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Interactions between different eating patterns on recurrent binge eating behavior: A machine learning approach

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Word Count

Abstract: 250

Manuscript: 4055

Abstract

Objective: Previous research has shown that certain eating patterns (rigid restraint, flexible restraint, intuitive eating) are differentially related to binge-eating. However, despite the distinctiveness of these eating patterns, evidence suggests that they are not mutually exclusive. Using a machine learning-based decision tree classification analysis, we examined the interactions between different eating patterns in distinguishing recurrent (defined as ≥4 episodes the past month) from non-recurrent binge eating. **Method:** Data were analyzed from 1,341 participants. Participants were classified as either with (n=512) or without (n=829) recurrent binge eating. **Results:** Approximately 70% of participants could be accurately classified as with or without recurrent binge eating. Intuitive eating emerged as the most important classifier of recurrent binge eating, with 75% of those with above-average intuitive eating scores being classified without recurrent binge eating. Those with concurrently low intuitive eating and high dichotomous thinking scores were the group most likely to be classified with recurrent binge eating (84% incidence). Low intuitive eating scores were associated with low binge eating classification rates only if both dichotomous thinking and rigid restraint scores were low (33% incidence). Low flexible restraint scores amplified the relationship between high rigid restraint and recurrent binge eating (81% incidence), and both a higher and lower BMI further interacted with these variables to increase recurrent binge eating rates. **Conclusion:** Findings suggest that the presence versus absence of recurrent binge

eating may be distinguished by the interaction among multiple eating patterns. Confirmatory

studies are needed to test the interactive hypotheses generated by these exploratory analyses.

Keywords: dietary restraint; intuitive eating; binge eating; decision tree classification

Introduction

Binge eating is defined as the excessive consumption of food during a short period of time while at the same time experiencing a sense of loss of control (American Psychiatric Association, 2013). Binge eating is prevalent in around 5-10% of adults (Mitchison, Hay, Slewa-Younan, & Mond, 2012), and the recurrence of this behavior in community samples (i.e., usually defined as one episode per week on average during a pre-specified time-period), independent of whether one has a confirmed binge-eating disorder (BED) diagnosis (Mitchison, Touyz, González‐Chica, Stocks, & Hay, 2017), has been linked with psychological distress (Becker & Grilo, 2015; Mitchison et al., 2018), functional impairment (Harrison, Mond, Rieger, & Rodgers, 2015; Mitchison, Mond, Slewa‐Younan, & Hay, 2013), and overweight and obesity (Da Luz et al., 2017). Thus, efforts to better understand, screen, and treat regular binge eating are needed.

Increasing attention has been devoted towards understanding which patterns of eating are and are not associated with binge eating. Dietary restraint is one eating pattern that has received significant research attention in this domain. According to some (Westenhoefer, Stunkard, & Pudel, 1999), dietary restraint is a multifaceted construct comprised of distinct forms that cannot be categorized as entirely adaptive or maladaptive. Westenhoefer et al. (1999) proposed that dietary restraint should be classified into a rigid or flexible form. Rigid restraint involves an all-or-none approach to dieting. Individuals who practice this form of restraint tend to think dichotomously about food and dieting, set themselves multiple demanding diet "rules", and engage in various regimented dieting behaviors (e.g., calorie counting, fasting, skipping meals; Westenhoefer et al., 1999). This form of restraint has been

consistently shown in experimental (Knight & Boland, 1989), prospective (Agras & Telch, 1998), and cross-sectional (Linardon, 2018; Tylka, Calogero, & Daníelsdóttir, 2015) studies to be strongly associated with more severe and frequent binge eating. Flexible restraint, however, reflects a more graded approach to dieting, defined by behaviors such as allowing oneself to eat a wide variety of food types while still paying attention to weight/shape, and opting for "healthier" foods if "unhealthier" foods were consumed earlier. When controlling for rigid restraint, several cross-sectional studies have reported inverse relationships between flexible restraint and binge eating (Linardon & Mitchell, 2017; Smith, Williamson, Bray, & Ryan, 1999; Westenhoefer et al., 1999), and increases in flexible restraint during BED treatment have been associated with binge eating abstinence (Blomquist & Grilo, 2011), suggesting that a flexible form of restraint may be a healthier alternative to a rigid form.

