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Probabilistic Non-Negative Matrix Factorization for the Analysis of Eating Disorder Survey Data

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Abstract

Eating disorders are complex, life-threatening mental illnesses that are still difficult to analyze because the data from surveys is complex and subjective. Existing approaches often rely on predefined hypotheses, which limit the discovery of underlying behavioral patterns. Methods such as Probabilistic Principal Component Analysis and Non-negative Matrix Factorization are commonly used, but they either lack interpretability or fail to account for uncertainty in the data.

Probabilistic Non-negative Matrix Factorization (PNMF) combines non-negative constraints with a probabilistic framework, which makes it well-suited for modeling high-dimensional, noisy survey data while maintaining interpretability.

In this work, we apply PNMF to analyze eating disorder survey data collected from 550 university students at Daffodil International University in Bangladesh. We show that PNMF identifies stable and interpretable latent behavioral patterns that correspond to distinct eating-related profiles. The results highlight the usefulness of PNMF as a data-driven approach for analyzing complex mental health data.

Keywords: Probabilistic Non-Negative Matrix Factorization, Eating Disorders, Latent Variable Modeling, Mental Health, Survey Analysis, Machine Learning

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 are not influenced by individual observable factors, but are a result of complex interactions between emotional states, cognitive control, and social perception. These interactions show up as latent variables in high-dimensional survey data and are difficult to observe directly. The identification of these latent patterns is important because it allows researchers to find the underlying patterns that influence eating behavior and go deeper than surface-level symptoms.

In this work, we adopt a fully data-driven approach, treating eating disorder survey responses as high-dimensional data. Our goal is to reduce this dimensionality in a fully data-driven manner, allowing latent variables to emerge naturally without imposing prior assumptions about which factors are important and related. This enables us to uncover hidden neuro-behavioral patterns directly from the data.

We use an eating disorder survey dataset from a population in Bangladesh. While mental disorders often have the reputation of being a problem primarily affecting high-income or Western populations (Heim et al., 2017), the dataset illustrates that these disorders also affect developing countries, demonstrating that eating disorders are a global issue. This dataset gives us a relatively large and structured set of responses, which makes it suitable for quantitative analysis. Also, the subjective and self-reported nature of survey data introduces noise and uncertainty, motivating the use of probabilistic modeling.

Since survey responses are subjective in nature, the data may not directly represent the latent behavioral patterns driving behavior. Therefore, using a method that can identify meaningful patterns while also accounting for uncertainty when analyzing this type of data is important.

Quantitative studies of eating disorders and other related conditions such as anxiety are often based on fairly small samples (Haynos et al., 2024; Edlund et al., 2024), which limits the kinds of models that can be used and the generalization of observed patterns. However, the Bangladeshi university dataset we analyze provides enough observations and participants to support more expressive models and allows for the use of matrix factorization methods that are commonly used in large-scale domains such as genomics, where non-negative matrix factorization methods are applied to data with millions of cells (Townes & Engelhardt, 2023; Shrestha et al., 2025). Since the survey responses are noisy and self-reported, a probabilistic model is used to represent uncertainty and non-negativity constraints are enforced so that latent factors can be interpretable and read as behavioral profiles.

Dimensionality reduction has been used in several fields to understand high-dimensional data. Methods like Probabilistic Principal Component Analysis (Tipping & Bishop, 1999; Bartholomew et al., 2011) and Non-negative Matrix Factorization (Lee & Seung, 1999, 2000) are widely used but both have limitations in this context. PPCA produces latent factors with both

positive and negative values, making them difficult to interpret in behavioral context. NMF improves interpretability through non-negativity constraints, but does not have a probabilistic framework and can be sensitive to noise and initialization.

Additionally, eating disorder survey datasets are relatively scarce and under-analyzed compared to fields such as genomics, where matrix factorization is widely applied. This sparsity, combined with the inherent noisy and subjective nature of survey data, motivates the need for a method that can extract a meaningful structure while accounting for uncertainty.

To address these challenges, we use the Probabilistic Non-Negative Matrix Factorization (PNMF) framework (Chumpitaz-Diaz, n.d.), which combines non-negative constraints with a probabilistic framework. This allows the model to produce interpretable latent factors while accounting for uncertainty in the data.

The contribution of this work is that it provides a principled and interpretable framework for analyzing eating disorder survey data using PNMF, which allows for the discovery of meaningful latent patterns while modeling uncertainty in noisy, self-reported data. Also, the latent factors that were learned correspond to relatively coherent and distinct eating-related behaviors, providing structured insight into the organization of these behaviors. This offers a more data-driven exploratory approach for analyzing complex mental health data, with the potential to inform future clinical and behavioral research applications.

2. Dataset

An eating disorder survey dataset was analyzed to study neurobehavioral factors corresponding with eating disorders among university students. The survey was given to students at Daffodil International University, Bangladesh, through email and social media platforms, and a total of 550 responses were collected between August and November 2024.

