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Applying machine learning to ecological momentary assessment data to identify predictors of loss-of-control eating and overeating severity in adolescents: A preliminary investigation☆

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A R T I C L E I N F O

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A B S T R A C T

Objective: Several factors (e.g., interpersonal stress, affect) predict loss-of-control (LOC) eating and overeating in adolescents, but most past research has tested predictors separately. We applied machine learning to simultaneously evaluate multiple possible predictors of LOC-eating and overeating severity in pooled and person-specific models.

Method: Twenty-eight adolescents (78.57% female, age = 15.87 ± 1.59 years, BMI %ile = 92.71 ± 8.86) who endorsed ≥ two past-month LOC-eating episodes completed a week-long ecological momentary assessment protocol. Pooled models were fit to the aggregated data with elastic-net regularized regression and evaluated using nested cross-validation. Person-specific models were fit and evaluated as proof-of-concept.

Results: Across adolescents, the median out-of-sample R^2 of the pooled LOC-eating severity model was .33. The top predictors were between-subjects food craving, sadness, interpersonal conflict, shame, distress, stress (inverse association), and anger (inverse association), and within- and between-subjects wishing relationships were better. The median out-of-sample R^2 for pooled overeating severity model was .20. The top predictors were between-person food craving, loneliness, mixed race, and feeling rejected (inverse association), and within-subjects guilt, nervousness, wishing for more friends (inverse association), and feeling scared, annoyed, and rejected (all inverse associations). Person-specific models demonstrated poor fit (median LOC-eating severity R^2 = .003, median overeating $R^2 = -.009$); 61% and 36% of adolescents' models performed better than chance for LOC-eating and overeating severity, respectively.

Discussion: Altogether, group-level models may hold utility in predicting LOC-eating and overeating severity, but model performance for person-specific models is variable, and additional research with larger samples over an extended assessment period is needed. Ultimately, a mix of these approaches may improve the identification of momentary predictors of LOC eating and overeating, providing novel and personalized opportunities for intervention.

1. Introduction

Loss-of-control (LOC) eating is the feeling of being unable to stop eating or control what or how much is eaten, irrespective of the amount consumed (World Health Organization, 2019), and overeating is characterized by eating an objectively large amount of food (American Psychiatric Association, 2022). LOC eating and overeating are the defining features of binge eating (American Psychiatric Association, 2022). Engagement in LOC eating and overeating in adolescence predicts the later onset of binge eating and binge-eating disorder (Hilbert

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et al., 2013; Sonneville et al., 2015; Tanofsky-Kraff et al., 2011). Elucidating the predictors of pediatric LOC and overeating may inform efforts to curtail these behaviors before they progress to threshold eating disorders.

LOC eating typically onsets in late childhood to early adolescence (Tanofsky-Kraff et al., 2005). It is prevalent among youth, with 23% of community-recruited adolescents across the weight spectrum reporting >1 LOC-eating episode within the past month (Schlüter et al., 2016). Among youth with high weight, rates of LOC eating are ~33% (He et al., 2017) and ~50% in those seeking weight-management treatment (Glasofer et al., 2007). Overeating without LOC is endorsed by 5–9% of adolescents (Goldschmidt et al., 2015; Zhou et al., 2022). LOC eating and overeating are associated with adverse psychological and physical sequelae in youth, including unhealthy or extreme weight-control behaviors (Goldschmidt et al., 2015), depression (Goldschmidt et al., 2015; Skinner et al., 2012; Sonneville et al., 2013), psychosocial impairment (Goldschmidt, 2017), excess weight gain (Schlüter et al., 2016), and poor cardiometabolic health (Goldschmidt, 2017; Zhou et al., 2022). Approximately 50% of youth with LOC eating will develop full- or sub-threshold binge-eating disorder (Hilbert et al., 2013; Tanofsky-Kraff et al., 2011).

Despite the negative consequences of LOC eating and overeating in youth, only a handful of emerging treatments have demonstrated preliminary success in reducing these behaviors (Boutelle et al., 2011; Hilbert et al., 2019; Mazzeo et al., 2016; Tanofsky-Kraff et al., 2014), and there are few evidence-based treatments for this population (Datta et al., 2023). This treatment gap may, in part, be attributed to an incomplete understanding of the real-time and real-world predictors of LOC eating and overeating in youth.

1.1. *Current approaches to identifying predictors of LOC-eating and overeating severity in youth*

Ecological momentary assessment (EMA) is an ambulatory method to identify real-time and real-world antecedents of experiences. In EMA, participants typically complete brief assessments on constructs of interest, such as mood, cognitions, and/or context (e.g., location, social setting, etc.), and report experiences like LOC-eating and overeating severity. Traditional approaches to analyzing EMA data permit the interrogation of a handful of predictors of behavior. For instance, these approaches have identified dietary restraint (D'Adamo et al., 2023), eating disorder-related cognitions (Hilbert et al., 2009), interpersonal problems (Ranzenhofer et al., 2014), and food craving (Bejarano et al., 2023; Goldschmidt et al., 2018; Parker et al., 2021) as temporal antecedents of LOC-eating severity in youth. Momentary antecedents of overeating severity in youth include eating because others are eating (Goldschmidt et al., 2018) and affective instability (Egbert et al., 2020). However, it is plausible that there are predictors of LOC-eating and overeating severity beyond those that have been theorized or found in previous studies, and traditional analytic approaches are limited in their ability to test which of the many assessed variables in EMA are most predictive of LOC-eating and overeating severity. Moreover, traditional analytic approaches allow us to infer predictors of behavior for the average person. However, there may be individual differences in antecedents of binge eating, and identifying such differences would be necessary for optimizing treatments.

1.2. *Applying machine learning to EMA data for a more comprehensive understanding of behavior*

Applying machine learning to EMA data could provide a more comprehensive understanding of the real-world and real-time predictors of LOC-eating and overeating severity in youth at the individual and group levels. Machine learning is a computational technique wherein statistical models learn from data to identify predictors of outcomes, such as LOC-eating and overeating severity. Machine-learning algorithms are equipped to handle high-dimensional and multicollinear data and ascertain which variables predict behavior (Shatte et al., 2019). Moreover, certain machine-learning approaches, such as elastic-net regularized regression, are well-suited for datasets with modest sample sizes (Zou & Hastie, 2005), which is often the case for adolescent EMA samples.

Although some predictors of LOC-eating and overeating severity are consistent across adolescents, there may be individualized predictors, in which case between-person findings may inconsistently extrapolate to the individual (Molenaar & Campbell, 2009). Thus, a complementary approach identifying group and individual predictors of LOC-eating and overeating severity in youth may improve understanding of mechanisms and inform treatment through two pathways. First, identifying personalized antecedents of LOC-eating and overeating severity may facilitate treatment tailored to the individual adolescent (i.e., just-in-time adaptive interventions). Second, identifying adolescent-specific predictors of LOC-eating and overeating severity may guide matching to existing treatments, thereby improving outcomes. For instance, interpersonal therapy may be recommended if interpersonal stressors are strong positive predictors of LOC-eating severity. In contrast, for an adolescent who experiences increased body dissatisfaction and dietary restraint before LOC eating, cognitive-behavioral therapy may be recommended.