Intuitive eating is another pattern of eating gaining significant research attention. Intuitive eating is a style of eating characterized by a strong connection with internal hunger and satiety cues, in which individuals eat when they feel hungry and stop when they feel full (Tylka & Kroon Van Diest, 2013). Intuitive eaters recognise that all foods serve a variety of important functions and are less likely to think of foods as "good" or "bad". Cross-sectional studies (for a review, see Bruce & Ricciardelli, 2016) and randomized controlled trials of interventions designed to nurture intuitive eating (Bacon & Aphramor, 2011) have reported consistent, strong, and inverse relationships between intuitive eating, all forms of dietary restraint, and binge eating behavior, suggesting that promoting eating based on internal cues may be important for binge eating prevention and early intervention.

Several key trends are evident from this extant literature. First, behaviors and cognitions that are characteristic of rigid restraint seem to increase risk for, or correlate highly with, binge eating patterns, whereas intuitive eating and flexible restraint behaviors seem to decrease this risk. Second, prior work has reported strong bivariate correlations between flexible and rigid restraint (e.g., Linardon & Mitchell, 2017; Tylka et al., 2015), indicating that these purportedly distinct restraint forms may co-occur to some extent, although the unique contributions of these variables in prior regression models demonstrate that this co-occurrence is variable. As it stands, research on the role of different dietary and intuitive eating patterns has only focused on examining their unique contributions to binge eating symptoms. This standard regression-based approach provides no information about the level of *co-occurrence* among these eating patterns, nor on the association between any possible co-occurrence and their interactions with recurrent binge eating behavior.

Thus, the present study uses machine learning-based, decision tree classification to explore whether the various behavioral and cognitive characteristics of distinct eating patterns, and their interactions, can be used to distinguish those with and without recurrent binge eating. Age and BMI were also examined as potential classifiers of recurrent binge eating, given the known association between a higher BMI and binge eating (Da Luz et al., 2017), and that representative data from large community samples show that recurrent binge eating is most prevalent in the late teen and early adult years (Mitchison, Hay, Slewa-Younan, & Mond, 2014). We defined recurrent binge eating as engaging in binge eating at least four times over the past month (once per week) based on participant self-report, consistent with earlier work (e.g., Harrison, Mitchison, Rieger, Rodgers, & Mond, 2016; Harrison et al., 2015; Mitchison

et al., 2018). We acknowledge that an interviewer-based assessment using a longer time-frame (three months for DSM-V and six months for DSM-IV) is the preferred method to assess recurrent binge eating or to establish the presence of a BED diagnosis (e.g., DeBar et al., 2011; Striegel-Moore et al., 2010). However, prior work has shown that (1) the two methods of recurrent binge eating classification (i.e., the 28-day self-report versus six-month interview criteria) are associated with comparable levels of eating pathology and functional impairment (Harrison et al., 2015), and (2) those who meet the 28-day self-report criteria report greater eating and general psychopathology than those who binge eat below this threshold (Harrison et al., 2015; Linardon, Messer, Lee, & Fuller-Tyszkiewicz, 2019). Thus, the validity and clinical significance of the self-report recurrent binge eating criteria have been established.

We also note that a key advantage of using a machine learning-based, decision tree approach the is that the model optimizes the best combination of variables to enhance the classification of group membership (i.e., recurrent binge eater), and is thus not reliant on researchers to specify which variables will co-occur and interact. However, we caution that, as argued by Stice and Desjardins (2018), this approach is exploratory hypothesis generating, and can be used in further research to follow-up risk pathways for key outcomes of concern.

Method

Participants

A total of 1,341 participants (91% female) were recruited for this study. Of these, 512 participants (38%) reported recurrent binge eating, which we defined as engaging in binge eating at least four times over the past month (once per week), consistent with prior work (e.g., Harrison et al., 2016; Harrison et al., 2015). The remaining 829 participants either did not

engage in any binge eating (*n* = 516) or engaged in binge eating below the required cut-off frequency (*n* = 329).