The dataset had various factors linked with eating disorders such as restricted eating behaviors, emotional eating, response to external cues, body image perception, weight preoccupation, impulsive eating behaviors, reward responses, habit formation, and perceptions about the eating disorder. Other demographic factors like age range, gender, education level, employment status, and marital status were also included.

The responses to the surveys were predominantly categorical and ordinal in nature. Behavioral variables were measured using frequency scales, which included answers like “Never”, “Seldom”, “Sometimes”, and “Often”. In addition, body image and dieting variables were measured on frequency scales in time, which included answers like “No days”, “1–12 days”, “13–27 days”, and “Every day”. Before modeling, categorical data was numerically coded to be used in the PNMF model as non-negative values.

Each subject is described using all the survey variables, resulting in a high-dimensional behavioral data set. Self-reported data in surveys involve subjective responses and therefore come with noise, response variation, and uncertainties. This explains why probabilistic latent variable modeling techniques that can detect meaningful behavioral structures despite noise are appropriate and used.

3. Materials and Methods

Model

Given a non-negative data matrix $Y \in R_+^{N \times D}$, the PNMF model assumes each entry follows a Poisson distribution:

$$y_{ij} \sim Poisson\left(\lambda_{ij}\right) \quad (1)$$

where the rate parameter λ_{ij} is given by:

$$\lambda_{ij} = \sum_{l=1}^{L} W_{jl} \exp exp\left(F_{il}\right) \quad (2)$$

with the following components:

- $W \in R_+^{D \times L}$ are the loadings (learned parameters)
- $F \in R^{N \times L}$ are the latent factors (random variables)

The latent factors follow a Gaussian prior:

$$F_{il} \sim N\left(0, \sigma^2\right) \quad (3)$$

For our implementation, we chose $\sigma = 1$.

Variational Inference

We use variational inference (Blei et al., 2017) to approximate the posterior distribution over the latent factors F. The variational distribution $q(F)$ is a Gaussian with learnable mean and scale parameters:

$$F_{il} \sim q\left(F_{il}\right) = N\left(\mu_{il}, \sigma_{il}^2\right) \quad (4)$$

The Evidence Lower Bound (ELBO) is:

$$L = E_{q(F)}[\log log\ p\ (Y|F)] - KL[q(F)||p(F)] \quad (5)$$

Expected Log-Likelihood Expansion

The expected log-likelihood term expands as follows. For a Poisson observation model, the log-likelihood is:

$$\log log\ p\left(Y_{ij}|\lambda_{ij}\right) = Y_{ij} \log log\ \lambda_{ij} - \lambda_{ij} - \log log\left(Y_{ij}!\right) \quad (6)$$

Substituting the PNMF parameterization $\lambda_{ij} = \sum_l W_{jl} e^{F_{il}}$, the expected log-likelihood becomes:

$$E_{q(F_i)}\left[\log log\, p\left(Y_{ij}|F_i\right)\right] = Y_{ij}E_{q(F_i)}\left[\log log \sum_l W_{jl}\, e^{F_{il}}\right] - \sum_l W_{jl}E_{q(F_{il})}\left[e^{F_{il}}\right] - \log log\left(Y_{ij}!\right) \quad (7)$$

The second expectation can be computed analytically using the moment-generating function of the Gaussian:

$$E_{q(F_{il})}\left[e^{F_{il}}\right] = \exp exp\left(\mu_{il} + \frac{1}{2}\sigma_{il}^2\right) \quad (8)$$

This gives the final form:

$$E_{q(F_i)}\left[\log log\, p\left(Y_{ij}|F_i\right)\right] = Y_{ij}E_{q(F_i)}\left[\log log \sum_l W_{jl}\, e^{F_{il}}\right] - \sum_l W_{jl} \exp exp\left(\mu_{il} + \frac{1}{2}\sigma_{il}^2\right) - \log log\left(Y_{ij}!\right) \quad (9)$$

where:

- The first term (log of sum) is estimated via Monte Carlo sampling with the reparameterization trick.
- The second term (sum of exponentials) is computed analytically.
- The third term is constant with respect to the parameters.

Optimization

The model is optimized by maximizing the ELBO using gradient ascent. The variational parameters μ_{il} and σ_{il} and the loadings W_{jl} are learned jointly.

Latent Dimensionality Selection

For the latent component analysis, the number of latent dimensions was set to $L = 10$ as an exploratory modeling choice. This dimensionality offered broad coverage of distinct behavioral dimensions while maintaining interpretability and without much overlap among latent factors.

Rather than making prior assumptions about the number of behavioral categories, the exploratory choice of $L = 10$ allowed the latent neurobehavioral dimensions to emerge directly from the data.

LLM-Assisted Topic Interpretation

In order to enhance interpretability and reduce subjectivity, an LLM-assisted two-stage analysis pipeline was used for the interpretation of latent factors.