Despite the therapeutic potential, no studies, to our knowledge, have examined whether group-level predictors accurately forecast LOC-eating and overeating severity at the individual adolescent level, nor have adolescent-specific models of these behaviors been developed. However, recent work has developed and tested person-specific and group-level models of binge eating from EMA data in adults. One study found that person-specific models built from EMA data from adults with binge-type eating disorders ($n = 13$) predicted future binge-eating episodes with high accuracy (mean area under the curve = .80) (Arend et al., 2023). Arend et al. (2023) also found that individual binge-eating predictors were highly variable across participants, and suggested that considering temporal antecedents of binge eating beyond those delineated by theory would be necessary for improving the prediction of binge eating. Another study found that group-level models predicted binge eating more accurately than person-specific models among adults with bulimia nervosa ($n = 50$) (Leenaerts et al., 2024). Moreover, Leenaerts et al. (2024) found that the most significant predictors of binge eating in group-level models were time of day and recent events, whereas the most significant predictors of binge eating in person-specific models were cognitions and mood. Together, these studies highlight the potential for investigating predictors of LOC-eating and overeating severity in youth with a data-driven approach.

1.3. *The present study*

Here, we applied elastic-net regression (machine learning) to EMA data collected from adolescents with LOC eating to identify contextual, interpersonal, affective, and temporal predictors of dimensionally-assessed LOC-eating and overeating severity. Variables in our EMA protocol were selected based on prominent theories of binge eating, including the transdiagnostic or cognitive-behavioral theory (Fairburn, 2008) and the interpersonal theory (Wilfley et al., 2000), as well as data suggesting that contextual (e.g., Bohon et al., 2021; Olsen et al., 2021) and temporal (Forester et al., 2023) factors are significant antecedents of binge eating. We developed a group model on a pooled dataset and tested this model's ability to identify LOC-eating and overeating severity in individual, hold-out data. This enabled us to test whether common influences of LOC-eating and overeating severity identified from the whole sample accurately predicted LOC-eating and overeating severity within the individual.

We hypothesized that there would be variability in the degree to which group-level models would predict LOC-eating and overeating severity at the adolescent level, based on previous work indicating high variability of group-level models predicting individual behavior (Soyster et al., 2022). Further, informed by past work on temporal antecedents of LOC-eating severity in youth, we predicted that the group-level model would identify interpersonal stress, body dissatisfaction, and food cravings as common influences of LOC-eating severity. In an exploratory analysis, we developed person-specific models of LOC-eating and overeating severity; however, results should be interpreted cautiously due to the limited number of observations per adolescent.

2. Method

2.1. Participants

Adolescents were recruited using print and electronic media, including direct mailings to families. Inclusion criteria for the parent study were: (1) aged 12–18 years; (2) ≥ 2 LOC eating episodes in the month before assessment [consistent with our prior EMA work in adolescents (Ranzenhofer et al., 2014)]; (3) BMI ≥70th %ile; (4) English-speaking; and (5) cognitively capable of completing study procedures (Ranzenhofer et al., 2022). Exclusion criteria were: (1) history of anorexia nervosa or bulimia nervosa; (2) current other psychiatric diagnosis (except full- or sub-threshold binge-eating disorder); (3) use of psychoactive medication or other medication with a known impact on body weight or the autonomic nervous system; and (4) pregnancy. Enrollment occurred between August 2017 and February 2020. Only participants with sufficient data were included in this secondary analysis. Characteristics of participants included in this study are presented in Table 1.

2.2. Procedure

Adolescents and their caregivers provided informed consent and assent for in-person screening. Screening procedures were approved by the New York State Psychiatric Institute (NYSPI) Institutional Review Board (IRB) (Protocol #7515, Real-Time Assessment of Stress, Mood, and Eating Behavior in Adolescents). Before the screening visit, adolescents were instructed to refrain from consuming food or drink after midnight before the morning of their visit; compliance was confirmed verbally. At the screening visit, adolescent height and weight were measured, and adolescents completed semi-structured diagnostic interviews to assess the presence and frequency of LOC eating and additional psychopathology (see 2.3.2 below). Procedures were described to eligible adolescents. If interested, informed consent was obtained from the adolescent's guardian, and the adolescent provided informed assent. Following informed consent/assent, adolescents were trained in EMA procedures, which included practice answering prompts, and began the week-long EMA protocol upon leaving the center.

2.3. Baseline measures

A trained bachelors-level clinical research coordinator administered semi-structured interviews.

2.3.1. Past-month LOC and binge eating

At baseline, the Eating Disorder Examination (Fairburn & Cooper, 1993) was administered to determine the presence and frequency of LOC and binge eating.

2.3.2. Psychopathology

To determine the presence of comorbid psychiatric disorders, the Kiddie Schedule of Affective Disorders and Schizophrenia (K-SADS-PL-5; Kaufman et al., 1997) was administered. Adolescents also completed the Patient Health Questionnaire-9 (Kroenke et al., 2001), a screening measure for major depression.

2.3.3. Food insecurity

Past-month food insecurity was assessed via the self-report Food

Table 1
Adolescent sociodemographic and clinical characteristics and compliance metrics (n = 28).

	M (SD) or *N* (%)	Range
Age	15.87 (1.6)	12.7–18.5
Body mass index percentile	92.7 (8.9)	68–99
Sex		
Male	6 (21.4)	–
Female	22 (78.6)	–
Race		
Black or African American	11 (39.3)	–
White	6 (21.4)	–
Native American	1 (3.6)	–
Other race	6 (21.4)	–
Mixed race	4 (14.3)	–
Ethnicity		
Hispanic or Latine	11 (39.3)	–
Not Hispanic or Latine	15 (53.6)	–
Missing or declined to respond	2 (7.1)	–
Maternal education		
<8th grade	0 (0)	–
Some high school	3 (10.7)	–
Completed high school	5 (17.9)	–
Some college	5 (17.9)	–
Vocational degree	1 (3.6)	–
Completed college (four year)	8 (28.6)	–
Graduate degree	4 (14.3)	–
Missing or declined to respond	2 (7.1)	–
Paternal highest education		
<8th grade	2 (7.1)	–
Some high school	0 (0)	–
Completed high school	8 (28.6)	–
Some college	4 (14.2)	–
Vocational degree	1 (3.6)	–
Completed college (four year)	3 (10.7)	–
Graduate degree	5 (17.6)	–
Missing or declined to respond	5 (17.8)	–
Current food security (past 28 days)		
High food security	11 (39.3)	–
Marginal food security	7 (25)	–
Low food security	6 (21.4)	–
Very low food security	1 (3.6)	–
Missing	3 (10.7)	–
Eating disorder diagnosis[a]		
BED	6 (21.4)	–
OSFED-BED	15 (53.6)	–
OSFED-Other	7 (25.0)	–
Past month LOC eating frequency	8.6 (7.1)	2–28
EDE-Q scores		
Global	2.2 (1.1)	.0–4.07
Restraint	1.5 (1.0)	.0–4.0
Eating concern	1.5 (1.1)	.0–4.2
Shape concern	3.2 (1.4)	.0–5.1
Weight concern	2.7 (1.4)	0.0. – 5.0
Depression score (PHQ-9)	7.0 (4.2)	.0–14.0
Compliance metrics		
Days in study	6.4 (1.1)	4.0–8.0
Compliance with signal-contingent notifications	.84 (.10)	.63–1.0
Before meal ratings/day	3.4 (1.1)	1.2–5.0
After meal ratings/day	2.7 (1.2)	.9–4.7
Total eating episodes/events included in analysis	10.5 (5.3)	5.0–22.0

Note. BED = binge-eating disorder; EDEQ = Eating Disorder Examination Questionnaire; LOC = loss-of-control; OSFED = other specified feeding or eating disorder; OSFED-BED = subthreshold frequency of objective binge-eating episodes and/or full cognitive symptoms for BED were not met; OSFED-other = subjective LOC-eating episodes (no objective binge-eating episodes) and cognitive features of binge eating; PHQ-9 = Patient Health Questionnaire-9.

[a] Eating disorder diagnoses were assigned using the K-SADS-PL, based on *DSM*-5 diagnostic criteria.

Security Survey Module for Youth Ages 12 and Older (United States Department of Agriculture Economic Research Service, 2012).