Procedure

We used a self-selected convenience sample, where participants were recruited mostly through social media outlets (Facebook, Twitter, Instagram), online forums, and through word-of-mouth. Advertisements indicated that the study was investigating how certain dietary patterns impact attitudes towards food, dieting, and our bodies. Respondents to the advertisements were provided with a link to the questionnaire battery. Participants completed the questionnaire battery online and at a time and place of convenience. The questionnaire took approximately 20 minutes to complete. Participants completed the survey once (which was checked through any duplicate IP address). Ethics approval was obtained. Informed consent was provided by all participants.

Measures

Independent Variables

Intuitive Eating Behaviors. The 23-item Intuitive Eating Scale-2 (IES-2; Tylka & Kroon Van Diest, 2013) was used to assess intuitive eating behaviors. Each item is rated along a 5-point scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Sample items include "I trust my body to tell me what to eat" and "*I rely on my fullness signals to tell me when to stop eating*". Scores on each item are averaged to produce a total intuitive eating score. Scores range from 1 to 5, with higher scores reflect higher levels of intuitive eating. The internal consistency ($\alpha > .77$), test-retest reliability (intraclass coefficients $> .80$), construct validity,

and incremental validity of the IES-2 have been upheld in student (Tylka & Kroon Van Diest, 2013) and community samples (Duarte, Gouveia, & Mendes, 2016). IES-2 total scores have also been shown to discriminate between those with and without clinically significant binge eating symptoms (Duarte et al., 2016).

Flexible Restraint Behaviors. The 12-item Flexible Control subscale of the Cognitive Restraint Scale (Westenhoefer et al., 1999) was used as a measure of flexible restraint. Each item receives one point if a participant provides a response indicative of flexible restraint. For example, on the sample flexible restraint item "*I pay attention to my figure, but I still enjoy a variety of foods*", participants are asked to indicate whether this statement is true or false of them. Participants who mark true on this item receive one point that contributes to their flexible restraint total score. Scores range from 0 to 12, with higher scores reflecting higher flexible restraint behaviors. The flexible control subscale has demonstrated good internal consistency ($\alpha > .80$) construct validity (e.g., via its association with lower self-reported energy intake and weight loss), and incremental validity in community samples (Linardon, 2018), in individuals who are obese (Westenhoefer et al., 1999), and in individuals with BED (Blomquist & Grilo, 2011).

Rigid Restraint Behaviors. The 16-item Rigid Control subscale of the Cognitive Restraint Scale (Westenhoefer et al., 1999) was used as a measure of rigid restraint behaviors. Similar to the flexible restraint subscale, each item receives one point if a participant provides a response indicative of rigid restraint. Sample items include "*Sometimes I skip meals to avoid gaining weight*" and "*I alternate between times when I diet strictly and times when I don't pay much attention to what and how much I eat*". Scores are summed to produce a total score.

Scores range from 0 to 16, with higher scores reflecting higher rigid restraint behaviors. The rigid control subscale is internally consistent ($\alpha > .82$) and has demonstrated construct validity (via its strong connection to other dietary restraint measures, binge eating symptomatology, and eating concerns) and incremental validity in community (Tylka et al., 2015), student (Timko & Perone, 2005), overweight/obese (Westenhoefer et al., 1999), and BED samples (Masheb & Grilo, 2002).

