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Behavioral Profiles of Eating Disorder Risk Among University Students in Bangladesh: A K-Means Clustering Analysis

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Abstract

Eating disorders are complex mental health conditions characterized by diverse eating-related behaviors that often co-occur and may not align neatly with predefined diagnostic categories. This study explored whether K-means clustering could identify naturally occurring behavioral profiles using responses to an eating disorder questionnaire from university students in Bangladesh. Data from 550 participants were preprocessed by encoding ordinal response categories and grouping questionnaire items into five conceptually constructed behavioral domains: Restrictive Eating, Emotional Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating. K-means clustering was then applied to identify groups of participants with similar behavioral response patterns. The number of clusters was selected based on the elbow method and silhouette scores, including a direct comparison of the two and three cluster solutions. Three behavioral profiles were identified, representing different combinations of eating-related behaviors across the five behavioral domains. Consistently high values of the Adjusted Rand Index (ARI), obtained through repeated clustering using 100 random seeds, indicated that the extracted behavioral profiles were stable across different model initializations. Overall, the findings suggest that K-means clustering provides a useful exploratory approach for identifying behavioral patterns in eating disorder questionnaire data and extends previous clustering-based research to an underrepresented population of university students in Bangladesh. The relationship between restrictive eating and body image concern observed in the present sample also highlights an area for further cross-cultural investigation.

Keywords: eating disorders, disordered eating, K-means clustering, machine learning (ML), behavioral profiling, university students, Bangladesh, South Asia

1. Introduction

Eating disorders are complex, life-threatening illnesses that affect millions of people worldwide, with significant impacts on both mental and physical health. They are associated with the highest mortality rate of any mental illness (Auger et al., 2021). Analyzing and understanding eating disorders remains difficult because of the complexity of the relationships between symptoms, behaviors, and psychological factors, making it difficult to observe and identify meaningful patterns. Despite their severity, quantitative analysis of the data from eating disorder surveys remains relatively limited, and existing studies often rely on predefined assumptions about the relationship between variables (Hasan et al., 2026). This can introduce bias and prevent the discovery of underlying behavioral patterns.

Eating disorders result from complex interactions among emotional, cognitive, and behavioral factors rather than from any single observable characteristic. Because eating disorder questionnaires measure many related aspects of eating behavior simultaneously, identifying meaningful patterns within this high-dimensional data remains challenging. Data-driven clustering methods provide an opportunity to analyze survey responses without relying on predefined diagnostic categories or assumptions regarding how individuals should be grouped. Participants are grouped according to similarity in their response patterns, allowing naturally occurring behavioral profiles to emerge directly from the data.

Recent studies have demonstrated that K-means clustering is a strong approach for identifying meaningful eating behavior profiles. Because eating disorder symptoms rarely occur in isolation, unsupervised learning can identify naturally occurring behavioral profiles without relying on diagnostic labels. In García-García et al. (2021), the use of K-means clustering on questionnaire responses led to the identification of three behavioral groups: an “uncontrolled eating” group characterized by high scores in uncontrolled and emotional eating, a “restrained eating” group characterized by high scores in cognitive restraint, and a “low problematic eating” group characterized by low scores across all three eating scales. The researchers further evaluated the clusters through the use of an independent eating disorder questionnaire, providing additional support that the identified groups reflected meaningful differences in eating behaviors rather than random variation. Similarly, another study involving anxiety, depression, and disordered eating among young adults used hierarchical clustering and K-means clustering to identify four distinct participant groups (Eck & Byrd-Bredbenner, 2021).
The study found that higher levels of anxiety and depression were associated with greater eating disorder concerns, behaviors, and overall symptom severity. Together, these studies suggest that meaningful eating disorder subtypes can be consistently identified using different unsupervised clustering techniques, supporting the robustness of clustering-based approaches (Soodla et al., 2024). More recently, large-scale machine learning studies have provided additional evidence that clustering methods identify clinically meaningful behaviour patterns rather than statistical groupings. Using K-means clustering, Yu et al. (2025) identified three eating behaviour profiles: healthy eaters, restrictive eaters, and emotional eaters. The results showed these groups differed not only in eating disorder symptom trajectories but also in psychopathology, genetic susceptibility to obesity, and patterns of brain maturation. These findings suggest that unsupervised clustering can capture biologically and psychologically meaningful differences among individuals, supporting its use as an exploratory approach for investigating complex eating behaviors.

Even though the use of clustering methods and other data-driven analytical approaches has been growing in research on eating disorders, much of the existing literature has focused on Western populations. In a recent systematic review of network analysis (Sala et al., 2024), the authors highlighted the need to expand quantitative studies of eating disorders to more diverse populations, as the existing evidence is largely based on Western samples. Expanding quantitative analyses to

these populations is important for determining whether similar behavioral patterns are observed across different cultural settings and for improving the generalizability of existing findings.

In the current study, an eating disorder survey dataset collected from university students in Bangladesh is used for the analysis. While mental disorders are often perceived as affecting primarily high-income or Western populations (Heim et al., 2017), the dataset illustrates that eating disorders are also an important concern in developing countries. The relatively large and structured dataset provides an opportunity to investigate eating disorder behaviors quantitatively while extending clustering-based analyses to a population that has received comparatively little attention in the existing literature. Unlike most clustering studies, which focus on clinical populations, the present study examines a nonclinical, community-based sample, offering a broader perspective on the distribution of eating-related behavioral patterns within a university setting.

In this work, we adopt a data-driven approach to analyze eating disorder survey responses as high-dimensional data. We apply K-means clustering to group participants according to similarities in their overall response patterns rather than examining each of the questionnaire items individually. This approach allows behavioral profiles to emerge directly from the data without relying on predefined categories or assumptions regarding how participants should be classified, providing an exploratory framework for investigating eating-related behaviors. This raises an important question: What behavioral profiles emerge from eating-disorder questionnaire responses among Bangladeshi university students, and how do they relate to patterns identified in previous clustering studies? After clustering, the demographic characteristics of the participants, including age range, gender, education level, employment status, and marital status, were examined across the identified clusters to further describe and compare the resulting behavioral profiles.

