trend within 1 day)	14
	Cubic Cycle (cubic trend within 1 day)	15
	Cos (1 day)	17
	Sin (1 day)	14
	Cos (2 days)	18
	Sin (2 days)	9
Global Trends	Linear Trend (linear trend across 14 days)	28
	Quadratic Trend (quadratic trend across 14 days)	25
	Cubic Trend (cubic trend across 14 days)	25
Clusters	Cluster1	12
	Cluster2	13
	Cluster3	10

Table 12

Numeric BISCWIT (fEMA)		
Category/ Instrument	Item	Frequency of selection
PANAS	How happy are you right now?	8
	How enthusiastic are you right now?	5
	How relaxed are you right now?	9
	How calm are you right now?	10
	How tense are you right now?	10
	How worried are you right now?	5
	How depressed are you right now?	5
	How bored are you right now?	8
	How nervous or stressed are you right now?	8
	How active are you right now?	8
PSS	Do you feel that you are on top of things?	10
	Do you feel that you can cope with all upcoming things that you will have to do?	11
	Did you experience an unpleasant stressful event since your last entry?	10
Consumed Food	Have you consumed some food since your last entry?	7
Consumed Food	How much food have you consumed since your last entry?	2
Amount		
Hunger	How hungry are you at the moment?	2
Retrospective	How strong was your urge for specific, palatable food since your last entry?	8
Craving		
Momentary	How strong is your urge for specific, palatable food at the moment?	7
Craving		
Time of day pings	Morning	10
	Midday	10
	Early afternoon	13
	Late afternoon	10
	Evening	9
	Night	11
Cycles	Linear Cycle (linear trend within 1 day)	9
	Quadratic Cycle (quadratic trend within 1 day)	8
	Cubic Cycle (cubic trend within 1 day)	10
	Cos (1 day)	12
	Sin (1 day)	6
	Cos (2 days)	12
	Sin (2 days)	8
Global Trends	Linear Trend (linear trend across 14 days)	23

	Quadratic Trend (quadratic trend across 14 days)	14
	Cubic Trend (cubic trend across 14 days)	15
Clusters	Cluster1	4
	Cluster2	4
	Cluster3	5

Table 13. *Root mean squared error (RMSE) of predictor ensembles and statistical methods in predicting continuous food cravings*

Method	Predictor Type	RMSE Mean	RMSE Range
Baseline		19.89 (<i>SD</i> = 8.05)	5.77 – 43.32
ENR	aEMA	20.52 (<i>SD</i> = 8.78)	5.59 – 44.84
	pEMA	22.91 (<i>SD</i> = 15.91)	5.77 – 109.35
	fEMA	20.70 (<i>SD</i> = 9.15)	5.77 – 53.60
BISCWIT	aEMA	21.21 (<i>SD</i> = 8.22)	6.75 – 47.35
	pEMA	20.72 (<i>SD</i> = 7.84)	5.93 – 40.82
	fEMA	21.29 (<i>SD</i> = 8.10)	6.02 – 44.73

Table 14. *Frequency of models outperforming the RMSE of the baseline model*

Method	Predictor Ensemble	Frequency
ENR	aEMA	16
	pEMA	18
	fEMA	16
BISCWIT	aEMA	9
	pEMA	12
	fEMA	32

Table 15. *Brier Score of predictor ensembles and statistical methods in predicting food craving classes*

Method	Predictor Type	Brier Mean	Brier Range
Baseline		0.42 (<i>SD</i> = 0.26)	0.05 – 0.86
ENR	aEMA	0.25 (<i>SD</i> = 0.09)	0.05 – 0.54
	pEMA	0.26 (<i>SD</i> = 0.13)	0.05 – 0.75

	fEMA	0.25 ($SD = 0.11$)	0.05 – 0.72
	aEMA	0.27 ($SD = 0.08$)	0.05 – 0.50
BISCWIT	pEMA	0.25 ($SD = 0.07$)	0.05 – 0.37
	fEMA	0.27 ($SD = 0.08$)	0.03 – 0.45

Table 16. *Frequency of models outperforming the baseline Brier Score*

Method	Predictor Ensemble	Frequency
ENR	aEMA	33
	pEMA	34
	fEMA	34
BISCWIT	aEMA	32
	pEMA	21
	fEMA	32

Table 17. *Frequency of Support Vector models (SVM) outperforming the baseline AUC*

Method	Predictor Ensemble	Frequency
SVM	aEMA	39
	pEMA	38
	fEMA	38

Table 18. *Frequency of Support Vector models (SVM) outperforming the baseline Brier*

Method	Predictor Ensemble	Frequency
SVM	aEMA	31
	pEMA	35
	fEMA	35

Table 19. *Average AUC and Brier Scores for SVM models*

Method	Predictor Type	AUC Mean	AUC range	Brier Mean	Brier range
Baseline		0.50	-	0.42 ($SD = 0.26$)	0.05 – 0.86

SVM	aEMA	0.63 ($SD = 0.12$)	0.39 – 0.95	0.24 ($SD = 0.07$)	0.06 – 0.37
	pEMA	0.63 ($SD = 0.12$)	0.40 – 0.90	0.24 ($SD = 0.08$)	0.05 – 0.47
	fEMA	0.61 ($SD = 0.12$)	0.37 – 0.89	0.23 ($SD = 0.07$)	0.05 – 0.35