Rigid Restraint Cognitions. Rigid restraint beliefs and cognitions were assessed via the Inflexible Eating Questionnaire (IEQ; Duarte, Ferreira, Pinto-Gouveia, Trindade, & Martinho, 2017) and the eating subscale from the Dichotomous Thinking in Eating Disorder Scale (DTES; Byrne, Allen, Dove, Watt, & Nathan, 2008). The 11-item IEQ assesses an individual's perceived importance of adhering to a set of arbitrary diet rules, a sense of control derived from meeting these rules, and the distress experienced when failing to meet these rules. Each item is rated along a 5-point scale, ranging from 1 (*fully disagree*) to 5 (*fully agree*), and are summed to produce a total score (score range = 11 to 55). Sample items include "*not following my eating rules makes me feel inferior*" and "*even if I feel satisfied with my weight, I do not allow myself to ease my eating rules*". The internal consistency ($\alpha > .85$), 4-week test-retest reliability ($r = .84$), unidimensional structure, construct validity, and incremental validity of the IEQ have been established in community samples of Australian (Linardon, Incerti, & McLean, 2019) and Portuguese (Duarte et al., 2017) adults. IEQ total scores have also been shown to successfully discriminate between those with and without elevated eating disorder symptomatology (Duarte et al., 2017). The 4-item eating subscale from the DTES assesses the extent to which an individual holds a polarized view towards food, eating, and dieting. Each item is rated along a

4-point scale, ranging from 1 (*never*) to four (*always*), and averaged (score range = 1 to 4).

Sample items include "*I think of food as either good or bad*" and "*I view my attempts to diet as either successes or failures*". Internal consistency ($\alpha > .77$) and construct validity of the eating subscale of the DTES have been established in a general community sample of adults (Linardon & Mitchell, 2017) and in individuals with obesity and an eating disorder (Byrne et al., 2008).

Dependent Variable

Recurrent Binge Eating. A single item from the Eating Disorder Examination Questionnaire (Fairburn & Beglin, 1994) was used to measure recurrent binge eating. This item asks participants to indicate the frequency with which they had engaged in binge eating (i.e., eating a large amount of food given the circumstances, accompanied by a sense of loss of control) over the past month. For this study, we dichotomized binge eating in terms of the presence versus absence of recurrent binge eating. Recurrent binge eating was defined as binge eating at least four times over the past four weeks.

Data Analytic Strategy

Decision tree classification was undertaken using *rpart* (Therneau & Atkinson, 2019) and *rattle* (Williams, 2011) packages in R (R Core Team, 2013). Decision tree classification is a recursive partitioning approach to classifying individuals into groups on a target outcome measure (i.e., recurrent binge eating). The researcher selects a collection of independent variables to aid classification of group membership, and decision tree classification then uses these independent variables to maximize separation of participants into groups based on scores on these variables. The decision tree starts with a parent node that contains all participants, and

then proceeds to split into subgroups (child nodes) that increase predictive accuracy beyond this base rate. This splitting procedure continues until further improvements cannot be achieved.

In decision tree parlance, these splits may constitute main effects or interactions, with interactions defined as the impact of a "predictor" on an "outcome" being dependent upon another predictor (Strobl, Malley, & Tutz, 2009). An interaction may arise, for instance, if the tree were split into low versus high intuitive eating scores, but only one of those branches is then further split by a second variable (e.g., rigid restraint). In contrast, if both low and high intuitive eaters are split into high versus low rigid restraint and the effect of high versus low rigid restraint on probability of belonging to the recurrent binge eating group is similar (i.e., high rigid restraint individuals are more likely to be recurrent binge eaters regardless of whether they are high or low intuitive eaters), then this would instead constitute a main effect. We refer the interested reader to Strobl et al (2009) for further discussion of the distinction between main effects and interactions within the context of decision tree analysis.

Because decision tree classification seeks to find the best predictive model for the data, there is risk of overfitting and subsequently poor replicability of results. Several commonly recommended steps were taken to mitigate this risk. First, the present sample was split into a training sample (approximately 70% overall sample, $n = 922$) for model building, and a test sample (approximately 30% overall sample, $n = 419$) to cross-validate model performance. Second, the optimal solution from the training set was pruned, a process whereby the number of branches within the overall decision tree are limited to reduce complexity (and, in turn, overfitting). This pruning was based on the cost-complexity criterion using a tuning parameter

that sought to strike a balance between model complexity (punishing more complex models) and misclassification (error in prediction of group membership). The tuning parameter (alpha) was chosen as the value that resulted in the lowest error in prediction. Finally, overall prediction accuracy of the pruned tree was compared against the unpruned tree to ensure that removal of child nodes does not diminish model predictive value. In this sample, 50 random samples of the test set were used to confirm that the pruned tree was not worse than the unpruned decision tree.