The primary contribution of this work is the application of K-means clustering to identify eating-related behavioral profiles among Bangladeshi university students, an underrepresented population in clustering-based eating disorder research. By extending previous clustering studies to a new cultural context, this work contributes to the growing use of data-driven methods for analyzing eating disorder survey data in underrepresented populations. The findings may support future psychological and behavioral research aimed at improving the understanding of eating disorders across diverse populations.

2. Dataset and Pre-processing

The dataset was collected as part of a study investigating neurobehavioral factors related to eating disorders among Bangladeshi university students (Hasan et al., 2026) and is publicly available as a dataset through Mendeley Data (Hasan et al., 2025). The survey was distributed to students at Daffodil International University in Bangladesh through email and social media platforms, and a total of 550 responses were collected between August and November 2024. The number of students invited or contacted to participate was not reported in the publicly available dataset or source study; therefore, a response rate could not be calculated. The original dataset covered seven factors: demographics, cognitive control, affective value representation, salience or taste processing, body image perception, reward processing or habit formation, and self-perception about eating disorders.

The dataset included questionnaire items measuring a broad range of eating-related behaviors, including restrictive eating, emotional eating, responses to external food cues, body image concerns, weight preoccupation, and habitual or loss-of-control eating behaviors. Demographic information, including age range, gender, education level, employment

status, and marital status, was also collected.

Participants were also asked a single self-perception question: "Do you think you have an eating disorder?" with two response options: "Yes, I believe I do" and "No, I don't believe I do." This item was not included in the clustering analysis but was used as an external indicator of eating disorder self-perception when characterizing the identified clusters.

The survey responses were predominantly categorical and ordinal in nature. Many behavioral variables were measured using frequency-based response scales, with response categories such as "Never", "Seldom", "Sometimes", and "Often". In addition, variables related to body image and dieting were measured using time-based frequency categories, including "No days", "1–12 days", "13–27 days", and "Every day". Before analysis, categorical survey responses were converted into numerical values while preserving the ordinal nature of the original response scales. Frequency-based responses were encoded from 0 to 3, with increasing number codes indicating greater frequency. Time-based responses were encoded likewise from 0 to 3. In addition, categorical demographic variables, including age range, gender, employment status, marital status, and participants' eating disorder self-perception, were converted into numerical values for data processing. These non-behavioral variables were subsequently excluded from the clustering analysis.

Initially, each participant provided answers across multiple questions in the questionnaire. Two ways of representing the behavioral data were analyzed in the cluster analysis. First, K-means clustering was performed on all the retained behavior variables. Next, the questionnaire items were averaged within five behavioral categories to create five composite behavioral scores, which served as the input features for a simplified clustering model. These five composite behavioral scores were analyzed using K-means clustering to identify groups of participants with similar eating-related response patterns.

Since the objective was to identify behavioral profiles based on eating-related responses rather than participant characteristics, demographic variables were excluded from the clustering process. All 50 behavioral questionnaire items contained complete responses across the 550 participants, and no behavioral items were excluded because of missing data.

The original questionnaire organized the behavioral items across five sections: Cognitive Control, Affective Value Representation, Salience/Taste Processing, Body Image Processing, and Reward Processing/Habit Formation. These questionnaire sections and the behaviors assessed by their individual items provided the basis for organizing the 50 behavioral items into five composite behavioral categories for the analysis. Category labels were used to describe the eating-related behaviors associated with the grouped items more directly. Specifically, Restrictive Eating included 13 items assessing food restriction or dieting behaviors, Emotional Eating included 14 items assessing eating in response to emotions, External Cue Eating included 10 items assessing responsiveness to external food-related cues, Body Image Concern included 9 items assessing body image and weight-related concerns, and Habitual/Loss-of-Control Eating included 4 items assessing habitual or loss-of-control eating behaviors. A composite score for each behavioral category was calculated as the mean of the questionnaire items assigned to that category. Because all behavioral items were encoded on a 0–3 scale, each composite behavioral score also had a possible range of 0 to 3, with 3 representing the maximum possible composite score. The complete mapping of all 50 behavioral items to their assigned behavioral categories and original survey sections, together with their response scales, is provided in Appendix Table A1. These five composite categories were conceptually constructed for the present analysis and were not treated as previously validated psychometric subscales. This representation reduced the dimensionality of the dataset and provided a conceptually organized summary of the questionnaire responses for clustering.

Prior to clustering, the five composite behavioral scores were standardized using StandardScaler from the scikit-learn library (Pedregosa et al., 2011), which transformed each behavioral category to have a mean of zero and a standard deviation of one. This standardization placed the behavioral categories on a common standardized scale, reducing the likelihood that variables with larger variances would disproportionately influence the Euclidean distance calculations used by the K-means algorithm. In the cluster analysis, each participant was therefore represented by five standardized behavioral composite scores.

Following the completion of the clustering process, the demographic variables were reintroduced to look at the distribution of age range, gender, education level, employment status, and marital status across the identified behavioral profiles. This approach ensured that the clusters were formed solely from eating-related behaviors while demographic information was used to describe and compare the characteristics of participants assigned to each cluster.