In the first stage, the variables from the survey that had the highest loadings for each PNMF latent factor were extracted from the loading matrix. These variables represented the strongest behavioral features contributing to each latent factor.

In the second stage, the identified groups of variables in each of the PNMF factors were interpreted using GPT-5.5 to identify shared behavioral patterns and generate interpretive labels. The model was prompted to interpret common psychological or behavioral themes represented by the variable groups while taking into account behaviors related to

eating, emotional regulation, impulsivity, body image concern, restrictive behaviors, rewards, and behavioral control where relevant. The generated labels were reviewed by the authors and used only as qualitative descriptions of the latent factors.

The following prompt structure was used during interpretation:

> *Given the following survey variables with the highest loadings from a PNMF latent behavioral factor, identify the shared behavioral theme connecting these variables and provide a concise behavioral interpretation label describing the common psychological or behavioral pattern represented by the variable group.*

4. Results

We applied PNMF to the eating disorder dataset to extract latent behavioral patterns.

Figure 1 shows the ten latent behavioral components learned by PNMF. Each topic groups together survey variables that frequently co-occurred across participants, allowing structured behavioral patterns to emerge directly from the data without imposing predefined behavioral categories. The behavioral labels assigned to each latent factor are qualitative interpretations based on the highest-weighted survey variables within each topic.

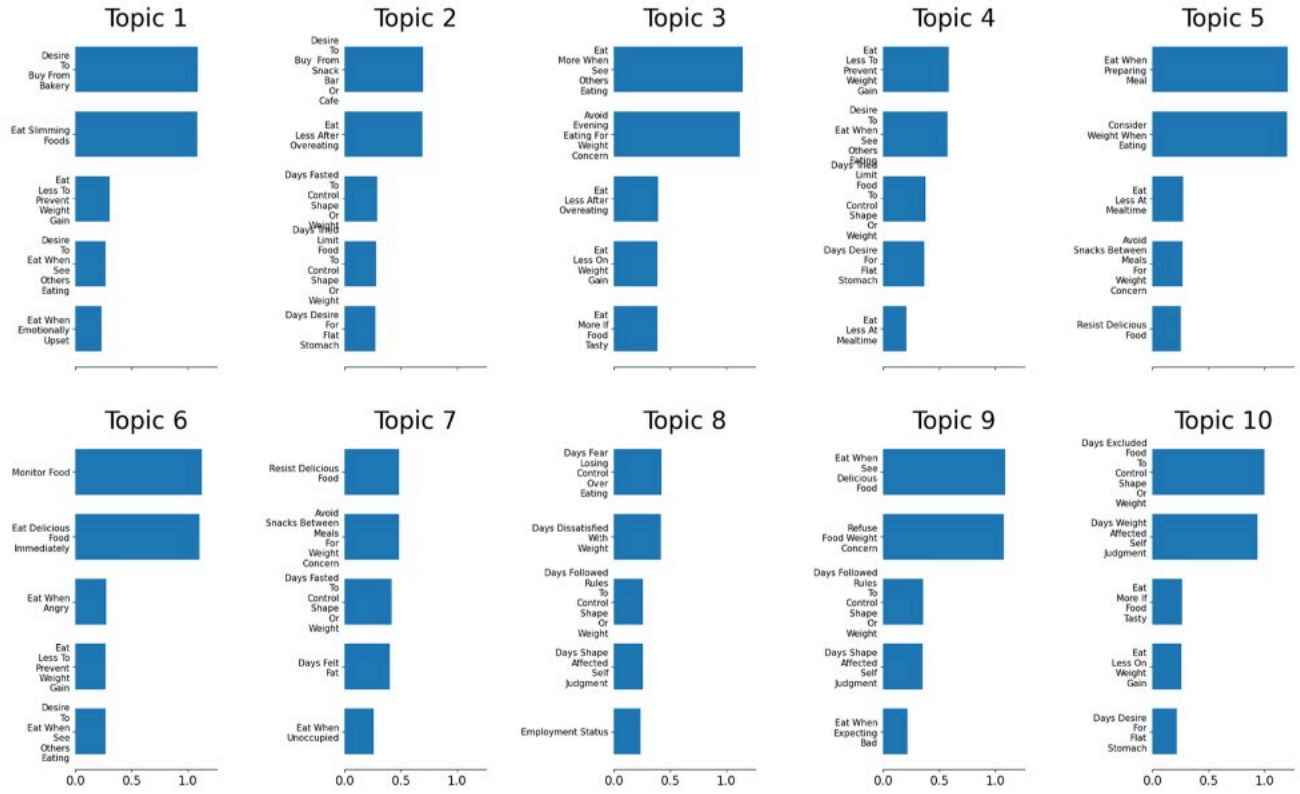


Figure 1: PNMF latent components. Each topic presents the highest-weighted variables within a factor, showing distinct and

interpretable patterns of eating-related behaviors and allowing for clearer identification of underlying behavioral profiles.