Several key outputs from the decision tree classification are reported in the present study (all with respect to the test dataset): (1) a visual representation of the decision tree, with all of the branches (nodes) that remain after pruning, (2) accuracy of prediction for the two categories of our DV (recurrent binge eating), and (3) variable importance, a statistic which quantifies how important an independent variable was for correctly classifying individuals into groups. Accuracy of the model overall was augmented with several additional statistics often reported for diagnostic tools: (1) sensitivity (or true positive rate) – the proportion of individuals with recurrent binge eating who were correctly identified, and (2) specificity (true negative rate) – the proportion of individuals who are not recurrent binge eaters who are correctly classified.

Results

Preliminary Analyses

Descriptive statistics are presented in Table 1 for the recurrent and non-recurrent binge eaters. Recurrent binge eaters reported a higher BMI, higher levels of rigid restraint, inflexible eating beliefs, and dichotomous thinking, and lower levels of intuitive eating than non-

recurrent binge eaters. Effect sizes were moderate to large. Negligible differences in flexible restraint scores, mean age, and percent female were observed between the two groups.

Correlations between study variables for recurrent and non-recurrent binge eaters are presented in Table 2. As seen, the bivariate correlations ranged from small to large, and correlations between the same pairs of constructs tended to be larger for the non-recurrent binge eaters than for the recurrent binge eaters.

Decision Tree Classification

Figure 1 shows the classification tree for recurrent binge eating based on the test subsample of the overall dataset (n = 419 of 1341). Intuitive eating, dichotomous thinking, rigid dietary restraint, flexible dietary restraint, and BMI were identified as the important classifiers of whether a participant would be categorized with recurrent binge eating. As seen in Figure 1, participants were split first by intuitive eating scores. Participants with higher intuitive eating scores ($\geq$ 2.9) constituted 67% of the overall test sample and, of these, only 25% were identified as recurrent binge eaters (bottom left-most box). The remaining 33% of the sample (who reported less than 2.9 on the IES-2) were next split based on scores on dichotomous thinking. Individuals with higher scores on dichotomous thinking ($\geq$ 3.3) constituted 13% of the overall sample, and comprised 84% recurrent binge eaters (see bottom right-most box). This accuracy could not be improved for this subgroup, so they were not split further.

Individuals with low intuitive eating scores ($<$ 2.9) and lower dichotomous thinking scores ($\leq$ 3.3) were split further by rigid dietary restraint, flexible dietary restraint, and BMI. Eighty-one percent of individuals with low intuitive eating scores ($<$ 2.9) and low dichotomous

thinking scores (≤ 3.3) who had high rigid (≥ 7.5) and low flexible (< 5.5) restraint scores were identified as recurrent binge eaters. If instead an individual had low intuitive eating, low dichotomous thinking, high rigid restraint, but also high flexible restraint, BMI scores were needed to determine whether they were binge eaters or not (11% of the overall sample); those with BMI less than or equal to 23 were more likely to be recurrent binge eat (70% of this subgroup), whereas those with BMI greater than 25 were also more likely to be recurrent binge eaters (76%). Thus, for a small band of BMI ranges within the normal weight category, the algorithm struggled to differentiate recurrent from non-recurrent binge eaters.

The overall accuracy of this model in classifying recurrent binge eaters was 70%, with specificity of .71 and sensitivity of .68. Accuracy was slightly higher for classifying non-recurrent binge eaters (71%, $n = 224$) than for classifying recurrent binge eaters (68%, $n = 69$; see Table 3). Finally, variable importance information ranked the variables (from most to least important for classifying recurrent binge eating status) as intuitive eating, dichotomous thinking, rigid restraint, inflexible eating beliefs, BMI, flexible restraint, and then demographic factors of age and gender.