3. Materials and Methods

3.1. K-means Clustering

K-means clustering was used to identify groups of participants with similar eating-related behavioral profiles. K-means is an unsupervised machine learning algorithm that partitions observations into a predefined number of clusters by minimizing the within-cluster variation. The algorithm begins by initializing K cluster centroids using the k-means++ initialization procedure. K-means++ improves the initialization of K-means by selecting initial centroids in a way that spreads them across the data, reducing the likelihood of poor initial cluster centers (Arthur & Vassilvitskii, 2007). Each participant is then assigned to the cluster whose centroid is closest to their behavioral profile, based on Euclidean distance, and the centroid of each cluster is recalculated as the mean of all participants assigned to it. This assignment and recalculation process repeats iteratively until cluster memberships no longer change, at which point the algorithm has converged on a stable solution that minimizes the sum of squared distances between each participant and their assigned cluster centroid. The clustering process is repeated using 20 different initial centroid configurations (n_init = 20), and the solution with the lowest within-cluster sum of squares (inertia) is retained. Each participant is then assigned to the cluster with the nearest centroid using Euclidean distance. Because all behavioral variables were standardized prior to clustering, the distance calculations were performed using features on a common standardized scale. After all participants have been assigned, the centroid of each cluster is recalculated as the mean of the observations assigned to that cluster. The assignment and centroid update steps are repeated until the algorithm satisfies its convergence criterion.

The objective function minimized by the K-means algorithm is:

$$\sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2$$

where K is the number of clusters, C_k represents the set of participants assigned to cluster k, x_i represents the standardized behavioral profile of participant i, and μ_k represents the centroid of cluster k. Minimizing this objective function produces clusters in which participants are assigned to groups with the smallest possible within-cluster squared Euclidean distances.

3.2. Selection of the number of clusters

To determine an appropriate number of clusters, K-means models with two to ten clusters were evaluated. The within-cluster sum of squares (inertia) and the silhouette score were calculated for each value of K. The elbow method was used to determine the number of clusters at which further increases in *K* yielded only small reductions in inertia, while silhouette scores were used to assess cluster cohesion and separation. The silhouette score compares how closely each observation is associated with its assigned cluster relative to neighboring clusters, with larger values indicating stronger within-cluster cohesion and between-cluster separation (Rousseeuw, 1987). Because the elbow plot suggested K=3 while the highest silhouette score occurred at K=2, the two and three cluster solutions were directly compared. The comparison involved examining the behavioral profiles represented by the cluster centroids, overall behavioral response levels, and changes in participant assignments between the two solutions. Because the elbow and silhouette criteria favored different solutions, K=3 was selected for exploratory behavioral profiling based on the elbow criterion and the additional behavioral response patterns represented by the three-cluster solution. This selection was not interpreted as establishing K=3 as an objectively optimal clustering of the data. The results of this comparison are presented in the Results section.

3.3. Stability Analysis

For the assessment of the stability of the clustering algorithm, the K-means model was repeatedly fitted using 100 different random seeds while keeping the preprocessing procedure, number of clusters, and number of initializations fixed. Each repeated model used 20 centroid initializations (n_init = 20). Cluster assignments from each run were compared with those obtained from the reference model using the Adjusted Rand Index (ARI). The ARI measures the similarity between two different clusterings and accounts for agreement expected by chance, where an index value closer to 1 indicates greater agreement. This was done to evaluate whether the identified behavioral profiles remained consistent across different random centroid initializations within the present dataset. The results of the stability analysis are presented in the Results section.

4. Results

4.1. Selection of the number of clusters

The number of clusters was evaluated by fitting K-means models with values of *K* ranging from 2 to 10. Both the within-cluster sum of squares (inertia) and silhouette score were calculated for each value of *K*.

The inertia value for the model containing all 50 behavioral variables decreased gradually with increasing cluster size, indicating progressively improved within-cluster compactness. However, the rate of improvement became smaller after about 3 clusters, producing an elbow around K=3. The highest silhouette score was recorded for K=2 (0.0353) and remained relatively low across larger values of K, indicating only modest separation between clusters when all questionnaire items were analyzed individually.

The clustering analysis was then repeated using the five composite behavioral categories. The inertia curve again suggested an elbow around *K*=3 (Figure 1A), with inertia decreasing from 2112.9 at *K*=2 to 1835.0 at *K*=3. In contrast, the silhouette score was highest at *K*=2 (0.2071), compared with 0.1776 at *K*=3 (Figure 1B). Because the elbow and silhouette criteria favored different solutions, the two- and three-cluster solutions were compared directly.

The *K*=2 solution primarily differentiated participants according to their overall levels of eating-related behavioral responses. The two clusters had overall mean behavioral scores of 1.43 and 1.71, respectively, with the second cluster showing higher mean scores across all five behavioral categories. In contrast, the *K*=3 solution provided additional differentiation in the patterns of behavioral responses. One cluster was characterized by relatively higher Restrictive Eating and External Cue Eating, another showed generally lower behavioral responses, and the third was characterized by relatively higher Body Image Concern and Habitual/Loss-of-Control Eating.

Comparison of participant assignments further showed that the *K*=3 solution did not simply reproduce the lower-versus-higher response distinction observed under *K*=2. Among participants in the higher-response *K*=2 cluster, 68.1% were assigned to *K*=3 Cluster 1 and 31.1% to *K*=3 Cluster 3. In addition, *K*=3 Cluster 3 included participants originating from both *K*=2 clusters. Thus, although *K*=2 produced the higher silhouette score, *K*=3 was selected for subsequent exploratory behavioral profiling because the elbow plot suggested a three-cluster solution and the additional cluster captured differences in behavioral response patterns that were not represented by the two-cluster solution. This choice reflects the exploratory objective of the analysis rather than establishing *K*=3 as an objectively optimal solution.

