**SUPPLEMENTAL MATERIALS**

**Additional Methods: Full Details for Machine Learning Analysis**

For the machine learning analyses, we used demographic and clinical measures from the baseline timepoint to predict the time to remission for the 137 participants with follow-up data. The predictors were selected based on our goals for machine learning. From a statistical perspective, our goal was to pose a well-defined prediction problem, which necessarily limited the number of predictors we could include given the sample size and the prevalence of censoring for the outcome of interest. From a practical and more important perspective, our goal was to predict time to remission using common and easily collected demographic and clinical measures. Due to these statistical and practical goals, we made three exceptions to our general principle of including all demographic and clinical information collected at baseline. First, we excluded as predictors those binary variables (i.e., Ethnicity and Past Anorexia Nervosa) with low frequencies (< 5) in one category, due to the limited data available to inform prediction for these categories. Second, we used BMI Suppression (i.e., Highest Lifetime BMI - Current BMI), rather than Highest Lifetime BMI, as a predictor because BMI Suppression had a much lower correlation with Current BMI (-0.05 vs. 0.87) and because weight suppression has predicted worse outcomes for eating disorders in some (but not all) other studies (Gorrell, Reilly, Schaumberg, Anderson, & Donahue, 2019). Third, for the SCID-IV, we included as predictors several pre-specified summary measures based on diagnostic class (e.g., any lifetime major mood disorder, any lifetime substance use disorder, etc.), instead of all items generated by the SCID-IV because these latter items are not common clinical measures and because many of them have little variation and/or are highly correlated with other items. Notably, our data reduction strategy for the SCID-IV was consistent with the approach taken in a recent study using machine learning to predict remission from binge eating at the end of treatment for BED (Forrest, Ivezaj, & Grilo, 2023), enhancing the comparability of our results. Finally, we standardized all continuous measures, and we coded all categorical measures (the vast majority of which were binary) as dummy variables with the most prevalent category as the reference category.

For the main machine learning analyses, we considered four machine learning methods: standard Cox proportional hazards model (i.e., Cox regression) from the *survival* package; penalized Cox regression with lasso or elastic-net penalties from the *glmnet* package; and random survival forests from the *randomForestSRC* package.[[1]](#footnote-1) We did not account for family clustering in these machine learning methods because the main goals of these methods are prediction, rather than statistical inference, and ignoring clustering effectively amounts to assuming an independence working covariance matrix, which is a reasonable assumption given that accounting for clustering in survival curves and standard Cox regressions had a trivial effect in our sample. For the main analyses, we included 38 demographic and clinical predictors (see Supplemental Table S1 for a list of all predictors), selected as described above. Because 1.0% of the predictor values were missing, we first used the *mice* package with predictive mean matching (predictors with missing values were all numeric) to create five imputed datasets. Then, for each imputed dataset, we performed 100 replicates of 5-fold cross-validation with pre-selected seeds to examine the performance of the four methods. For a given seed, we used the *caret* package to create folds. We used 5-fold nested cross-validation to tune the hyper-parameters for penalized Cox regression and random survival forests. To evaluate the prediction performance, we used both the concordance index (i.e., C-index) and R2 based on Schmid’s robust estimate of prediction error (i.e., R2 (Schmid)) (Rahman, Ambler, Choodari-Oskooei, & Omar, 2017; Schmid, Hielscher, Augustin, & Gefeller, 2011).[[2]](#footnote-2) To obtain a summary of our chosen performance statistics, we then calculated the mean of the 500 performance statistics (5 folds times 100 replicates) for each method for a given imputed dataset, and then took the median of the mean performance statistic for each method across imputations (Marshall, Altman, Holder, & Royston, 2009; Wood, Royston, & White, 2015).