2.4. EMA measures

Adolescents were trained to complete EMA recordings using the smartphone web application Real-Time Assessment In the Natural Environment (ReTAINE, Neuropsychiatric Research Institute, Fargo, ND, USA). Adolescents who did not own a smartphone were provided one for the study.

Adolescents completed random and event-contingent recordings for one week. Event-contingent recordings were completed before and after eating. Random recordings occurred in stratified intervals throughout the day (9:30–12:00, 12:01–14:30, 14:31–17:00, 17:01–19:30, and 19:31–22:00) to ensure adequate sampling. During these intervals, adolescents received text messages prompting them to make a report. Text messages included a hyperlinked URL for direct access to the app. At the beginning of each prompt, adolescents were asked if they had eaten since the previous recording and had forgotten to report it. If so, and if the eating episode occurred in the past hour, the adolescent answered the "after meal" questions about the eating episode. All other random recordings included context, mood, interpersonal relationships, and stress questions. Specifically, adolescents reported on: 1) their **location** [school, home, friend/relative's home, out (e.g., the mall, movies, etc.), work, or other]; 2) their **social context** [alone, family member(s), friend (s), significant other, coworker(s), and other]; 3) **LOC-eating severity** (see 2.4.1 below); 4) **overeating severity** (see 2.4.2 below); 5) **negative affect** (e.g., afraid, upset, nervous, scared, etc.); 6) **hunger level**; 7) **food craving intensity**; 8) **interpersonal problems** (e.g., wishing your relationships were better, etc.); and 9) **stress level**. Table 2 depicts all constructs queried and when adolescents received prompts. Adolescents were not queried during the school day.

At event-contingent recordings before eating, adolescents reported, "I am about to eat a …" and could select: "meal," "snack," or "drink only." After eating, adolescents reported LOC-eating and overeating severity (see 2.4.1 and 2.4.2 below).

2.4.1. LOC-eating severity

Four EMA questions based on past work and modified from relevant EDE questions assessed LOC-eating severity. Specifically, adolescents were asked, "During the meal/snack:" "… Did you feel a sense of loss of control?" "… To what degree did you lose control?" "Did you feel like your eating was out of control at any point?" and "… Did you binge eat?" Adolescents rated each question using a slider bar anchored in *no, not at all* (0) to *yes, very much* (100). Responses were averaged to create the primary outcome, LOC-eating severity.

2.4.2. Overeating severity

Adolescents rated overeating severity with the following question: "Compared to how much you planned to eat, the amount you ate was …" Using a sliding bar, adolescents rated the amount consumed from *less than planned* (0) to *more than planned* (100).

Table 2
Timing of contextual, interpersonal, affective, stress and eating-related questions for stratified random prompts and before- and after-meal ratings.

Questions	Before eating	After eating	Stratified random
Timestamp	x	x	x
Meal or snack	x		
Location		x	x
Who with		x	x
Interpersonal functioning			x
Mood			x
Stress			x
Hunger level			x
Food craving level			x
Amount eaten (overeating severity)		x	
Loss-of-control eating severity		x	

2.5. Data analysis

2.5.1. Data preparation

First, temporal variables were added representing the hour (i.e., from 2 to 23 o'clock), day of the week, time since participation in the study (linear, quadratic, cubic), and cycles of 12 h, 24 h, and weekly frequency (Flury & Levri, 1999). These additions were based on previous studies (Leenaerts et al., 2024; Soyster et al., 2022). Second, for the pooled models, continuous EMA variables were split into within- and between-person effects through person-mean-centering to account for the nesting of data within participants. Third, random and event-contingent recordings before eating were lagged by one assessment within the same day. Fourth, entries with missing values were removed. Fifth, past-month LOC-eating frequency and sociodemographic variables (i.e., race/ethnicity, age, BMIz, sex) were added.

This resulted in a dataset where the temporal variables could predict LOC-eating and overeating severity at a given time point at that time point, the EMA variables of the previous time point, past-month LOC-eating frequency, and current sociodemographic variables.

2.5.2. Model training and evaluation

First, pooled models were built for LOC-eating and overeating severity, after which person-specific models were built for the same outcomes as proof-of-concept. The models were trained and evaluated using elastic-net wrappers previously applied in eating disorder research: https://github.com/nicolasleenaerts/NLML (Leenaerts et al., 2024). These wrappers used the ensr, glmnet, pROC, splitTools, and caret packages in R, version 4.1.1 (DeWitt, 2019; Friedman et al., 2019; Kuhn, 2021; Robin et al., 2011). Our code is available at https://osf.io/4wzcq/.

2.5.3. Pooled models

Pooled models were fit and evaluated using nested *k*-fold cross-validation. Detailed information on this method can be found in the Supplementary **Materials** (see Fig. S1). A 5-fold cross-validation was used for the outer loop, whereby each participant's data was randomly allocated to a fold. Due to this random allocation, the entries within each fold were not temporally contiguous. Afterward, the training folds of each participant were aggregated into one training set.

For the inner loop, an elastic-net regularized regression model was fit on the aggregated training data of the outer loop (Zou & Hastie, 2005). This attenuates overfitting and deals with high-dimensional data while elucidating the strength and nature of the predictor-outcome association. Elastic-net regularized regression achieves this by combining regression with two regularization methods. Ridge regression shrinks the estimates, and LASSO regression sets estimates to 0 if variables do not contribute to the model. The proportion of the regularization methods is defined by a variable alpha, which ranges from 0 (exclusively ridge regression) to 1 (exclusively LASSO). In turn, the amount of regularization is expressed by a variable lambda, where higher values indicate more shrinkage.

Here, the optimal alpha and lambda were selected using a grid search of 10 alphas and 100 lambdas, the default *ensr* setting. For each possible combination, a cross-validation error was calculated using 10-fold cross-validation. Then, the combination with the lowest amount of cross-validation error was used to fit the definitive elastic-net model on the aggregated training folds of the outer loop.

Finally, elastic-net models were used to predict LOC-eating and overeating severity on the individual test data of each participant in the outer loop. Because outcome measures were continuous, model performance was evaluated by calculating the median out-of-sample R^2 (i.e., the proportion of variance explained by the prediction model compared to the mean of the training data), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) across the five folds of the outer loop. The out-of-sample R^2 was interpreted using Cohen's interpretation grids (Cohen, 1988). Due to the nested cross-validation, a participant needed to report enough meals or snacks with an answered prior beep on the same day ($n > 4$) to be included in the analysis.

2.5.4. Adolescent-specific models

As a proof-of-concept, person-specific models were fit and evaluated using an 80/20 train/test split. A nested cross-validation procedure could not be applied due to the limited number of eating episodes per participant. A 10-fold cross-validation applied to a participant's training data determined the most optimal alpha and lambda. Next, an elastic-net model was fit, after which the out-of-sample R^2, RMSE, and MAE were calculated on the test data of each participant. Like the pooled models, a participant needed to report enough meals or snacks with an answered prior beep on the same day ($n > 4$) to be included in the analysis.

We identified the top 10% predictors for each model type (pooled, individual) and outcome (LOC-eating, overeating severity), based on the estimate of the predictor-outcome association, regardless of the direction (positive, negative). For the adolescent-specific models, we averaged the estimates for each predictor across all participants, as everyone had their own set of estimates. For the pooled model, we did not aggregate the estimates for each predictor since only one estimate per variable was available.