Table 1 highlights that several latent factors correspond to partially related behavioral profiles while still remaining behaviorally distinguishable.

Restrictive and controlling eating behavior can be attributed to several latent factors. Variables from topics 1, 5, 7, and 8 reflect aspects such as dieting behavior, body-image concerns, self-monitoring, food avoidance, and habitual self-evaluation in eating behaviors. While topic 1 is reflective of restrictive dieting and sensitivity to external food cues, topics 5 and 7 focus on the aspect of body-image and avoidance. Topic 8, on the other hand, relates to persistent dieting behavior and self-evaluation as a consequence of long-term behavior control.

Other latent factors appeared associated with impulsive and externally prompted behaviors related to eating. Topics 3, 6, and 9 are made up of variables that pertain to lack of control, emotional impulsivity, immediate food consumption, and externally triggered eating behavior. Topic 3 contains variables involving guilt after eating and reduced behavioral self-regulation. On the other hand, Topic 6 contains variables associated with emotional eating behavior and reward-seeking responses toward food. Finally, topic 9 involves impulsive behavior with respect to eating triggered by externally prompted food visual cues.

Additionally, emotionally reactive eating-related behaviors are also found among multiple latent dimensions. Topics 2, 4, and 10 contain variables associated with emotional distress, craving, emotional eating triggers, and eating behaviors with emotional comfort seeking. Topic 2 focuses on emotional distress and behaviors that are craving oriented, while topic 4 concerns emotional and physiological reactivity to eating behaviors. On the other hand, topic 10 concerns emotional comfort-seeking eating behaviors.

The components demonstrate a clear structure in eating-related behaviors. Each latent factor groups together related survey responses that tend to occur together, which forms distinct behavioral patterns. This allows the model to identify relationships between co-occurring eating-related behaviors rather than analyzing each survey variable independently.

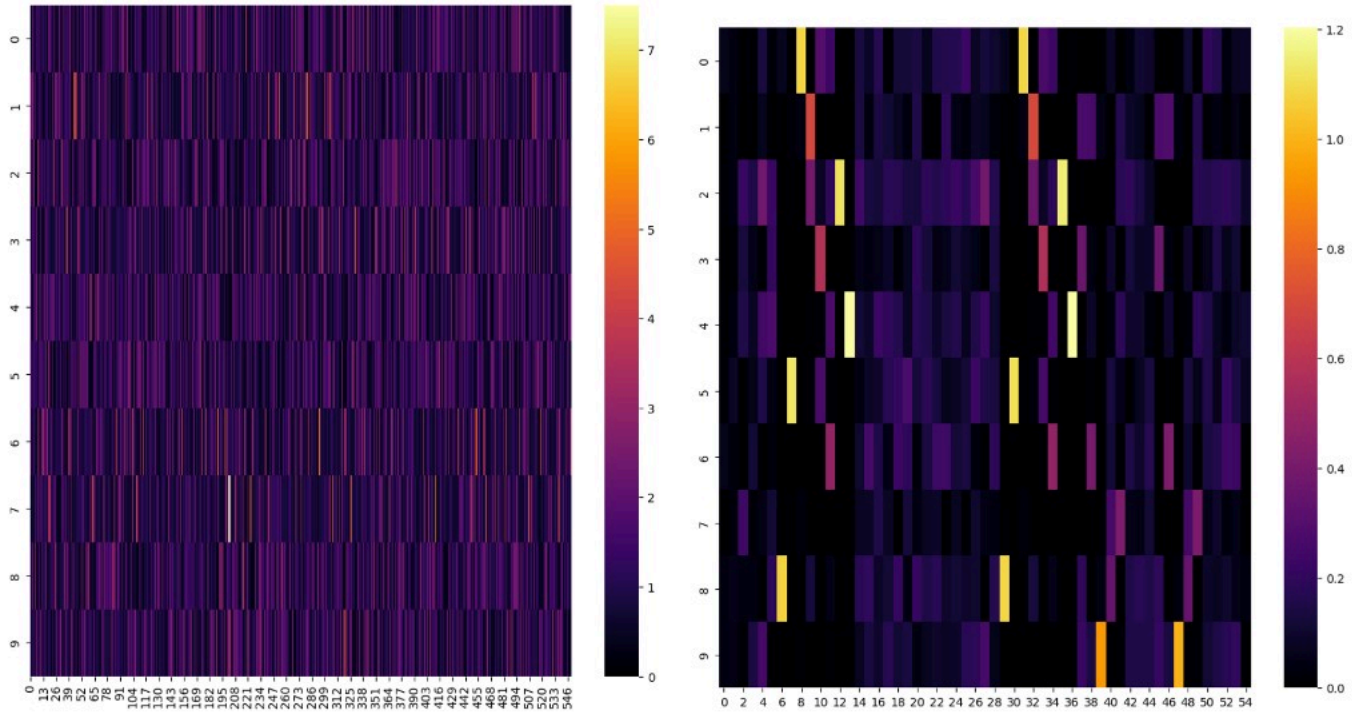
Despite partial overlap between related behavioral dimensions, the sparse structure enforced by PNMF allowed the latent factors to remain behaviorally distinguishable and interpretable.