For all four methods, we performed sensitivity analyses by repeating the procedures for the main analyses (described above), but: (1) using 10-fold (rather than 5-fold) cross-validation; (2) using 10-fold (rather than 5-fold) nested cross-validation to select hyperparameters; (3) using a subset of 27 variables (rather than all 38 variables) as predictors, with that subset selected by retaining only one variable in each variable pair with Pearson correlations above 0.4[[3]](#footnote-3) (see footnote 3 and the \* in Table S1 for information on the 27 retained variables); or (4) using 38 scores from a principal components analysis of the 38 baseline variables (rather than the 38 variables themselves) as predictors. For the random survival forests, we performed additional sensitivity analyses (5) by using (a) log-rank score splitting or (b) gradient-based Brier score splitting (rather than log-rank splitting) for the splitting rule.

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**Table S1. Baseline Variables Included as Predictors in Machine Learning Main Analyses, With Results for Univariable Cox Regressions for Time to Remission in 137 Participants with Follow-Up Data**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Univariable Cox Regression Results for Time to Remission as a Function of Each Predictor** | | | | |
| **Predictora** | **Coef** | **exp(Coef)** | **Robust SE** | ***z*** | **Pr(>|*z*|)** |
| Sex [Male vs. Female]\* | 0.08 | 1.08 | 0.14 | 0.55 | 0.58 |
| Race [Black vs. White]\* | -0.28 | 0.76 | 0.16 | -1.72 | 0.09 |
| Age (years; standardized)\* | 0.01 | 1.01 | 0.14 | 0.05 | 0.97 |
| Education [Seventh to Twelfth Grade Without High School Degree vs. Partial College] | -0.04 | 0.96 | 0.14 | -0.29 | 0.77 |
| Education [Completed High School or Equivalent vs. Partial College]\* | -0.30 | 0.74 | 0.19 | -1.59 | 0.12 |
| Education [Completed Two-Year College vs. Partial College]\* | -0.21 | 0.81 | 0.21 | -0.99 | 0.33 |
| Education [Completed Four-Year College vs. Partial College]\* | 0.22 | 1.24 | 0.13 | 1.66 | 0.10 |
| Education [Partial Graduate or Professional School vs. Partial College]\* | 0.09 | 1.09 | 0.12 | 0.74 | 0.47 |
| Education [Completed Graduate or Professional School vs. Partial College]\* | 0.10 | 1.11 | 0.13 | 0.79 | 0.44 |
| Marital Status [Widowed vs. Married]\* | -0.02 | 0.98 | 0.13 | -0.16 | 0.88 |
| Marital Status [Divorced vs. Married]\* | -0.24 | 0.79 | 0.16 | -1.52 | 0.13 |
| Marital Status [Separated vs. Married]\* | 0.13 | 1.14 | 0.11 | 1.26 | 0.21 |
| Marital Status [Never Married vs. Married] | 0.03 | 1.03 | 0.14 | 0.18 | 0.86 |
| Current BMI (kg/m2; standardized)\* | -0.08 | 0.92 | 0.17 | -0.48 | 0.64 |
| BMI Suppressionb (kg/m2; standardized)\* | -0.14 | 0.87 | 0.17 | -0.85 | 0.40 |
| Lowest BMI Since Eighteen Years (kg/m2; standardized) | -0.02 | 0.98 | 0.12 | -0.16 | 0.88 |
| BED Duration (years; standardized) | -0.10 | 0.91 | 0.15 | -0.66 | 0.52 |
| BED Family Historyc (proportion with BED; standardized)\* | -0.22 | 0.81 | 0.15 | -1.43 | 0.16 |
| Past bulimia nervosad [present vs. absent]\* | 0.17 | 1.18 | 0.11 | 1.48 | 0.14 |
| Any lifetime substance use disordere [present vs. absent]\* | -0.28 | 0.76 | 0.15 | -1.83 | 0.07 |
| Any lifetime major anxiety disorderf [present vs. absent]\* | -0.18 | 0.84 | 0.15 | -1.17 | 0.25 |
| Lifetime post-traumatic stress disorder [present vs. absent]\* | 0.15 | 1.17 | 0.10 | 1.50 | 0.14 |
| Lifetime obsessive-compulsive disorder [present vs. absent]\* | -0.07 | 0.93 | 0.14 | -0.50 | 0.62 |
| Any lifetime major mood disorderg [absent vs. present]\* | 0.23 | 1.26 | 0.13 | 1.73 | 0.09 |
| BIS–11 Attentional Impulsiveness (standardized) | 0.01 | 1.01 | 0.12 | 0.09 | 0.94 |
| BIS–11 Motor Impulsiveness\* (standardized) | -0.10 | 0.91 | 0.13 | -0.74 | 0.46 |
| BIS–11 Nonplanning Impulsiveness (standardized) | -0.19 | 0.83 | 0.14 | -1.35 | 0.18 |
| EDI–2 Drive for Thinness (standardized) | 0.01 | 1.01 | 0.14 | 0.04 | 0.97 |
| EDI–2 Bulimia (standardized)\* | -0.29 | 0.75 | 0.13 | -2.21 | 0.03 |
| EDI–2 Body Dissatisfaction (standardized) | -0.16 | 0.85 | 0.14 | -1.14 | 0.26 |
| EDI–2 Ineffectiveness (standardized)\* | -0.01 | 0.99 | 0.14 | -0.04 | 0.98 |
| EDI–2 Perfectionism (standardized)\* | -0.01 | 0.99 | 0.15 | -0.09 | 0.94 |
| EDI–2 Interpersonal Distrust (standardized) | -0.14 | 0.87 | 0.14 | -1.01 | 0.32 |
| EDI–2 Interoceptive Awareness (standardized) | -0.06 | 0.95 | 0.15 | -0.37 | 0.72 |
| EDI–2 Maturity Fears (standardized) | 0.06 | 1.06 | 0.15 | 0.41 | 0.68 |
| TFEQ Dietary Restraint (standardized)\* | 0.09 | 1.10 | 0.13 | 0.69 | 0.49 |
| TFEQ Disinhibition (standardized)\* | -0.16 | 0.85 | 0.13 | -1.29 | 0.20 |
| TFEQ Hunger (standardized)\* | -0.11 | 0.89 | 0.14 | -0.81 | 0.42 |