Discussion

We used a machine learning-based decision tree analysis to explore the relationships between various eating patterns with recurrent binge eating. In terms of recurrent binge eating classification, results suggested a complex 5-way interaction between intuitive eating, dichotomous thinking, rigid restraint, flexible restraint, and BMI. Intuitive eating emerged as the most important classifier of recurrent binge eating, with 75% of those who scored above average on the IES-2 (> 2.9) *not* being classified with recurrent binge eating. This finding is

consistent with numerous studies demonstrating that those whose eating is guided by internal body cues are less likely to exhibit regular binge eating patterns (Bruce & Ricciardelli, 2016). Intuitive eating's relationship with recurrent binge eating also interacted with dichotomous thinking and rigid dietary restraint. Those with concurrently low intuitive eating and high dichotomous thinking scores were the group most likely to receive a recurrent binge eating classification (84% incidence), while those with low intuitive eating scores were less likely to receive a recurrent binge eating classification (33% incidence rate) *only* if they also had both low dichotomous thinking and rigid restraint scores. Thus, it appears that the interaction between certain cognitive and behavioral characteristics that underpin a rigid dietary approach are also important features that distinguish recurrent from non-recurrent binge eaters, which is consistent with predictions from the restraint theory (Herman & Mack, 1975) and the cognitive model of eating disorders (Fairburn, 2008). Flexible restraint and BMI also contributed to the classification, with low flexible restraint scores amplifying rigid restraints relationship with binge eating (81% incidence rate), and both a lower (< 23) and higher (> 25) BMI being associated with recurrent binge eating (70% and 62% incidence rate, respectively). However, these latter splits with flexible restraint and BMI included few participants (< 4% of total sample for each of the nodes), so confirming these findings with larger samples is necessary.

This study highlights the complexity of eating behavior, in terms of the degree of co-occurrence among purportedly distinct eating patterns and how they interact with recurrent binge eating behavior. Present findings suggest that it may be beneficial for practitioners to screen, assess, and enquire about the degree to which one endorses each of these different behavioral and cognitive eating patterns, as this may provide additional insight towards the

nature, function, frequency of their clients' binge eating behavior. Gathering this information may, in the long-term, assist in formulating a treatment plan tailored towards the individual needs of their client (Macneil, Hasty, Conus, & Berk, 2012).

This study has limitations that should be considered. First, this was a cross-sectional design, so we cannot make any conclusions regarding the directions of the modelled relationships. Well-designed prospective studies are needed to clarify and confirm these exploratory findings. Second, the psychometric properties (e.g., test retest reliability, unidimensional structure etc.) of some of the measures used in the present study have not been clearly established in individuals exhibiting recurrent binge eating. This must be taken into account. Third, although our model identified which eating styles are associated with recurrent binge eating, we recognize that different statistical approaches with more variables to model may produce different results, and might indeed improve classification accuracy (sensitivity and specificity indices). Fourth, participants self-selected to complete this study, which may have led to biases in the sample, such that only those with access to the Internet and who were interested in understanding more about their eating behaviors participated. Fifth, our criteria for defining recurrent binge eating was based on participant self-report over the prior 28-days. A semi-structured interview that assesses binge eating over the prior three months is considered the gold-standard for establishing the presence of recurrent binge eating and a BED diagnosis. This is because an interviewer has the opportunity to clarify any misunderstandings around the nature of binge eating and thus gain a more accurate assessment of its occurrence (Berg, Peterson, Frazier, & Crow, 2011). Even though the clinical significance of self-reported recurrent binge eating has been established (i.e., via its comparably strong link to functional

impairment to those with an established BED diagnosis; Harrison et al., 2015), replicating our findings in those with a confirmed BED diagnosis is necessary.

This was the first study to use a decision tree classification analysis to explore the relationships and interactions between various eating patterns with recurrent binge eating behavior. Present findings suggest that recurrent binge eaters may be distinguished by the complex interaction among various eating and weight-related characteristics. It will be important for future confirmatory studies to test the interactive hypotheses generated by these exploratory analyses, as this could have important implications for the assessment, formulation, and treatment of recurrent binge eating.