Topic	Representative Highest-Weighted Variables	Interpreted Behavioral Pattern
1	Desire for bakery foods, eating slimming foods, eating when seeing others eating, eating when smelling food	Restrictive dieting behavior combined with heightened external food cue sensitivity
2	Desire for sweet foods, emotional discomfort, weight concern, stress-related eating	Emotionally conflicted eating behavior associated with craving and body-image concern
3	Eating despite concern, loss of control over eating, guilt after eating	Loss-of-control eating behavior associated with external food cues and impaired regulation
4	Attention to food, emotional eating triggers,	Emotionally and physiologically reactive

	stomach fullness awareness	eating behavior
5	Worrying about eating, body dissatisfaction, avoidance due to weight concern	Body-image anxiety and socially mediated eating concern
6	Monitoring food intake, eating immediately after seeing food, eating when angry	Emotion-driven impulsive eating behavior linked to external reward sensitivity
7	Avoidance behavior, stress-related eating, weight concern	Restrictive and avoidance-based dieting behavior associated with weight concern
8	Long-term dieting behavior, emotional state changes, self-judgment	Persistent self-evaluative dieting and control-oriented eating behavior
9	Eating when seeing food, emotional concern, loss of control	Cue-triggered impulsive eating behavior with reduced behavioral control
10	Comfort food cravings, emotional discomfort, stomach fullness awareness	Emotionally mediated comfort-seeking eating behavior

Table 1: Behavioral interpretation of PNMF latent components based on representative highest-weighted survey variables.

The latent structure learned by PNMF is further illustrated in Figures 2a and 2b. Figure 2a depicts the participant-factor matrix and illustrates the level of association between participants and each latent behavioral factor. The darker areas in the matrix show stronger associations between participants and particular latent factors, while the lighter areas highlight weaker associations of participants with particular latent factors. The matrix demonstrates that participants do not exhibit the same behavioral patterns uniformly across the dataset. Instead, different participants show varying levels of association with different latent behavioral dimensions.



(a) PNMF factor matrix

(b) PNMF loading matrix

Figure 2: PNMF factor and loading matrices illustrating structured relationships between latent behavioral dimensions and survey variables. The factor matrix shows how participants distribute across latent factors, while the loading matrix shows which survey variables contribute most strongly to each behavioral dimension. Sparse concentration of loadings allows clearer separation between distinct eating-related behavioral profiles while still preserving partial overlap between related emotional and impulsive eating behaviors.

Certain latent factors show stronger association among smaller groups of participants compared to the participant population as a whole. This suggests that the latent factors capture more specific behavioral tendencies rather than broad generalized eating behaviors shared equally across all participants. Although some participants appear associated with multiple related latent factors, particularly among emotional and impulsive eating-related dimensions, the darker areas in the matrix still remain mostly concentrated rather than uniformly spread across all latent factors. This pattern is consistent with partially separable latent behavioral profiles while still capturing related psychological behaviors.

Figure 2b presents the loading matrix between survey variables and latent behavioral factors. This matrix shows how strongly individual survey variables contribute to each latent dimension. Darker regions correspond to higher loading values, indicating stronger contributions of particular survey variables to specific latent factors, whereas lighter regions indicate weaker contributions.

As seen in the matrix above, the survey items mostly influence only a limited number of latent factors as opposed to equally influencing all latent factors. There are clusters of darker regions that can be seen on the matrix, demonstrating that survey items tend to cluster within certain latent behavioral factors as opposed to distributing themselves evenly among all factors.

The variables associated with restrictive dieting behavior, emotional eating, impulsive eating, body image concern, and reward sensitivity seem to be clustered in particular areas of the matrix, which correspond to particular latent factors. This organization is consistent with the behavioral interpretations presented in Table 1, suggesting that related eating variables are clustered in particular latent dimensions.

Even though several adjacent latent factors have some associated common variables, the darker zones still tend to remain fairly localized rather than spreading broadly across the whole matrix. This suggests that most latent dimensions retain their behavioral distinctiveness while still capturing partially related psychological behaviors.

The relatively sparse concentration of stronger loading values improves interpretability because each latent factor is influenced primarily by a smaller subset of related behavioral variables. Overall, Figure 2b suggests that PNMF can help reveal structured and interpretable latent behavioral dimensions from noisy self-report survey data

5. Discussion

As can be seen from Figure 1, the latent structure identified by PNMF suggests that eating-related behaviors may not be fully explained by one generalized behavior pattern, but instead may reflect complex interactions between emotional, cognitive, and behavioral processes. Instead of grouping all behaviors related to the survey questions under one generalized category of eating behaviors, PNMF divided the observations into several latent factors that were still behaviorally meaningful while allowing partial overlap between related psychological behaviors. This structure suggests that eating behaviors may co-occur within latent behavioral patterns rather than being evenly distributed across all participants.