Abbreviations: BED = binge-eating disorder; BIS–11 = Barratt Impulsiveness Scale – 11; BMI = body mass index; Coef = coefficient; EDI–2 = Eating Disorder Inventory – 2; SE = standard error; TFEQ = Three Factor Eating Questionnaire

a For continuous predictors, the original unit of measure (before standardization) is listed first within the parentheses. For categorical predictors, the relevant categories are listed within square brackets, with the reference (i.e., most prevalent) category listed second.

b BMI Suppression defined as Highest Lifetime BMI – Current BMI.

c BED Family History defined as the proportion of the participant’s interviewed relatives who met criteria for (full) DSM-IV BED based on the SCID-IV at baseline.

c Past Bulimia Nervosa defined as meeting criteria for DSM-IV bulimia nervosa.

e Any Lifetime Substance Use Disorder defined as meeting criteria for any of the following lifetime DSM-IV disorders based on the SCID-IV: alcohol abuse; alcohol dependence; drug abuse; drug dependence.

f Any Lifetime Major Anxiety Disorder defined as meeting criteria for any of the following lifetime DSM-IV disorders based on the SCID-IV: panic disorder without agoraphobia; panic disorder with agoraphobia; agoraphobia without panic disorder; social phobia; generalized anxiety disorder.

g Any Lifetime Major Mood Disorder defined as meeting criteria for any of the following lifetime DSM-IV disorders based on the SCID-IV: bipolar I disorder; bipolar II disorder; major depressive disorder.

\* Predictor included in Sensitivity Analyses 3.

**Supplemental Figure 1. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Main Analyses).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. The models were used to predict time to remission (i.e., no BED) from 38 baseline predictors (specifically, the variables in Table S1). For each of the 5 imputed datasets, we performed 5-fold cross-validation to examine the performance of all models. For all methods except standard Cox regression, which has no hyperparameters, we used a nested 5-fold cross-validation to optimize hyperparameters (lasso: lambda; elastic-net: lambda and alpha; random forests: number of trees, number of variables to possibly split at each node, and minimum size of terminal nodes) on the training set. For random survival forests, we used the log-rank splitting rule.