2.5.5. Exploratory analyses

To elucidate whether model performance was impacted by the amount of data used to build the model, we examined the association between compliance and model performance. We hypothesized that if a teen had lower compliance (i.e., completed fewer ratings), the data used to build the model would be less representative, leading to lower-quality models. In other words, an association between lower compliance and lower model performance would suggest that insufficient data contributes to overall model performance. We, therefore, analyzed the association between three indices of compliance and R^2 for the pooled and person-specific models for LOC-eating and overeating severity. Given the number of predictors and independent variables, $p < .01$ was considered the threshold for significance. Due to the non-normal distribution, Spearman correlations were performed. Additionally, information on food insecurity was collected at baseline. However, as this information was not available for three participants, this variable was not included as a predictor in the main analyses. Nevertheless, as research suggests that food insecurity is an important predictor of LOC-eating and overeating severity, a sensitivity analysis was performed where food insecurity was added to the pooled models of the other 25 participants (Bidopia et al., 2023).

3. Results

Of the 51 adolescents who attended a screening appointment, 41 enrolled in the study, and 10 were excluded after screening procedures (two were uninterested, and eight were ineligible). Of those enrolled, 28 had sufficient data (providing >4 meals or snacks with an answered prior beep on the same day) to be included in this study. Adolescents provided, on average, 2.7 ± 1.2 after-meal ratings per day over an average study period of 6.4 ± 1.1 days. Of these, 10.5 ± 5.3 ratings were preceded by a random prompt where predictor variables were reported, for 295 included paired ratings (predictor variables plus subsequent ratings of LOC-eating and overeating severity). The average time of day when ratings were completed was 17:30 $\pm$ 3 h and 25 min. Average LOC-eating severity was 24.4 ± 17.3 and average overeating severity was 48.4 ± 18.2. Average compliance with signal-contingent recordings was $84 \pm 10\%$.

3.1. LOC-eating severity

3.1.1. Group-level LOC-eating severity model

Model performance for predicting an individual adolescent's LOC-eating severity was substantial, with median out-of-sample R^2 of .33 [interquartile range (IQR) = .06, .74], median RMSE of 15.71 (IQR = 9.81, 19.38) and median MAE of 15.27 (IQR = 9.73, 18.08).

The top 10% of predictors for the group-level LOC-eating severity model are presented in Fig. 1a. Recall that all predictors were measured at the random prompt immediately before the eating episode. Positive predictors of LOC-eating severity included between-person food craving, sadness, interpersonal conflict, shame, distress, and within- and between-person wishing relationships were better. Negative predictors were between-person anger and stress level.

3.1.2. Adolescent-specific LOC-eating severity model

Overall performance was weak, with a median out-of-sample R^2 of .003 (IQR = −.049, .215). However, 61% of adolescent-specific models had an $R^2 > 0$, indicating a higher predictive value than the mean of the training data. Model performance (R^2) was negatively correlated with the number of observations in the training data, $r_s = -.38$, $p = .04$.

Fig. 1b depicts the top 10% of predictors for this model. Positive predictors of LOC-eating severity included loneliness in relationships, wishing relationships were better, experiencing peer rejection, hunger, and food craving. Negative predictors were two negative affect variables: distress and loneliness.

3.2. Overeating severity

3.2.1. Group-level overeating severity model

Model performance for predicting an individual adolescent's overeating severity was moderate, with a median R^2 of .20 (IQR = −.03, .49), a median RMSE of 20.3 (IQR = 14.44, 26.75), and a median MAE of 18.42 (IQR = 14.02, 25.24).

The top 10% of predictors for the group-level overeating severity model are presented in Fig. 2a. Positive predictors of overeating severity included between-person food craving, loneliness, and within-person guilt and nervousness. Mixed race also positively predicted overeating. Negative predictors of overeating severity were between-person feeling rejected by peers and within-person wishing for more friends and feeling scared, irritable, or annoyed.

3.2.2. Adolescent-specific overeating severity model

Overall performance was very weak, with median out-of-sample R^2 of −.009 (IQR = −.536, .003). However, 36% of adolescents had a person-specific model that performed better than the mean of the training data, as they had an out-of-sample $R^2 > 0$. Model performance was not correlated with the number of observations in the training data, $r_s = -.007$, $p = .97$.

The top 10% of predictors for this model are depicted in Fig. 2b. Positive predictors of overeating severity included feeling lonely in relationships and feeling irritable/annoyed. Negative predictors of overeating severity were fear, anger, feeling rejected by peers, and food craving.

3.2.3. Exploratory analysis

EMA compliance was examined as a predictor of model performance; the results suggested a negative correlation between adolescent-specific model performance for LOC-eating and the number of after-meal ratings ($r_s = -.479$, $p = .001$). No other variable was significantly associated with model performance (p's > .01). Additionally, adding food security did not change the performance of the pooled prediction models for LOC-eating ($\Delta R^2 = 0$, ΔRMSE = 0, ΔMAE = 0) or overeating ($\Delta R^2 = 0$, ΔRMSE = 0, ΔMAE = 0) severity, and only remained as a predictor in one fold of the model for LOC-eating severity with a standardized estimate of −.008, while being removed as a predictor in all folds of the

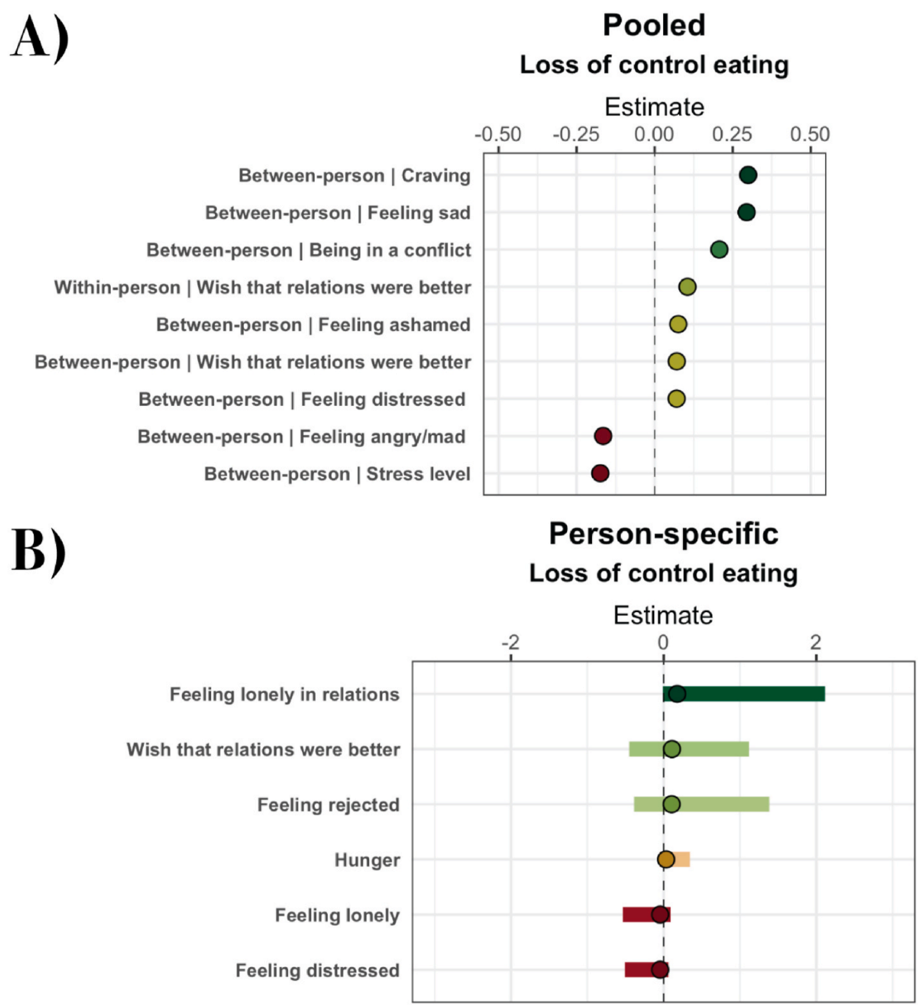

Fig. 1. Top Predictors of Loss-of-control Eating Severity in Group-level and Adolescent-Specific Models
Note. The single aggregate estimate is displayed for group-level models (Fig. 1A). For adolescent-specific models (Fig. 1B), the mean estimate with a 95% range is displayed.

model for overeating severity.