The identified latent dimensions may also indicate the presence of partially separable behavioral mechanisms underlying restrictive, impulsive, and emotionally reactive eating behaviors. The variables concerning restrictive eating habits, such as body-image concern, dieting, self-monitoring, and food avoidance, were localized within particular latent dimensions instead of being equally distributed across all dimensions. Variables associated with impulsive eating behavior, emotional impulsivity, eating-induced guilt, and responses to external food cues were grouped across several latent dimensions instead of collapsing into a generalized dimension of impulsive eating behavior. Also, the emotional eating variables, including craving for certain food products, emotional distress, comfort-seeking behavior, and physiological eating responses, were distributed across various latent dimensions. Together, these patterns may point toward heterogeneity in eating-related behavioral mechanisms rather than one singular behavioral process that underlies all eating-related behavior.

This is generally consistent with previous findings linking eating-disorder-related behaviors to emotional, cognitive, body-image, and reward-related processes. Haynos et al. discuss anorexia nervosa in relation to affective symptoms and problems with reward processing, which is consistent with the reward- and emotion-related behavioral dimensions identified in this study (Haynos et al., 2024). Similar findings were reported by Edlund et al., who found associations between body dissatisfaction, drive for thinness, exercise for weight control, and depression among elite gymnasts (Edlund

et al., 2024). Furthermore, the initial survey-based study carried out by Hasan et al. used similar eating disorder-related variables and arranged them into dimensions like cognitive control, emotional triggers, body image perception, sensory processing, and reward processing (Hasan et al., 2026). Although the latent factors identified here are exploratory in nature and not associated with specific clinical diagnoses, the extracted structure appears consistent with behavioral dimensions identified in previous eating disorder research.

As a result, the sparse loading matrix created by PNMF improves the interpretability of the model since it enables stronger associations between subsets of survey variables and the specific latent dimensions. Rather than all survey variables contributing equally across latent dimensions, higher loading values remained concentrated within localized regions of the loading matrix. This sparsity pattern allowed related behavioral variables to cluster together while keeping various types of behavioral characteristics separate. Moreover, the probabilistic approach used in PNMF may also prove beneficial in the analysis of surveys since the self-reported data may involve some degree of uncertainty. Additionally, the non-negative structure imposed by PNMF allows latent factors to be interpreted as additive behavioral profiles rather than combinations of positive and negative behavioral contributions.

However, there are several limitations that should be considered. First, the data comes from self-reported surveys, and therefore contains subjective biases. While the Poisson likelihood provides a good foundation for analyzing sparse and non-negative data, the survey data is categorical rather than count-based observations. One possible future improvement would be exploring alternative likelihood formulations to fit categorical or ordinal survey data.
Another limitation is that the data was collected from a single university in Bangladesh. While this produces useful information on an under-researched population, there might still be limits as to how much of the discovered latent structure can apply to other groups.

Future work could explore how these behavioral patterns change over time, examine clinical populations, and compare PNMF with alternative probabilistic latent variable models. Clinical validation and other types of external behavioral measurements might be used to establish whether the factors found are clinically relevant.

Overall, the above findings suggest that PNMF may provide a useful and interpretable framework for identifying reasonably structured and interpretable behavioral profiles from noisy self-reported survey data while preserving relatively sparse latent structure. These latent dimensions may provide structured insight into eating-related behavioral organization with the potential to inform future clinical and behavioral research applications.

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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.

AI Tools Statement

GPT-5.5 was used as part of the analysis pipeline to propose candidate behavioral labels from the variables identified by PNMF as highest-loading on each latent factor. This use is methodological in nature — the LLM did not write any part of the manuscript, generate arguments, or select references. All interpretive choices were reviewed and finalized by the authors.

Data & Code Availability Statement

The eating disorder survey dataset analyzed in this study is publicly available through Kaggle and is based on the dataset introduced by Hasan et al. The dataset contains responses from 550 university students at Daffodil International University in Bangladesh, collected between August and November 2024.

Dataset repository:
https://www.kaggle.com/datasets/jocelyndumlao/neurobehavioral-factors-in-eating-disorders-study/data

PNMF repository:

https://github.com/luisdiaz1997/Probabilistic-NMF

The figures and analyses presented in this study were generated using these publicly available resources.

Mentor Contribution Statement

Mentor 1 provided instruction and guidance on the PNMF framework and the mathematical concepts underlying its use in this paper. They covered probabilistic models, latent variables, variational inference, and how to interpret results.

Mentor 2 provided editorial feedback on organization, paragraph structure, clarity, and the presentation of the results. This helped with making the paper easier to read and its findings clearer.

Decision: Desk revise and resubmit (with promise of external peer review after the following concerns are addressed).