Abbreviations: Cox = (Standard) Cox regression; LS = Lasso model of “Cox” family; EN = Elastic-net model of “Cox” family; RF = Random survival forests



**Supplemental Figure 2. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 1).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that we performed 10-fold cross-validation.

Abbreviations: Cox = (Standard) Cox regression; LS = Lasso model of “Cox” family; EN = Elastic-net model of “Cox” family; RF = Random survival forests



**Supplemental Figure 3. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 2).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that we used a nested 10-fold cross-validation to optimize hyperparameters on the training set.

Abbreviations: Cox = (Standard) Cox regression; LS = Lasso model of “Cox” family; EN = Elastic-net model of “Cox” family; RF = Random survival forests



**Supplemental Figure 4. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 3).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that we used 27 baseline variables (see \* in Table S1) selected by removing one member of each variable pair with correlations greater than 0.4, rather than all 38 baseline variables, as predictors (see Footnote 3 above).

Abbreviations: Cox = (Standard) Cox regression; LS = Lasso model of “Cox” family; EN = Elastic-net model of “Cox” family; RF = Random survival forests

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**Supplemental Figure 5. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 4).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that we used 38 scores from a principal components analysis of the 38 baseline variables (rather than the 38 variables themselves) as predictors.

Abbreviations: Cox = (Standard) Cox regression; LS = Lasso model of “Cox” family; EN = Elastic-net model of “Cox” family; RF = Random survival forests

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**Supplemental Figure 6. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 5a).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that, for random survival forests, we used a log rank score splitting rule.

Abbreviations: RF = Random survival forests



**Supplemental Figure 7. Distribution of Performance Statistics for Imputed Datasets, by Method (Machine Learning Sensitivity Analyses 5b).** Each boxplot represents the mean (box middle line), mean +/- 1 SD (box end lines), mean +/- 3 SD (whisker end points) C-index value (Plot A) or R2 (Schmid) value (Plot B) for the test set, across seeds and folds, for a specific method and a given imputed dataset; the dotted colored horizontal line represents the median, across imputed datasets, of the mean C-index values (Plot A) or R2 (Schmid) values (Plot B) for a given method. The black horizontal line represents the C-index value (Plot A) or R2 (Schmid) value (Plot B) corresponding to random guess. Analysis details are the same as in Supplemental Figure 1, except that, for random survival forests, we used a gradient-based Brier score splitting rule.

Abbreviations: RF = Random survival forests



1. Briefly, penalized regression models are similar to standard regression models, except that they penalize model complexity, which tends to shrink predictors’ coefficients toward (or to) zero. Random forests are similar to decision trees, which would predict lower or higher event risk based on values of a series of predictors included in the tree; however, with random forests, there are multiple trees and overall predictions are based on their collective predictions, and each tree is trained on only a random subset of participants and a random subset of variables at each node. [↑](#footnote-ref-1)
2. The C-index (Wood, Royston, & White, 2015) quantifies the discrimination power of a prediction model (i.e., whether a model can correctly predict the temporal order of remission of a set of participants). We reported results for Harrell’s C-index (Harrell, Califf, Pryor, Lee, & Rosati, 1982) because it is commonly used for machine learning with survival outcomes (e.g., in the *glmnet* package); although Harrell’s C-index is biased in the presence of censoring and Uno’s C-index (Uno, Cai, Pencina, D’Agostino, & Wei, 2011) has thus been recommended for datasets with moderate censoring (Rahman, Ambler, Choodari-Oskooei, & Omar, 2017), in practice the values of Harrell’s and Uno’s C-indexes were very similar in our machine learning analyses (results for Uno’s C-index not reported). R2 (Schmid) is calculated as one minus the ratio of the prediction error for the model in question relative to the prediction error for the null model (Rahman et al., 2017). Notably, the C-index can take values smaller than 0.5, and R2 (Schmid) can take negative values, in the test set. [↑](#footnote-ref-2)
3. *A priori*, we decided to retain Sex and Race (because they are important demographic variables that are almost always assessed) and, otherwise, to retain the variable that was more conceptually or empirically relevant to remission from binge-eating disorder (BED) (with empirical relevance based on the limited existing research in this area) as determined by consensus of the first and last authors. For example, Current BMI is more conceptually relevant to remission from BED than Lowest BMI Since Eighteen Years. Also, EDI–2 Bulimia is more conceptually relevant to remission from BED than the various other Eating Disorder Inventory – 2 subscales with which it correlated.