4. Discussion

In this preliminary study, we applied machine learning to EMA data collected from adolescents with LOC eating, which allowed us to concurrently test multiple unique, between- and within-person contextual, affective, interpersonal, and stress-related antecedents of LOC-eating and overeating severity. Results should be interpreted as provisional, considering the small sample size, modest number of observations, lack of sampling during the school day, and primarily sub-clinical sample. On balance, findings supported the utility of group-level models to predict individual-level LOC-eating and overeating severity. However, there was substantial variability in the ability of person-specific models to predict LOC-eating and overeating severity. Although the one-week EMA protocol and resultant limited eating observations may have contributed to the poor fit of person-specific models, this approach is novel and, when applied to datasets with more observations per person, may reveal individual predictors of LOC-eating and overeating severity that could be targeted in treatment.

4.1. Predictive ability of adolescent-specific versus pooled models

Comparing model performance, the pooled models outperformed the adolescent-specific models in predicting a teen's LOC-eating and overeating severity. Pooled models demonstrated a moderate-to-substantial fit to an individual teen's data, whereas person-specific models had a very weak fit. Person-specific model performance for LOC-eating severity was surprisingly negatively correlated with training data size and the number of after-meal ratings. One explanation could be that the smaller datasets in this study show less variance in the association between the predictors and LOC-eating severity, causing the training and testing data to be more similar and, therefore, increasing model performance. Previous studies that included more data have constructed good-fitting person-specific models for behavior. This suggests that more than one week of data is needed to derive good person-specific models, even for the most compliant participants (Leenaerts et al., 2024). However, pooled models may still be superior to person-specific models for predicting experiences at the individual level, even in those person-specific models derived from datasets with more observations per participant. Supporting this possibility, a prior study examining pooled and person-specific models in adults with bulimia nervosa – which collected data over a year and produced a dataset around 10-fold larger than the dataset used here – also found that pooled models outperformed person-specific models (Leenaerts et al., 2024).

4.2. Predictors of LOC-eating and overeating severity in adolescents

4.2.1. Food craving

In group-level LOC-eating and overeating severity models,

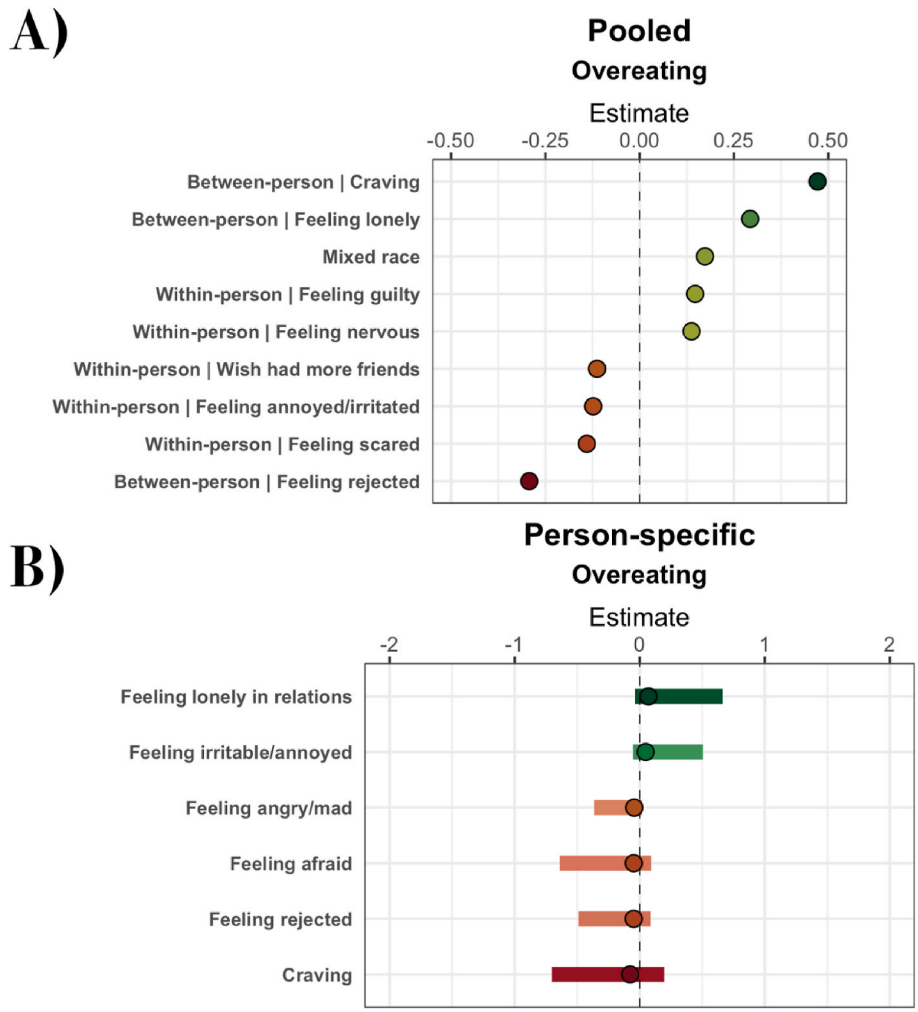

Fig. 2. Top Predictors of Overeating Severity in Group-level and Adolescent-Specific Models"
Note. The single aggregate estimate is displayed for group-level models (Fig. 2A). For adolescent-specific models (Fig. 2B), the mean estimate with a 95% range is displayed.

adolescents with the highest average food cravings reported the highest average LOC-eating and overeating severity. Dovetailing our results, others have also identified food craving as an antecedent of LOC-eating severity in adolescents (Bejarano et al., 2023; Goldschmidt et al., 2018; Parker et al., 2021). However, none, to our knowledge, have demonstrated food craving as an antecedent of overeating severity in youth. Food craving may be a meaningful proximal predictor of disinhibited eating in adolescents.

4.2.2. Interpersonal distress

Group-level models demonstrated that within-subjects interpersonal distress was strongly tied to LOC-eating severity. Specifically, wishing one's relationships were better was the strongest within-subjects predictor of LOC-eating severity. Among adolescent-specific models, feeling lonely in relationships and feeling rejected were among the top 10% of predictors of LOC-eating severity. This strong temporal association between interpersonal distress and LOC-eating severity is consistent with past EMA research on adolescent LOC eating, which found that interpersonal problems were associated with subsequent LOC-eating severity (Ranzenhofer et al., 2014). Adolescence is a developmental phase during which the importance of peer relationships increases, and interpersonal variables, such as wishing relationships are better or getting into a conflict, may be especially salient for eating disorder behavior.

4.2.3. Negative affect

Negative-affective states (loneliness, guilt, nervousness) were the strongest within-person predictors of overeating severity in the group-level model. Similarly, negative-affective states (sad, shame, distressed) were among the top 10% of predictors of overeating in adolescent-specific models. Some facets of negative affect positively predicted overeating severity, whereas others were inversely associated with these experiences. For instance, feeling lonely was a *positive* between-subjects predictor, and guilt and nervousness were *positive* within-subjects predictors of overeating severity, whereas feeling rejected was a *negative* between-subjects predictor and feeling irritable and scared were *negative* within-subjects predictors of overeating severity. Contrasting prior EMA research on LOC eating in youth (Bejarano et al., 2023; Hilbert et al., 2009; Parker et al., 2022; Ranzenhofer et al., 2014), we found that some facets of negative affect predicted LOC-eating severity in group-level models. Specifically, feeling sad was a *positive* between-subjects predictor of LOC-eating severity, whereas feeling angry/mad was a *negative* between-subjects predictor. It is noteworthy that feeling rejected was the only negative-affective variable that positively predicted LOC-eating severity in adolescent-specific models.