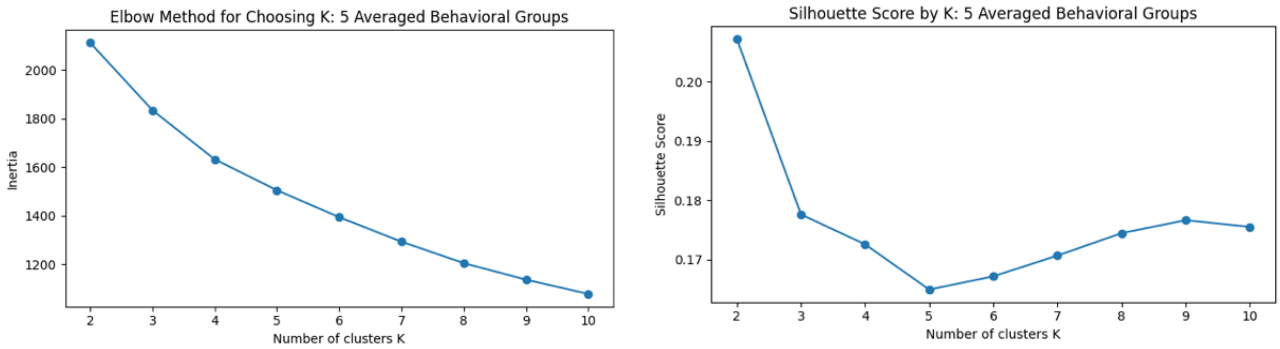

Figure 1: *Selection of the number of clusters using the 5 averaged behavioral groups.*

Note. (A) Elbow plot and (B) silhouette scores for K-means clustering with values of K=2–10.

Overall, averaging the questionnaire items into broader behavioral categories reduced the dimensionality of the behavioral data and produced higher silhouette scores than the 50-item representation. Though the silhouette scores remained modest overall, they increased substantially compared with the analysis using all retained behavioral variables, indicating improved separation between behavioral profiles. Therefore, further exploratory analyses were based on the five-composite behavioral representation with three clusters.

4.2. Behavioral profiles identified by K-means clustering

The final K-means model assigned all 550 participants into three behavioral clusters, with 184 (33.5%), 186 (33.8%), and 180 (32.7%) participants, respectively.

The average behavioral scores for all three clusters across the five behavioral categories are provided in Table 1.

Table 1: *Average behavioral scores across the five behavioral categories for each identified cluster*

Feature	Cluster 1	Cluster 2	Cluster 3
Participants number (%)	184 (33.5%)	186 (33.8%)	180 (32.7%)
Restrictive eating	1.89	1.33	1.55
Emotional eating	1.71	1.67	1.54
External cue eating	2.00	1.37	1.50
Body image concern	1.44	1.21	1.69
Habitual/Loss-of-control eating	1.43	1.31	1.91

To provide an additional descriptive characterization of response patterns within each cluster, the proportion of participants with composite scores above the scale midpoint (>1.5) was examined. This midpoint threshold was used solely as a descriptive heuristic to aid interpretation and does not represent a clinically validated cutoff for eating-disorder symptoms or risk. For Cluster 1, 98.9% and 98.4% of participants scored above the midpoint on restrictive eating and external cue eating, respectively. Additionally, 90.8% of participants from Cluster 1 scored above the midpoint on three or more behavioral categories simultaneously, and 50.5% scored above the midpoint on four or more behavioral categories. For Cluster 3, 72.8% of the participants scored above the midpoint on Body Image Concern and 73.9% on Habitual/Loss-of-Control Eating, with 71.7% scoring above the midpoint on three or more categories simultaneously. In Cluster 2, Emotional Eating was above the midpoint for 66.7% of participants, whereas above-midpoint rates for the other four behavioral categories ranged from 11.8% to 29.0%; only 18.8% scored above the midpoint on three or more categories. These results give further information about the mean composite scores by demonstrating the proportion of participants with above-midpoint responses across individual and multiple behavioral categories.

To descriptively quantify the separation in composite behavioral scores across the resulting clusters, Kruskal–Wallis tests were conducted for each of the five composite behavioral scores. Statistically significant differences across clusters were found for all five categories: Restrictive Eating ($H=312.16$, $p<0.001$), Emotional Eating ($H=21.83$, $p<0.001$), External Cue Eating ($H=294.95$, $p<0.001$), Body Image Concern ($H=195.98$, $p<0.001$), and Habitual/Loss-of-Control Eating ($H=131.66$, $p<0.001$). These comparisons quantify differences in the variables used to construct the clusters but do not provide independent statistical validation of the cluster solution, because the same five composite variables were used to determine cluster membership.



Figure 2: *Radar chart showing the mean composite behavioral scores across the five behavioral categories for the three identified clusters.*

Note. Composite scores range from 0 to 3.

Differences in behavioral response patterns were observed among the three clusters. Cluster 1 had the highest scores for Restrictive Eating and External Cue Eating, suggesting that participants assigned to this cluster exhibited relatively greater restrictive eating behaviors and responsiveness to external food cues. Cluster 2 had the lowest mean scores on

four of the five behavioral categories, representing a comparatively lower-response profile on these measured domains. Cluster 3 had high Body Image Concern and Habitual/Loss-of-Control Eating, while Restrictive Eating and External Cue Eating were moderately high compared to the other clusters.

The behavioral profiles are shown in Figure 2. The clusters showed different patterns of average behavioral scores across the five measured domains.

4.3. Demographic characteristics

Demographic variables were analyzed following clustering to describe the identified behavioral profiles. These variables were not included in the clustering process but were only employed in the description of the clusters.