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Table 1

Comparison of Groups on Study Variables

Table 2

Pearson Correlations (95% CI) between Study Variables

Variable	Total Sample (n = 1541) M	SD	Recurrent Binge Eater No (n = 829) M	SD	Yes (n = 512) M	SD	α	d [95% CIs]
Age	29.23	8.11	29.42	8.25	28.94	7.87		0.06 [-0.05, 0.17]
BMI	24.48	4.29	24.11	3.78	25.24	4.67		0.27 [0.16, 0.38]
Sex (female)	91%	-	90%	-	93%	-		0.01 [-0.08, 0.10]
Intuitive eating	3.09	0.34	3.20	0.31	2.92	0.30	.71	0.93 [0.81, 1.04]
Flexible restraint	6.88	2.88	6.80	2.94	7.02	2.79	.73	0.07 [0.04, 0.18]
Rigid restraint	8.10	3.34	7.24	3.27	9.50	2.98	.74	0.71 [0.60, 0.83]
Inflexible eating beliefs	35.30	10.10	33.07	10.31	38.93	8.62	.83	0.60 [0.49, 0.72]
Dichotomous thinking	2.45	0.93	2.18	0.84	2.90	0.82	.85	0.86 [0.74, 0.97]

Variable	1	2	3	4	5	6	7
1. Intuitive eating	-	.02 [-.07, .10]	-.38 [-.31, -.45]	-.22 [-.14, -.30]	-.43 [-.35, -.49]	[-.16, .02]	-.15 [-.05, -.24]
2. Flexible control	-.22 [-.15, -.28]	-	.50 [.43, .56]	.45 [.38, .52]	.12 [.04, .21]	[-.12, .06]	-.22 [-.13, -.30]
3. Rigid control	-.50 [-.44, -.55]	.63 [.58, .67]	-	.58 [.52, .64]	.48 [.41, .54]	.01 [-.08, .10]	.05 [-.04, .14]
4. Inflexible eating beliefs	-.40 [-.34, -.45]	.54 [.49, .59]	.68 [.64, .71]	-	.46 [.39, .53]	-.08 [-.17, .01]	-.08 [-.17, .01]
5. Dichotomous thinking	-.49 [-.44, -.54]	.34 [.27, .39]	.61 [.56, .65]	.60 [.55, .64]	-	-.01 [-.10, .08]	.13 [.03, .21]
6. Age	.07 [.00, -.14]	-.05 [-.02, .11]	.02 [-.05, .09]	.02 [-.05, .09]	.05 [-.05, .09]	-	.16 [.06, .25]
7. BMI	-.19 [-.12, -.25]	.01 [-.08, .06]	.14 [.07, .20]	.08 [.01, .15]	.06 [.06, .19]		-