Physiological arousal associated with different emotions may impact LOC eating and overeating at the within- and between-subjects levels. For instance, emotions characterized by greater arousal, such as fear and anger, may inhibit LOC eating or overeating, whereas emotions with lower arousal, like sadness or guilt, may promote disinhibited eating. This idea is consistent with research demonstrating that guilt (low arousal) is more predictive of binge eating than fear (high arousal) (Berg et al., 2013). However, other studies suggest the opposite pattern, demonstrating that high-arousal emotions were highest before binge eating (Becker et al., 2018). Given these mixed findings, individual differences may exist in the influence of valence and arousal of the emotional state. Indeed, research has suggested trait-level moderators of the impact of emotions on binge eating in eating disorders (Culbert et al., 2016; Fischer et al., 2018), highlighting the potential utility of individual models. Additionally, recent research has found that affective instability may play a role in LOC-eating and overeating severity. For instance, research in racially and ethnically diverse samples of adolescents with LOC eating found that higher positive-affective instability was associated with greater LOC-eating and overeating severity (Egbert et al., 2020, 2022), and lower negative-affect instability was associated with greater LOC-eating severity (Egbert et al., 2020). Although not investigated in the present study, these data warrant future investigations of the role of affective instability in LOC eating.

4.2.4. Contextual variables

Time-of-day and contextual variables did not predict LOC-eating severity, despite research demonstrating that LOC eating and binge eating are more likely to occur in the afternoon and evening (Forester et al., 2023). Results also did not support our hypothesis that binge eating is more likely to occur when an individual is alone or at home. Thus, in contrast to adults with binge eating, adolescent LOC eating may occur more opportunistically in a wider variety of settings, including in the presence of others and/or when food is available.

4.2.5. Sociodemographic and cultural variables

Our models incorporated sociodemographic variables assessed at baseline, including race, ethnicity, sex, and food-security status. These variables did not predict LOC-eating or overeating severity, except that identifying as mixed-race positively predicted overeating severity in the pooled model. However, given the small number of participants who identified as mixed race and the heterogeneity of the mixed-race category, we are cautious to interpret this finding or relate it to previous research concerning culture and eating behavior. Although biological sex did not predict LOC-eating or overeating severity, our sample was predominantly female sex, which could impact the generalizability of findings in light of research demonstrating that gonadal hormones differentially moderate the association between food cravings in boys versus girls (Parker et al., 2021).

4.3. Strengths and limitations

One study strength was a racially and ethnically diverse sample. Another strength included multiple contextual (e.g., time of day, location) and psychosocial (e.g., interpersonal, affective) variables, as well as hunger and food-craving levels. We also included sociodemographic variables in machine-learning models. Finally, this study was one of the first to compare pooled and person-specific machine-learning models of behavior in adolescents.

Study results should be considered alongside study limitations. First, our sample size was modest. It was not possible to perform a sample-size calculation, as no methods for such an analysis exist for elastic-net regularized regression models. Even though calculations based on other regularized regression techniques indicate that a larger sample size might have been necessary, it is important to note that elastic-net regularized regression models are better suited to small data sets (Riley et al., 2020; Rintala et al., 2020; Zou & Hastie, 2005). Second, because the study only lasted one week, the total number of observations per adolescent-specific model was limited. This made it impossible to perform cross-validation for the adolescent-specific models, which is preferential over a train-test split, because it results in more robust performance estimates less influenced by the data distribution. Third, the ability to examine time-relevant predictors, such as the day of the week, was also limited (because, for example, each day of the week would either enter the training or the testing dataset, but not both. Designs that sample participants over a more extended period are needed to provide more data points and better detection of patterns over time. In turn, such designs will support the development of robust, well-fitting person-specific models. Additionally, prior EMA research has demonstrated that higher positive affect is positively associated with overeating (Egbert et al., 2020) and that higher levels of positive-affect instability are associated with higher LOC-eating severity (Egbert et al., 2022) among racially and ethnically diverse youth. This study did not assess positive affect; thus, investigating positive affect in future studies is warranted. Finally, our measure of overeating (eating more than planned) was subjective and imperfect; however, research suggests subjective eating experiences may be more salient (Goldschmidt, 2017).

4.4. Conclusions and future directions

Results from group-level models confirm the importance of interpersonal problems as proximal predictors of LOC-eating severity in adolescents and underscore the relevance of food cravings. Future research may include other potentially important predictors of binge eating, such as exposure to discrimination (Brown et al., 2022). Moreover, additional research is needed on person-specific machine-learning models of LOC-eating severity in a larger sample of adolescents over a longer time to extend the preliminary results of this study. From a methodological perspective, evaluating whether incorporating EMA and passive-sensing tools into treatment increases patients' awareness of momentary predictors of LOC-eating and overeating severity and reduces these symptoms could be warranted.

CRediT authorship contribution statement

Kelsey Hagan: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Nicolas Leenaerts:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **B. Timothy Walsh:** Writing – review & editing, Supervision. **Lisa Ranzenhofer:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

IRB statement

The New York State Psychiatric Institute (NYSPI) Institutional Review Board approved the research procedures described in our manuscript (Protocol #7515, Real-Time Assessment of Stress, Mood, and Eating Behavior in Adolescents).

Data and code availability statement

The data supporting this study's findings are available from the corresponding author, Lisa Ranzenhofer, upon reasonable request. The code used to complete analyses is available at: https://osf.io/4wzcq/.

Ethical statement

This research involved human participants and was performed in accordance with the Declaration of Helsinki. The research was approved by the New York State Psychiatric Institutional Review Board (Protocol #7515, Real-time Assessment of Stress, Mood, and Eating Behavior in Adolescents). All participants provided informed assent/consent prior to participation in any study procedures.

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Declaration of competing interest

This research was supported by the National Institutes of Health (R03 HD090206; K23 MH121780; K12AR084233; T32 MH096678) and the Special Research Fund KU Leuven (ECA-D4671- C14/18/096). The sponsors did not have a role in the collection, analysis, and interpretation of data, writing of this manuscript, nor the decision to submit this manuscript for publication. The content is solely the authors' responsibility and does not necessarily represent the views of respective funding agencies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.appet.2025.107900.

Data availability

Data will be made available on request.

References

American Psychiatric Association. (2022). *Diagnostic and statistical Manual of mental disorders fifth edition text revision DSM-5-TR (5th, text rev*. American Psychiatric Pub Inc.