Review: Thank you for your submission. The paper's application of probabilistic non-negative matrix factorization to eating-related survey responses is interesting, and the methods you are attempting to apply are advanced for a high school student. I am impressed by your willingness to engage with latent-variable modeling, variational inference, and the interpretability of computational results throughout your narrative.

However, before forwarding this paper to external peer review, I would ask you to substantially revise the manuscript. The most important revisions concern the suitability of the computational model for the dataset, the explanation and validation of your results, the scope of the claims you make from those results, and the connection between your data-inferred latent factors and the existing psychological literature. The manuscript currently presents an interesting exploratory analysis, but it does not yet provide enough technical evidence to support several of its strongest conclusions.

Concern 1: Clarify the research question and the scope of your claims.

Already from your abstract, I am concerned that you are focused too much on the method being applied rather than what precisely it is being applied to and what research question it is intended to answer. In machine learning, a model is only as good as the data it is trained on and its suitability for that data. Hence, you should not simply state that you apply PNMF in this setting. You should explain what sorts of trends or patterns the method is trying to discover, show, or model.

For instance, are you asking whether eating-related survey responses can be represented by a smaller number of co-occurring behavioral profiles? Are you asking whether a probabilistic factorization method recovers *recognizable* and *already-identified* patterns involving restrained eating, emotional eating, external food cues, body-image concerns, or loss of control? (What do you even mean by "eating disorders" here? This should be clear in your abstract.) Are you asking whether PNMF provides a clearer or more stable representation than conventional NMF or other dimensionality-reduction methods?

Please define a concise research question near the end of the Introduction and return to it explicitly in the Results and Discussion.

Concern 2: Describe the dataset and preprocessing in substantially more detail.

"An eating disorder survey dataset was analyzed to study neurobehavioral factors corresponding with eating disorders among university students. The survey was given to students at Daffodil International University, Bangladesh, through email and social media platforms, and a total of 550 responses were collected between August and November 2024."

- Could you be more specific about the information contained in this dataset? Please provide the reader with a clearer summary of the participant demographics, the number and types of survey items, the response scales used, and the construction of the dataset. Relevant descriptive statistics can be placed in an appendix if they take up too much space in the main text.

More importantly, please explain your preprocessing procedure precisely. The current statement that categorical data were “numerically coded” as non-negative values is not enough to make the analysis reproducible or to establish that the encoding is appropriate. Please provide a table or appendix identifying the survey variables used in the analysis, the possible responses for each item, the numerical encoding assigned to each response, the treatment of missing values and whether any variables were excluded, and whether any demographic variables were included in the factorization.

Moreover, how did you handle or control for nominal variables (gender, geographic origin, employment status, marital status), and did you rescale/normalize/center the data at all before applying the factorization?

- This distinction is important because ordinal and nominal variables cannot necessarily be treated in the same way. A frequency scale such as “Never,” “Seldom,” “Sometimes,” and “Often” may have a natural ordering, but assigning ordered integers to nominal demographic categories would introduce arbitrary relationships into the model. If nominal demographic variables were included, they should be encoded appropriately or excluded from the factorization.

Concern 3: Justify the use of a Poisson likelihood for ordinal and categorical survey responses.

This is the most important methodological issue in the current manuscript. Your model assumes that each observed value follows a Poisson distribution, as commonly used for non-negative count data. However, the survey responses in this dataset are primarily categorical or ordinal rather than counts. Numerically encoding a response as 0, 1, 2, or 3 makes the values non-negative, but it does not automatically make them count observations.

For example, a response coded as 3 does not necessarily mean that the respondent experienced three events, nor does it necessarily justify the mean-variance relationship implied by a Poisson model. The numerical encoding also assumes that the difference between “Never” and “Seldom” is comparable to the difference between “Sometimes” and “Often.”

You recognize this concern briefly in the limitations section: “While the Poisson likelihood provides a good foundation for analyzing sparse and non-negative data, the survey data is categorical rather than count-based observations.” This point should be addressed much earlier and in considerably more depth. Please explain whether you view the Poisson likelihood as a heuristic approximation, why you believe it remains informative in this context, and how sensitive the resulting factors are to the response encoding.

Ideally, you should include at least a compact sensitivity analysis to justify why PNMF actually provides a meaningful improvement over the NMF baseline. For example, you could compare results under reasonable alternative codings of the ordinal responses, compare the PNMF results with a conventional NMF baseline, or discuss an ordinal latent-variable alternative.

Concern 4: Improve the explanation and reproducibility of the computational methods.

The technical section currently presents a sequence of equations but does not provide enough explanation for readers to understand the model or reproduce the analysis.

- Please define the dimensions and interpretation of each matrix clearly. Explain which matrix corresponds to participants, which corresponds to survey items, and which quantities are random variables versus learned point estimates. In particular, explain the relationship between the Gaussian latent variable and its exponentiated form in the Poisson rate. A reader should be able to understand why the exponentiation is used and how it ensures non-negativity, as this is emphasized multiple times in the Introduction.
- Please ensure that the final equations are correctly typeset (e.g., I saw a bunch of duplicate “log” and “exp” terms in the equations), that every symbol is defined, and that the same notation is not used for two different concepts. For example, using the same letter for the evidence lower bound and the number of latent dimensions could confuse the reader.