Note. Correlations are presented above the main diagonal for recurrent binge eaters, and below the diagonal for non-recurrent binge eaters
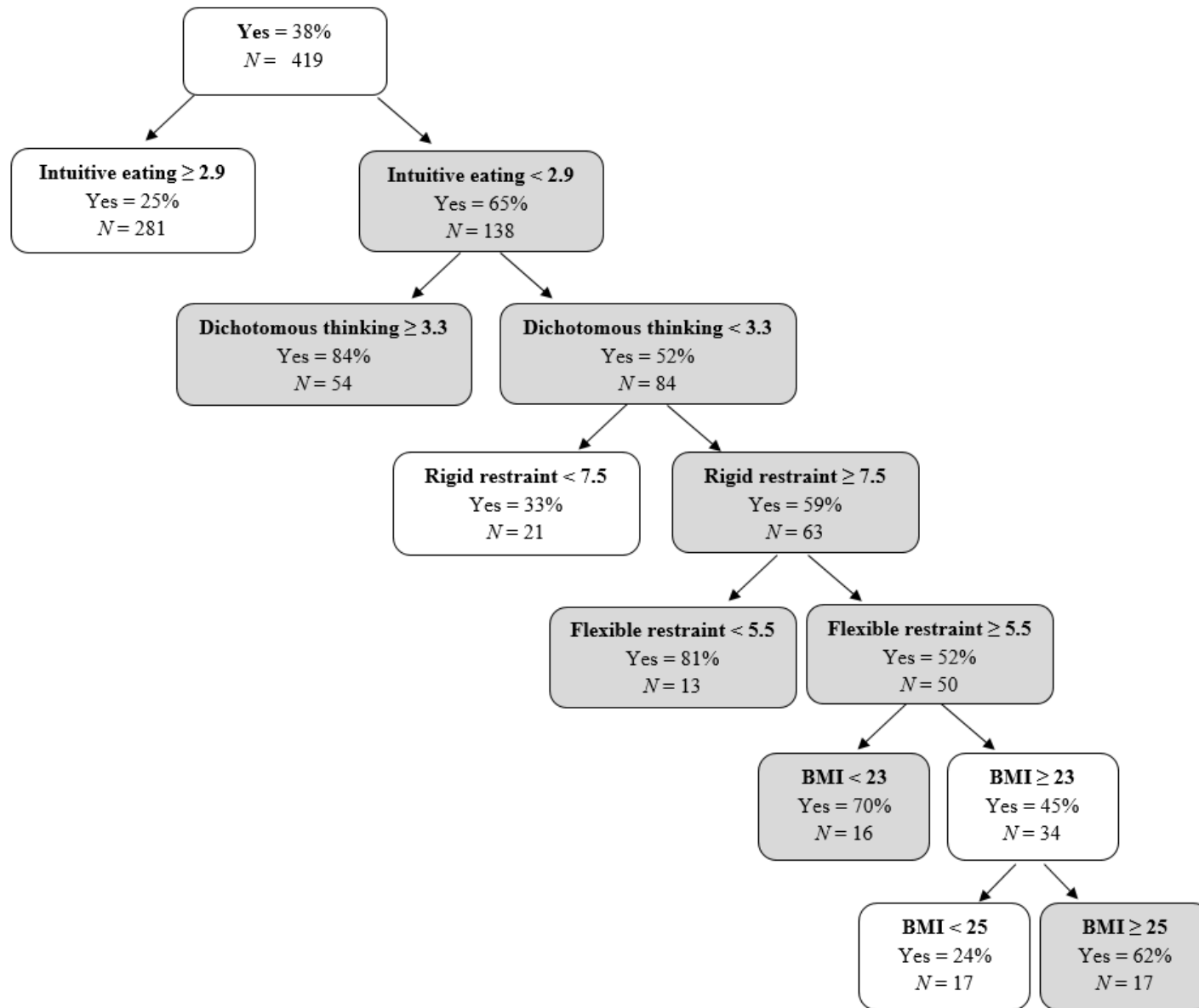
Figure 1: Decision Tree for Classifying Recurrent Binge Eating

Note: White boxes indicate a subgrouping where non-recurrent binge eaters are more prevalent, whereas grey boxes indicate where the subgroups have more recurrent binge eaters; Yes = The percentage of participants meeting criteria for recurrent binge eating in that split. Reported N at each step reflects total remaining sub-sample at each partition starting with a full sample of 419 for the parent node. Hence, the first split separates into subsamples of 281 and 138.

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Table 3
Classification Accuracy

		Actual Grouping	
		Non-recurrent	Recurrent
Predicted Grouping	**Non recurrent**	224	33
	Recurrent	93	69

Note: Actual grouping based on self-reported frequency of binge eating; non-recurrent = non-recurrent binge eater; recurrent = recurrent binge eater.

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Title:

Interactions between different eating patterns on recurrent binge-eating behavior: A machine learning approach.

Date:

2020-04

Citation:

Linardon, J., Messer, M., Helms, E. R., McLean, C., Incerti, L. & Fuller-Tyszkiewicz, M. (2020). Interactions between different eating patterns on recurrent binge-eating behavior: A machine learning approach.. International Journal of Eating Disorders, 53 (4), pp.533-540. https://doi.org/10.1002/eat.23232.

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