Arend, A.-K., Kaiser, T., Pannicke, B., Reichenberger, J., Naab, S., Voderholzer, U., & Blechert, J. (2023). Toward individualized prediction of binge-eating episodes based on ecological momentary assessment data: Item development and pilot study in patients with bulimia nervosa and binge-eating disorder. *JMIR Medical Informatics, 11*, Article e41513. https://doi.org/10.2196/41513

Becker, K. R., Fischer, S., Crosby, R. D., Engel, S. G., & Wonderlich, S. A. (2018). Dimensional analysis of emotion trajectories before and after disordered eating behaviors in a sample of women with bulimia nervosa. *Psychiatry Research, 268*, 490–500. https://doi.org/10.1016/j.psychres.2018.08.008

Bejarano, C. M., Hesse, D. R., & Cushing, C. C. (2023). Hedonic appetite, affect, and loss of control eating: Macrotemporal and microtemporal associations in adolescents. *Journal of Pediatric Psychology, 48*(5), 448–457. https://doi.org/10.1093/jpepsy/jsad004

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, 122*(1), 111–118. https://doi.org/10.1037/a0029703

Bidopia, T., Carbo, A. V., Ross, R. A., & Burke, N. L. (2023). Food insecurity and disordered eating behaviors in children and adolescents: A systematic review. *Eating Behaviors, 49*, Article 101731. https://doi.org/10.1016/j.eatbeh.2023.101731

Bohon, C., Matheson, B., & Welch, H. (2021). Descriptive analysis of binge eating in adult and adolescent females. *Eating and Weight Disorders: EWD, 26*(4), 1149–1158. https://doi.org/10.1007/s40519-020-01013-3

Boutelle, K. N., Zucker, N. L., Peterson, C. B., Rydell, S. A., Cafri, G., & Harnack, L. (2011). Two novel treatments to reduce overeating in overweight children: A randomized controlled trial. *Journal of Consulting and Clinical Psychology, 79*(6), 759–771. https://doi.org/10.1037/a0025713

Culbert, K. M., Lavender, J. M., Crosby, R. D., Wonderlich, S. A., Engel, S. G., Peterson, C. B., Mitchell, J. E., Crow, S. J., Le Grange, D., Cao, L., & Fischer, S. (2016). Associations between negative affect and binge/purge behaviors in women with anorexia nervosa: Considering the role of negative urgency. *Comprehensive Psychiatry, 66*, 104–112. https://doi.org/10.1016/j.comppsych.2016.01.010

D`Adamo, L., Sonnenblick, R. M., Juarascio, A. S., & Manasse, S. M. (2023). Relations between forms of dietary restraint, restriction, and loss-of-control eating among adolescents seeking weight control: An ecological momentary assessment study. *Eating Behaviors, 50*, Article 101791. https://doi.org/10.1016/j.eatbeh.2023.101791

Datta, N., Hagan, K., Bohon, C., Stern, M., Kim, B., Matheson, B. E., Gorrell, S., Le Grange, D., & Lock, J. D. (2023). Predictors of family-based treatment for adolescent eating disorders: Do family or diagnostic factors matter? *International Journal of Eating Disorders, 56*(2), 384–393. https://doi.org/10.1002/eat.23867

DeWitt, P. (2019). ensr: Elastic net SearcheR Version 0.1.0. https://CRAN.R-project.org/package=ensr.

Egbert, A. H., Haedt-Matt, A., Smith, K. E., Culbert, K., Engel, S., & Goldschmidt, A. B. (2020). Momentary associations between positive affect dimensions and dysregulated eating during puberty in a diverse sample of youth with overweight/obesity. *International Journal of Eating Disorders, 53*(10), 1667–1677. https://doi.org/10.1002/eat.23342

Egbert, A. H., Smith, K. E., Ranzenhofer, L. M., Goldschmidt, A. B., & Hilbert, A. (2022). The role of affective instability in loss of control eating in youth with overweight/obesity across development: Findings from two EMA studies. *Research on Child and Adolescent Psychopathology, 50*(7), 945–957. https://doi.org/10.1007/s10802-021-00886-x

Fairburn, C. G. (2008). *Cognitive behavior therapy and eating disorders*. The Guilford Press.

Fischer, S., Wonderlich, J., Breithaupt, L., Byrne, C., & Engel, S. (2018). Negative urgency and expectancies increase vulnerability to binge eating in bulimia nervosa. *Eating Disorders, 26*(1), 39–51. https://doi.org/10.1080/10640266.2018.1418253

Flury, B. D., & Levri, E. P. (1999). Periodic logistic regression. *Ecology, 80*(7), 2254–2260. https://doi.org/10.2307/176907

Forester, G., Schaefer, L. M., Dodd, D. R., Burr, E. K., Bartholomay, J., Berner, L. A., Crosby, R. D., Peterson, C. B., Crow, S. J., Engel, S. G., & Wonderlich, S. A. (2023). Time-of-day and day-of-week patterns of binge eating and relevant psychological vulnerabilities in binge-eating disorder. *International Journal of Eating Disorders, 56*(9), 1694–1702. https://doi.org/10.1002/eat.23995

Friedman, J. H., Hastie, T., Tibshirani, R., Narasimhan, B., Simon, N., & Qian, J. (2019). glmnet: Lasso and elastic-net regularized generalized linear models Version 3.0-2. https://CRAN.R-project.org/package=glmnet.

Glasofer, D. R., Tanofsky-Kraff, M., Eddy, K. T., Yanovski, S. Z., Theim, K. R., Mirch, M. C., Ghorbani, S., Ranzenhofer, L. M., Haaga, D., & Yanovski, J. A. (2007). Binge eating in overweight treatment-seeking adolescents. *Journal of Pediatric Psychology, 32*(1), 95–105. https://doi.org/10.1093/jpepsy/jsl012

Goldschmidt, A. B. (2017). Are loss of control while eating and overeating valid constructs? A critical review of the literature. *Obesity Reviews: An Official Journal of the International Association for the Study of Obesity, 18*(4), 412–449. https://doi.org/10.1111/obr.12491

Goldschmidt, A. B., Loth, K. A., MacLehose, R. F., Pisetsky, E. M., Berge, J. M., & Neumark-Sztainer, D. (2015). Overeating with and without loss of control: Associations with weight status, weight-related characteristics, and psychosocial health. *International Journal of Eating Disorders, 48*(8), 1150–1157. https://doi.org/10.1002/eat.22465

Goldschmidt, A. B., Smith, K. E., Crosby, R. D., Boyd, H. K., Dougherty, E., Engel, S. G., & Haedt-Matt, A. (2018). Ecological momentary assessment of maladaptive eating in children and adolescents with overweight or obesity. *International Journal of Eating Disorders, 51*(6), 549–557. https://doi.org/10.1002/eat.22864

He, J., Cai, Z., & Fan, X. (2017). Prevalence of binge and loss of control eating among children and adolescents with overweight and obesity: An exploratory meta-analysis. *International Journal of Eating Disorders, 50*(2), 91–103. https://doi.org/10.1002/eat.22661

Hilbert, A., Hartmann, A. S., Czaja, J., & Schoebi, D. (2013). Natural course of preadolescent loss of control eating. *Journal of Abnormal Psychology, 122*(3), 684–693. https://doi.org/10.1037/a0033330

Hilbert, A., Petroff, D., Neuhaus, P., & Schmidt, R. (2019). Cognitive-behavioral therapy for adolescents with an age-adapted diagnosis of binge-eating disorder: A randomized clinical trial. *Psychotherapy and Psychosomatics, 89*(1), 51–53. https://doi.org/10.1159/000503116

Hilbert, A., Rief, W., Tuschen-Caffier, B., de Zwaan, M., & Czaja, J. (2009). Loss of control eating and psychological maintenance in children: An ecological momentary assessment study. *Behaviour Research and Therapy, 47*(1), 26–33. https://doi.org/10.1016/j.brat.2008.10.003

Kaufman, J., Birmaher, B., Brent, D., Rao, U., Flynn, C., Moreci, P., Williamson, D., & Ryan, N. (1997). Schedule for affective disorders and Schizophrenia for school-age children-present and lifetime version (K-SADS-PL): Initial reliability and validity data. *Journal of the American Academy of Child & Adolescent Psychiatry, 36*(7), 980–988. https://doi.org/10.1097/00004583-199707000-00021

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9. *Journal of General Internal Medicine, 16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Kuhn, M. (2021). caret: Classification and regression training Version 6.0-90. https://CRAN.R-project.org/package=caret.