Table 2: *Participant demographic characteristics overall and by behavioral cluster.*

Characteristic	Overall, n (%)	Cluster 1, n (%)	Cluster 2, n (%)	Cluster 3, n (%)	p-value	Cramer's V
Gender					0.252	0.071
Male	296 (53.8%)	91 (30.7%)	108 (36.5%)	97 (32.8%)		
Female	254 (46.2%)	93 (36.6%)	78 (30.7%)	83 (32.7%)		
Age range					0.68	0.037
18-24	356 (64.7%)	120 (33.7%)	116 (32.6%)	120 (33.7%)		
25-34	194 (35.3%)	64 (33.0%)	70 (36.1%)	60 (30.9%)		
Education level					0.887	0.068
Bachelor's degree 1st year	94 (17.1%)	32 (34.0%)	27 (28.7%)	35 (37.2%)		

Bachelor's degree 2nd year	96 (17.5%)	35 (36.5%)	28 (29.2%)	33 (34.4%)		
Bachelor's degree 3rd year	108 (19.6%)	34 (31.5%)	38 (35.2%)	36 (33.3%)		
Bachelor's degree 4th year	74 (13.5%)	26 (35.1%)	26 (35.1%)	22 (29.7%)		
Master's degree 1st year	97 (17.6%)	28 (28.9%)	37 (38.1%)	32 (33.0%)		
Master's degree 2nd year	81 (14.7%)	29 (35.8%)	30 (37.0%)	22 (27.2%)		
Employment status					0.503	0.070
Student	242 (44.0%)	77 (31.8%)	85 (35.1%)	80 (33.1%)		
Self-employed	103 (18.7%)	38 (36.9%)	27 (26.2%)	38 (36.9%)		
Employed full-time	107 (19.5%)	32 (29.9%)	42 (39.3%)	33 (30.8%)		
Employed part-time	98 (17.8%)	37 (37.8%)	32 (32.7%)	29 (29.6%)		
Marital status					0.268	0.069
In a relationship	169 (30.7%)	46 (27.2%)	62 (36.7%)	61 (36.1%)		
Married	173 (31.5%)	64 (37.0%)	52 (30.1%)	57 (32.9%)		
Single	208 (37.8%)	74 (35.6%)	72 (34.6%)	62 (29.8%)		

Note. Overall percentages represent the proportion of the total sample in each demographic category. Cluster percentages represent the distribution of cluster membership within each demographic category and therefore sum to approximately 100% across Clusters 1–3 for each row

Gender

Gender distributions were relatively similar across the three behavioral profiles (Table 2). Among male participants, 30.7% were assigned to Cluster 1, 36.5% to Cluster 2, and 32.8% to Cluster 3. Among female participants, 36.6% were assigned to Cluster 1, 30.7% to Cluster 2, and 32.7% to Cluster 3. No significant difference in gender distribution was observed across clusters, $\chi^2(2, N = 550) = 2.76$, $p = .252$, Cramér's V = .071.

Age

Cluster membership was similarly distributed across age groups (Table 2). Among participants aged 18–24, 33.7% were assigned to Cluster 1, 32.6% to Cluster 2, and 33.7% to Cluster 3. Among participants aged 25–34, 33.0% were assigned to Cluster 1, 36.1% to Cluster 2, and 30.9% to Cluster 3. Age range did not differ significantly across the three clusters, $\chi^2(2, N = 550) = 0.77$, $p = .680$, Cramér's V = .037.

Educational level

Cluster membership showed relatively similar distributions across education levels (Table 2). Across the six education categories, the proportions assigned to each cluster were generally similar. Education level showed no significant difference across clusters, $\chi^2(10, N = 550) = 5.07$, $p = .887$, Cramér's V = .068.

Employment and Marital Status

No significant difference in cluster membership was observed across employment-status categories, $\chi^2(6, N = 550) = 5.32$, $p = .503$, Cramér's V = .070. Similarly, no significant difference in cluster membership was observed across marital-status categories, $\chi^2(4, N = 550) = 5.20$, $p = .268$, Cramér's V = .069.

These findings should be interpreted with caution given the relative homogeneity of the sample. The majority of participants were aged 18–24 (64.7%), university-enrolled, and single (37.8%), which limits the demographic variability available to detect potential associations between demographic characteristics and behavioral profiles.

4.4. Eating Disorder Self-Perception

Eating disorder self-perception differed significantly across the three behavioral clusters (χ^2 (2, N = 550) = 64.47, $p < .001$). The proportion of participants who reported believing they have an eating disorder was 76.6% in Cluster 1, 48.9% in Cluster 2, and 35.6% in Cluster 3, a 41-percentage-point difference between the highest and lowest groups. Among the demographic and self-perception variables examined after clustering, eating disorder self-perception was the only measured characteristic that differed significantly across the identified behavioral profiles.

4.5. Stability Analysis

The stability of the final clustering was analyzed through repeating the K-means algorithm 100 times using different random seeds, while maintaining identical preprocessing procedures, three clusters, and 20 centroid initializations for each model.

The cluster assignments produced by each repeated model were compared with the reference clustering solution employing the Adjusted Rand Index (ARI). Across all repetitions, the ARI values remained high at an average value of 0.996, a minimum value of 0.968, and a maximum value of 1.0. The high ARI values suggest that the three behavioral profiles generated were stable across different random centroid initializations within the present dataset.

5. Discussion

This study used K-means clustering to identify behavioral profiles among university students in Bangladesh through responses on an eating disorder questionnaire. Clusters were formed on the basis of similarities of eating-related behaviors, rather than by using any predefined diagnostic categories. As a result, three behavioral profiles emerged, representing different patterns of eating-related questionnaire responses within the present sample. Furthermore, the stability analysis indicated that these behavioral profiles were highly consistent across different random centroid initializations within the present dataset.

While the two-cluster solution had a higher silhouette score, it seemed to primarily differentiate the participants based on the overall behavioral response levels. The three-cluster solution captured additional differences in behavioral response patterns, supporting its use for the subsequent exploratory analyses. This choice should not be interpreted as demonstrating that K=3 is the uniquely optimal representation of the data.