   The full list of baseline variable pairs with correlations greater than 0.4 is:

   |  |  |  |
   | --- | --- | --- |
   | **First Variable** | **Second Variable** | **Description of and Rationale for Decision** |
   | Sex [Male vs. Female] | EDI–2 Body Dissatisfaction | Sex [Male vs. Female] retained due to *a priori* decision to retain Sex and Race |
   | Age | Marital Status [Never Married vs. Married] | Age retained due to Cachelin et al. (1999) |
   | Age | BED Duration | Age retained due to Cachelin et al. (1999) |
   | Education [Seventh to Twelfth Grade Without High School Degree vs. Partial College] | Lifetime Post-Traumatic Stress Disorder [Present vs. Absent] | Lifetime Post-Traumatic Stress Disorder [Present vs. Absent] retained due to being deemed as having greater conceptual relevance to BED |
   | Current BMI | Lowest BMI Since Eighteen Years | Current BMI retained due to being deemed as having greater conceptual relevance to BED |
   | Lifetime Post-Traumatic Stress Disorder [Present vs. Absent] | EDI–2 Interpersonal Distrust | Lifetime Post-Traumatic Stress Disorder [Present vs. Absent] retained due to being deemed as having greater conceptual relevance to BED |
   | BIS–11 Attentional Impulsiveness | BIS–11 Motor Impulsiveness | BIS–11 Motor Impulsiveness retained due to being deemed as having greater conceptual relevance to BED |
   | BIS–11 Motor Impulsiveness | BIS–11 Nonplanning Impulsiveness | BIS–11 Motor Impulsiveness retained due to being deemed as having greater conceptual relevance to BED |
   | BIS–11 Attentional Impulsiveness | BIS–11 Nonplanning Impulsiveness | Both variables already being removed (see above) |
   | BIS–11 Attentional Impulsiveness | EDI–2 Ineffectiveness | BIS–11 Attentional Impulsiveness already being removed (see above) |
   | EDI–2 Drive for Thinness | EDI–2 Bulimia | EDI–2 Bulimia retained due to being deemed as having greater conceptual relevance to BED |
   | EDI–2 Drive for Thinness | EDI–2 Interoceptive Awareness | EDI–2 Drive for Thinness already being removed (see above) |
   | EDI–2 Drive for Thinness | TFEQ Dietary Restraint | EDI–2 Drive for Thinness already being removed (see above) |
   | EDI–2 Bulimia | EDI–2 Interoceptive Awareness | EDI–2 Bulimia retained due to being deemed as having greater conceptual relevance to BED |
   | EDI–2 Interoceptive Awareness | EDI–2 Ineffectiveness | EDI–2 Interoceptive Awareness already being removed (see above) |
   | EDI–2 Body Dissatisfaction | TFEQ Disinhibition | EDI–2 Body Dissatisfaction already being removed (see above) |
   | EDI–2 Ineffectiveness | EDI–2 Maturity Fears | EDI–2 Ineffectiveness retained due to being deemed as having greater conceptual relevance to BED |
   | EDI–2 Ineffectiveness | EDI–2 Interpersonal Distrust | EDI–2 Interpersonal Distrust already being removed (see above) |

   Abbreviations: BED = binge-eating disorder; BIS–11 = Barratt Impulsiveness Scale – 11; BMI = body mass index; EDI–2 = Eating Disorder Inventory – 2; hTFEQ = Three Factor Eating Questionnaire [↑](#footnote-ref-3)