Leenaerts, N., Soyster, P., Ceccarini, J., Sunaert, S., Fisher, A., & Vrieze, E. (2024). Person-specific and pooled prediction models for binge eating, alcohol use and binge drinking in bulimia nervosa and alcohol use disorder. *Psychological Medicine*, 1–16. https://doi.org/10.1017/S0033291724000862

Mazzeo, S. E., Lydecker, J., Harney, M., Palmberg, A. A., Kelly, N. R., Gow, R. W., Bean, M. K., Thornton, L. M., Tanofsky-Kraff, M., Bulik, C. M., Latzer, Y., & Stern, M. (2016). Development and preliminary effectiveness of an innovative treatment for binge eating in racially diverse adolescent girls. *Eating Behaviors, 22*, 199–205. https://doi.org/10.1016/j.eatbeh.2016.06.014

Molenaar, P. C. M., & Campbell, C. G. (2009). The New person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*(2), 112–117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Olsen, E. M., Koch, S. V., Skovgaard, A. M., & Strandberg-Larsen, K. (2021). Self-reported symptoms of binge-eating disorder among adolescents in a community-based Danish cohort-A study of prevalence, correlates, and impact. *International Journal of Eating Disorders, 54*(4), 492–505. https://doi.org/10.1002/eat.23458

Parker, M. N., Tanofsky-Kraff, M., Crosby, R. D., Byrne, M. E., LeMay-Russell, S., Swanson, T. N., Ramirez, E., Shank, L. M., Djan, K. G., Kwarteng, E. A., Faulkner, L. M., Yang, S. B., Zenno, A., Chivukula, K. K., Engel, S. G., Brady, S. M., Yanovski, S. Z., & Yanovski, J. A. (2021). Food cravings and loss-of-control eating in youth: Associations with gonadal hormone concentrations. *International Journal of Eating Disorders, 54*(8), 1426–1437. https://doi.org/10.1002/eat.23530

Parker, M. N., Tanofsky-Kraff, M., Crosby, R. D., Shank, L. M., Kwarteng, E. A., Loch, L. K., Faulkner, L. M., Haynes, H. E., Gupta, S., Fatima, S., Dzombak, J. W., Zenno, A., Engel, S. G., Brady, S. M., Yanovski, S. Z., & Yanovski, J. A. (2022). State negative affect in relation to loss-of-control eating among children and adolescents in the natural environment. *Appetite, 178*, Article 106166. https://doi.org/10.1016/j.appet.2022.106166

Ranzenhofer, L. M., Engel, S. G., Crosby, R. D., Anderson, M., Vannucci, A., Cohen, L. A., Cassidy, O., & Tanofsky-Kraff, M. (2014). Using ecological momentary assessment to examine interpersonal and affective predictors of loss of control eating in adolescent girls. *International Journal of Eating Disorders, 47*(7), 748–757. https://doi.org/10.1002/eat.22333

Ranzenhofer, L. M., Solhjoo, S., Crosby, R. D., Kim, B. H., Korn, R., Koorathota, S., Lloyd, E. C., Walsh, B. T., & Haigney, M. C. (2022). Autonomic indices and loss-of-control eating in adolescents: An ecological momentary assessment study. *Psychological Medicine, 1–9*. https://doi.org/10.1017/S0033291722001684

Riley, R. D., Ensor, J., Snell, K. I. E., Harrell, F. E., Martin, G. P., Reitsma, J. B., Moons, K. G. M., Collins, G., & van Smeden, M. (2020). Calculating the sample size required for developing a clinical prediction model. *BMJ, 368*, m441. https://doi.org/10.1136/bmj.m441

Rintala, A., Wampers, M., Myin-Germeys, I., & Viechtbauer, W. (2020). Momentary predictors of compliance in studies using the experience sampling method. *Psychiatry Research, 286*, Article 112896. https://doi.org/10.1016/j.psychres.2020.112896

Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C., & Müller, M. (2011). pROC: An open-source package for R and S+ to analyze and compare ROC curves. *BMC Bioinformatics, 12*, 77. https://doi.org/10.1186/1471-2105-12-77

Schlüter, N., Schmidt, R., Kittel, R., Tetzlaff, A., & Hilbert, A. (2016). Loss of control eating in adolescents from the community. *International Journal of Eating Disorders, 49*(4), 413–420. https://doi.org/10.1002/eat.22488

Shatte, A. B. R., Hutchinson, D. M., & Teague, S. J. (2019). Machine learning in mental health: A scoping review of methods and applications. *Psychological Medicine, 49*(9), 1426–1448. https://doi.org/10.1017/S0033291719000151

Skinner, H. H., Haines, J., Austin, S. B., & Field, A. E. (2012). A prospective study of overeating, binge eating, and depressive symptoms among adolescent and young adult women. *Journal of Adolescent Health: Official Publication of the Society for Adolescent Medicine, 50*(5), 478–483. https://doi.org/10.1016/j.jadohealth.2011.10.002

Sonneville, K. R., Calzo, J. P., Horton, N. J., Field, A. E., Crosby, R. D., Solmi, F., & Micali, N. (2015). Childhood hyperactivity/inattention and eating disturbances predict binge eating in adolescence. *Psychological Medicine, 45*(12), 2511–2520. https://doi.org/10.1017/S0033291715000148

Sonneville, K. R., Horton, N. J., Micali, N., Crosby, R. D., Swanson, S. A., Solmi, F., & Field, A. E. (2013). Longitudinal associations between binge eating and overeating and adverse outcomes among adolescents and young adults: Does loss of control matter? *JAMA Pediatrics, 167*(2), 149–155. https://doi.org/10.1001/2013.jamapediatrics.12

Soyster, P. D., Ashlock, L., & Fisher, A. J. (2022). Pooled and person-specific machine learning models for predicting future alcohol consumption, craving, and wanting to drink: A demonstration of parallel utility. *Psychology of Addictive Behaviors: Journal of the Society of Psychologists in Addictive Behaviors, 36*(3), 296–306. https://doi.org/10.1037/adb0000666

Tanofsky-Kraff, M., Faden, D., Yanovski, S. Z., Wilfley, D. E., & Yanovski, J. A. (2005). The perceived onset of dieting and loss of control eating behaviors in overweight children. *International Journal of Eating Disorders, 38*(2), 112–122. https://doi.org/10.1002/eat.20158

Tanofsky-Kraff, M., Shomaker, L. B., Olsen, C., Roza, C. A., Wolkoff, L. E., Columbo, K. M., Raciti, G., Zocca, J. M., Wilfley, D. E., Yanovski, S. Z., & Yanovski, J. A. (2011). A prospective study of pediatric loss of control eating and psychological outcomes. *Journal of Abnormal Psychology, 120*(1), 108–118. https://doi.org/10.1037/a0021406

Tanofsky-Kraff, M., Shomaker, L. B., Wilfley, D. E., Young, J. F., Sbrocco, T., Stephens, M., Ranzenhofer, L. M., Elliott, C., Brady, S., Radin, R. M., Vannucci, A., Bryant, E. J., Osborn, R., Berger, S. S., Olsen, C., Kozlosky, M., Reynolds, J. C., & Yanovski, J. A. (2014). Targeted prevention of excess weight gain and eating disorders in high-risk adolescent girls: A randomized controlled trial. *The American Journal of Clinical Nutrition, 100*(4), 1010–1018. https://doi.org/10.3945/ajcn.114.092536

United States Department of Agriculture Economic Research Service. (2012). Self-administered food security Survey Module for youth ages 12 and older. *USDA Economic Research Service*.

World Health Organization. (2019). *International statistical classification of diseases and related health problems* (11th ed.) https://icd.who.int/.

Zhou, J. C., Rifas-Shiman, S. L., Haines, J., Jones, K., & Oken, E. (2022). Adolescent overeating and binge eating behavior in relation to subsequent cardiometabolic risk outcomes: A prospective cohort study. *Journal of Eating Disorders, 10*(1), 140. https://doi.org/10.1186/s40337-022-00660-4

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B, 67*(2), 301–320.