Cluster 1 was characterized by the highest average scores for Restrictive Eating and External Cue Eating, together with moderately high levels of emotional eating. Participants who were assigned to this cluster exhibited more frequent restrictive eating behaviors, while at the same time showing increased responsiveness to external food-related cues, such as sights and smells or availability of food. Interestingly, Body Image Concern was not the highest in this cluster. This suggests that restrictive eating behavior in this group does not always correlate with the highest body image concerns within this population. Instead, restrictive eating and increased sensitivity to food cues in the environment were found to be the key characteristics of this behavioral profile. The coexistence of these behaviors may reflect individuals who attempt to regulate food intake while remaining highly responsive to external food-related cues.

Cluster 2 represented a lower-response profile, with comparatively lower mean scores on four of the five measured behavioral categories: Restrictive Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating, while Emotional Eating remained comparatively moderate. These results indicate that participants in this cluster reported lower levels of several of the measured eating-related behaviors relative to the other profiles. It should be noted that 48.9% of participants in Cluster 2 reported believing that they had an eating disorder, even though this cluster showed comparatively lower mean responses on four of the five behavioral composites. This discrepancy may reflect eating-related experiences not accounted for by the five composites, subjective distress or self-perception not reflected in the measured behavioral responses, measurement limitations, or other unmeasured factors. The present analysis cannot determine which, if any, of these explanations accounts for this discrepancy.

Therefore, this profile should not be interpreted as indicating low clinical risk or the absence of an eating disorder, particularly because the clustering analysis was exploratory and based on questionnaire responses rather than clinical diagnoses.

Cluster 3 was characterized by the highest average scores for Body Image Concern and Habitual/Loss-of-Control Eating. Restrictive Eating and External Cue Eating were still moderate compared to those of the other two clusters. Participants in this cluster exhibited more body image concerns along with more habitual or loss-of-control eating behaviors. As opposed to Cluster 1, such a behavior pattern was characterized less by intentional restriction of one's diet but rather by concerns about body image and eating behaviors associated with habitual or reduced control over food intake. These findings suggest that body image concerns and habitual eating behaviors may represent a distinct behavioral pattern within this population.

The behavioral profiles identified in the present study are broadly consistent with previous research applying clustering methods to eating-related behaviors. García-García et al. (2021) identified three different behavioral profiles characterized by restricted eating, uncontrolled eating, and a low-problematic eating group through the use of K-means clustering. While the questionnaires and behavioral variables differed from those used in this study, both results suggested that participants naturally organized into multiple distinct behavioral groups, as opposed to existing along a single continuum of eating disorder symptoms. Similarly, Eck and Byrd-Bredbenner (2021) identified several clusters of participants characterized by different levels of anxiety, depression, and eating disorders symptoms, which further shows the usefulness of clustering methods for identifying meaningful subgroups within heterogeneous populations. These findings together support the application of unsupervised clustering methods for exploring complex eating-related behavioral patterns.

An observation of particular cultural interest concerns Cluster 1, which was characterized by the highest scores on Restrictive Eating and External Cue Eating but did not show correspondingly high Body Image Concern scores. Restrictive eating in Western eating disorder literature is often associated with body image dissatisfaction and fear of weight gain. However, literature suggests that the association may vary across cultural contexts. Studies of South Asian populations have documented restrictive eating presentations involving less fat phobia and weight preoccupation than those commonly described in Western populations (Tareen et al., 2005). Research focused on British South Asian communities has also highlighted presentations involving somatic concerns and, in some cases, an absence of prominent fat phobia (Cini et al., 2024). A narrative review of eating disorders in Bangladesh identified eating-disorder risk among university students. It emphasized the potential importance of sociocultural factors in understanding eating-related behaviors in this population (Banna et al., 2025). The profile of Cluster 1 in the present study, relatively high restriction without correspondingly high body image concern, may therefore warrant further investigation in relation to these previously documented cultural differences. This observation is exploratory and requires replication in clinical samples with validated diagnostic instruments before stronger conclusions can be drawn. These observations motivate further research examining whether assessment tools and conceptual frameworks developed primarily in Western contexts capture eating-related experiences similarly in Bangladeshi university populations.

The stability analysis evaluated the sensitivity of the identified profiles to different random centroid initializations. Repeating the K-means algorithm using 100 different random seeds resulted in consistently high Adjusted Rand Index (ARI) values, suggesting that participant assignments remained highly consistent despite different centroid

initializations. Based on the high average ARI score, along with the low variance between the minimum and maximum ARI scores, the results suggest that the three identified behavioral profiles represent stable patterns within the dataset rather than clusters produced by random initialization. However, this analysis evaluates stability within the present dataset and does not establish whether the same profiles would be reproduced in an independent sample.

Future studies could use bootstrap or participant subsampling analyses along with independent samples to evaluate whether the identified behavioral profiles remain stable across different samples of participants.

An additional finding of interest was the significant difference in eating disorder self-perception across the three clusters ($\chi^2 = 64.47$, $p < .001$). Cluster 1 had the highest proportion of participants reporting belief that they have an eating disorder (76.6%), while Cluster 3 had the lowest (35.6%). The 41-percentage-point difference between these groups indicates that eating disorder self-perception varied across the identified behavioral profiles. This finding supports the potential relevance of behavioral profiling as an exploratory tool for understanding variation in eating disorder self-perception within university populations.

Within this relatively homogeneous university sample, no significant demographic differences in cluster membership were observed. However, the limited demographic variability in the sample means this finding should not be interpreted as evidence that demographic factors are broadly unrelated to eating-related behavioral profiles. The sample was predominantly young (64.7% aged 18–24), entirely university-enrolled, and mostly single (37.8%), which limits the range of demographic variation available to detect potential associations. Studies including more demographically diverse participants, spanning wider age ranges, varied educational backgrounds, different employment situations, and mixed clinical and non-clinical populations, would be needed to examine whether demographic characteristics predict cluster membership more clearly.

Several limitations should be considered when interpreting these findings. First, the study relied on self-reported questionnaire responses, which may be influenced by recall bias or social desirability bias. Second, participants were recruited from a single university in Bangladesh, which may limit the generalizability of the identified behavioral profiles to other populations. Third, K-means clustering requires the number of clusters beforehand and assumes that the clusters are approximately spherical with respect to Euclidean distance. Alternative clustering algorithms may identify different behavioral structures within the same dataset. Fourth, because the Kruskal–Wallis comparisons were conducted on the same five composite variables used to construct the clusters, these analyses describe separation among the resulting profiles but do not provide independent validation of the cluster solution. Additionally, the five behavioral composites were conceptually constructed and were not empirically validated as psychometric subscales in the present study, which may limit the interpretation of the resulting behavioral profiles. Lastly, since the current study adopted an exploratory cross-sectional design, the clusters revealed should not be considered as clinical diagnoses, but rather as behavioral profiles, and causal relationships between behavioral categories cannot be established.

Overall, this study suggests that K-means clustering was able to identify different behavioral response profiles in university students by using the data from an eating disorder questionnaire. The three identified clusters captured different patterns of eating-related behaviors, but at the same time, they were highly stable across different random centroid initializations. By applying clustering analysis to a relatively unexplored Bangladeshi population and showing a stable clustering solution within the present dataset, this study contributes to the increasing use of data-driven methods for investigating

eating-related behaviors across diverse cultural settings. Further research could include testing these behavioral profiles on larger samples and in more geographically dispersed samples, utilizing other psychological or clinical measures to validate these clusters externally, and looking into whether these behavioral profiles are stable over time by conducting longitudinal studies. Such work may lead to increased insight into the heterogeneity of eating-related behaviors and aid in the development of culturally informed approaches for the early detection of eating disorders.

6. Conclusion

This study explored whether K-means clustering could identify naturally occurring behavioral profiles among university students in Bangladesh using their responses to an eating disorder questionnaire. Instead of relying on predefined diagnostic categories, the study applied an unsupervised learning approach to group participants into clusters according to similarities in their eating-related behavioral patterns.

Three behavioral profiles were identified from the analysis that differed across Restrictive Eating, Emotional Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating. The three-cluster solution was retained based on the elbow criterion and direct comparison with the two-cluster solution because the additional cluster revealed differences in behavioral response patterns that were not represented by the two-cluster solution. Additionally, the resulting profiles were highly stable across different random centroid initializations within the present dataset. Eating disorder self-perception also differed significantly across clusters (χ^2 (2, N = 550) = 64.47, $p < .001$), suggesting that the identified behavioral profiles were significantly associated with participants' self-perceptions of their eating disorder status. The use of broader behavioral categories enhanced the interpretability of the clustering results while preserving meaningful differences between participants.

Overall, the results suggest that K-means clustering is a useful exploratory tool for identifying behavioral patterns from eating disorder questionnaires. By analyzing an underrepresented group of university students from Bangladesh, the present study extends previous clustering-based research conducted on predominantly Western populations and lays the groundwork for further research involving larger and more diverse datasets, additional psychological measures, and longitudinal study designs.

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Ethics Statement

This study used a publicly available, de-identified dataset previously collected and published by Hasan et al. No new data were collected from human participants by the authors. All analyses were conducted using anonymized survey responses obtained from publicly available sources.

Data & Code Availability Statement

The eating disorder survey dataset analyzed in this study is publicly available through Mendeley Data (Hasan et al., 2025). The dataset contains responses from 550 university students at Daffodil International University in Bangladesh, collected between August and November 2024.

Dataset repository:
https://data.mendeley.com/datasets/64v6ym37dw/1

The Python scripts used for data preprocessing, K-means clustering, cluster evaluation, and statistical analyses are publicly available through GitHub.

Code repository:
https://github.com/ellac730/eating-disorder-behavioral-clustering-

The figures and analyses presented in this study were generated using the publicly available dataset and the accompanying analysis code.

Author Biography

Ella Choe is a high school student at Mercer Island High School with interests in neuroscience, cognitive science, and artificial intelligence. Her research explores the application of computational methods to understanding human behavior, particularly eating-related behavioral patterns. She is also involved in developing AI-based accessibility tools and promoting eating disorder awareness. She hopes to pursue interdisciplinary research at the intersection of neuroscience, psychology, and technology.

Mentor Contribution Statement

Luis Fernando Chumpitaz Diaz provided initial guidance during the early stages of the research project, helping establish its foundation and offering feedback on its preliminary direction.

Dr. Hamid Foroughi provided instruction and guidance on the K-means clustering framework and the data analysis approach, including preprocessing, cluster selection, and stability analysis.

Appendix A

Table A1: *Questionnaire Items, Original Survey Sections, Behavioral Categories, and Response Scales*

Item_Number	Dataset_Variable	Exact_Questionnaire_Item	Original_Survey_Section	Behavioral_Category	Response_Scale	Minimum_Score	Maximum_Score
1	EatLess_OnWeightGain	If you have put on weight, do you eat less than you usually do?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
2	EatLess_AtMealtime	Do you try to eat less at mealtimes than you would like to eat?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
3	RefuseFood_WeightConcern	How often do you refuse food or drink offered because you are concerned about your weight?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
4	Eat_SlimmingFoods	Do you deliberately eat foods that are slimming?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

5	EatLess_AfterOvereating	When you have eaten too much, do you eat less than usual the following days?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
6	EatLess_ToPreventWeightGain	Do you deliberately eat less in order not to become heavier?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
7	AvoidSnacks_BetweenMealsForWeightConcern	How often do you try not to eat between meals because you are watching your weight?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
8	AvoidEveningEating_ForWeightConcern	How often in the evening do you try not to eat because you are watching your weight?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
9	ConsiderWeight_WhenEating	Do you take into account your weight with what you eat?	Section B: Cognitive Control	Restrictive Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

10	Days_TriedLimitFoodToControlShapeOrWeight	On how many of the past 28 days have you been deliberately trying to limit the amount of food you eat to influence your shape or weight (whether or not you have succeeded)?	Section F: Reward Processing/Habit Formation	Restrictive Eating	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
11	Days_FastedToControlShapeOrWeight	On how many of the past 28 days have you gone for long periods of time (8 waking hours or more) without eating anything at all in order to influence your shape or weight?	Section F: Reward Processing/Habit Formation	Restrictive Eating	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
12	Days_ExcludedFoodToControlShapeOrWeight	On how many of the past 28 days have you tried to exclude from your diet any foods that you	Section F: Reward Processing/Habit	Restrictive Eating	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3

		like in order to influence your shape or weight (whether or not you have succeeded)?	Formation				
13	Days_FollowedRulesToControlShapeOrWeight	On how many of the past 28 days have you tried to follow definite rules regarding your eating (for example: a calorie limit) in order to influence your shape or weight (whether or not you have succeeded)?	Section F: Reward Processing/Habit Formation	Restrictive Eating	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
14	Eat_WhenIrritated	Do you have the desire to eat when you are irritated?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
15	Eat_WhenUnoccupied	Do you have a desire to eat when you have nothing to do?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

16	Eat_WhenDepressedOrDiscouraged	Do you have a desire to eat when you are depressed or discouraged?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
17	Eat_WhenLonely	Do you have a desire to eat when you are feeling lonely?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
18	Eat_WhenSomeoneLetYouDown	Do you have a desire to eat when somebody lets you down?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
19	Eat_WhenAngry	Do you have a desire to eat when you are cross (feeling angry, irritated, or annoyed)?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
20	Eat_WhenExpectingBad	Do you have a desire to eat when you are approaching something unpleasant to happen?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

21	Eat_WhenAnxious	Do you get the desire to eat when you are anxious, worried, or tense?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
22	Eat_WhenThingsGoWrong	Do you have a desire to eat when things are going against you or when things have gone wrong?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
23	Eat_WhenFrightened	Do you have a desire to eat when you are frightened?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
24	Eat_WhenDisappointed	Do you have a desire to eat when you are disappointed?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
25	Eat_WhenEmotionallyUpset	Do you have a desire to eat when you are emotionally upset?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

26	Eat_WhenBoredOrRestless	Do you have a desire to eat when you are bored or restless?	Section C: Affective Value Representation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
27	AutomaticEating_WhenExperiencingStrongEmotion	Do you feel an automatic urge to eat when experiencing strong emotions?	Section F: Reward Processing/Habit Formation	Emotional Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
28	EatMore_IfFoodTasty	If food tastes good to you, do you eat more than usual?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
29	EatMore_IfFoodSmellsOrLooksGood	If food smells and looks good, do you eat more than usual?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
30	Eat_WhenSeeDeliciousFood	If you see or smell something delicious, do you have a desire to eat it?	Section D: Salience/Taste Process	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

			ing				
31	Eat_DeliciousFoodImmediately	If you have something delicious to eat, do you eat it straight away?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
32	DesireToBuy_FromBakery	If you walk past the baker, do you have the desire to buy something delicious?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
33	DesireToBuy _FromSnackBarOrCafe	If you walk past a snack bar or a café, do you have the desire to buy something delicious?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
34	DesireToEat_WhenSeeOthersEating	If you see others eating, do you also have the desire to eat?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
35	EatMore_WhenSeeOthersEating	Do you eat more than usual when you see others eating?	Section D: Salience/Taste Process	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

			ing				
36	Eat_WhenPreparingMeal	When preparing a meal, are you inclined to eat something?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
37	Resist_DeliciousFood	Can you resist eating delicious foods?	Section D: Salience/Taste Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
38	Monitor_Food	Do you watch exactly what you eat?	Section B: Cognitive Control	Body Image Concern	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
39	Days_DesireForFlatStomach	On how many of the past 28 days have you had a definite desire to have a totally flat stomach?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
40	Days_FeltFat	On how many of the past 28 days have you felt fat?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3

41	Days_WeightAffectedSelfJudgment	On how many of the past 28 days has your weight influenced how you think about (judge) yourself as a person?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
42	Days_ShapeAffectedSelfJudgment	On how many of the past 28 days has your shape influenced how you think about (judge) yourself as a person?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
43	Days_DissatisfiedWithWeight	On how many of the past 28 days how dissatisfied have you been with your weight?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
44	Days_DissatisfiedWithShape	On how many of the past 28 days how dissatisfied have you been with your shape?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
45	Days_UncomfortableToSeeOwnBody	On how many of the past 28 days how uncomfortable have you felt seeing your body (for example:	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3

		seeing your shape in the mirror, in a shop window reflection, while undressing or taking a bath or shower)?					
46	Days_UncomfortableOthersSeeingYourShape	On how many of the past 28 days how uncomfortable have you felt about others seeing your shape or figure (for example: in communal changing rooms, when swimming, or wearing tight clothes)?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
47	Days_FearLosingControlOverEating	On how many of the past 28 days have you had a definite fear of losing control over eating?	Section F: Reward Processing/Habit Formation	Habitual/Loss-of-Control Eating	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3
48	Eat_SpecificFoodsHabitually	Do you eat specific foods habitually, even when you don't	Section F: Reward Processing/Ha	Habitual/Loss-of-Control Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3

		crave them?	bit Formation				
49	Location_TriggersHabitualEating	Do specific locations (like the kitchen) prompt you to eat habitually?	Section F: Reward Processing/Habit Formation	Habitual/Loss-of-Control Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
50	Realize_AfterEatingOutOfHabit	How often do you realize you're eating out of habit only afterward?	Section F: Reward Processing/Habit Formation	Habitual/Loss-of-Control Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3