Moreover: “For our implementation, we chose $\sigma = 1$.” Why? Please explain the role of this prior scale and provide either a justification or a brief sensitivity analysis. The question is not simply whether variational inference converges, but whether the inferred factors are meaningfully affected by this modeling choice.

“The first term (log of sum) is estimated via Monte Carlo sampling with the reparameterization trick.” Monte Carlo estimation can refer to a *massive* range of computational choices. Please state the implementation details and hyperparameters you used in an appendix and report, at a minimum:

- The number of Monte Carlo samples
- The optimizer
- Learning rate
- Number of iterations
- Stopping criterion
- Initialization procedure
- Random seed
- Software version
- Any additional model settings

Please also clarify that this is Monte Carlo estimation within a variational-inference procedure, rather than something like Markov chain Monte Carlo.

Concern 5: Justify the choice of 10 latent dimensions.

“For the latent component analysis, the number of latent dimensions was set to L = 10 as an exploratory modeling choice. This dimensionality offered broad coverage of distinct behavioral dimensions while maintaining interpretability and without much overlap among latent factors.”

Some justification or supporting data for this choice would be helpful. The manuscript itself identifies substantial conceptual overlap among several topics. This does not necessarily mean that ten factors are inappropriate, but it raises the possibility that the model may be dividing broader psychological constructs into partially redundant subcomponents.

If possible, please include a compact latent-dimension sensitivity analysis. For example, you could fit the model with several nearby values of L and compare reconstruction quality, held-out likelihood or deviance, factor stability across repeated runs, redundancy among factors, and interpretability. A figure or appendix table summarizing this comparison would be sufficient.

Concern 6: Provide stronger *quantitative* support for the results.

The Results section currently relies heavily on visual, qualitative inspection of bar charts and heatmaps. The figures gesture at interesting patterns, but the text frequently moves from qualitative observations to stronger claims without sufficient evidence. For example, the abstract states that PNMF identifies “stable and interpretable latent behavioral patterns.” However, the manuscript does not report a stability analysis. Were the same factors recovered across different random initializations? How sensitive were the factors to the number of latent dimensions? Were bootstrap resamples or repeated fits performed? Until stability has been tested, please remove or qualify such claims that the factors are stable.

Similarly, the manuscript repeatedly states that sparse structure was “enforced by PNMF,” but non-negativity and sparsity are not the same property. If your implementation included a sparsity-inducing prior, penalty, or constraint, please describe it explicitly. If not, please revise this wording.

Please provide a table with the actual loading values for the highest-weighted variables in each factor. At present, Table 1 reports representative variables and interpreted labels, but not the numerical weights (i.e., how significant were they?). Please also explain the rule used to select the displayed variables: Did you show the top three, top four, or all variables above a particular threshold?

For Figure 2, please explain exactly what quantity is plotted in the participant-factor matrix. Is it the posterior mean of the Gaussian latent variable, the exponentiated posterior mean, the expectation of the exponentiated latent variable, or another quantity?

Concern 7: Provide stronger *qualitative* support for the results, especially via connections to the literature.

The Discussion section focuses too much on the limitations and general justifications of the method rather than going into sufficient detail about the psychological literature. I appreciate the

attempt to connect the results to prior studies, but I would like to see a more developed discussion of how meaningful these data-driven latent factors are when compared with categories and factors identified through existing psychological, qualitative, or clinical studies.

- How do your factors compare with established psychological constructs in the literature? Which latent factors appear to recover recognized constructs, and which appear to divide them into potentially new subconstructs? Are some of the distinctions produced by your model psychologically meaningful, or could they be artifacts of the chosen number of factors and numerical encoding?

This is particularly important because the source survey draws upon pre-existing questionnaires and behavioral domains. Your Discussion should explain whether PNMF recovers expected patterns, modifies them, or suggests distinctions that would merit further study. Even better, you could show how your results clarify an existing question or tension in the literature, or at least confirm prior findings in a new population and methodological setting.

- Please add references from the psychometric and eating-behavior literature that more directly address the structure and interpretation of eating-related questionnaire responses.

You should also revise the discussion of generalizability. The fact that this dataset was collected at a university in Bangladesh makes the setting valuable and underrepresented in the literature. However, a single-university sample does not establish that the identified structure generalizes across countries, cultures, age groups, or clinical populations. Hence, the statement that the dataset demonstrates that eating disorders are a global issue is too broad unless supported by appropriate literature. A more careful framing would be that the study provides an exploratory analysis in an underrepresented setting and motivates replication across additional populations.

At the same time, you can also make the potential broader contribution clearer: Given larger and more varied datasets, this approach could be applied to other survey populations and compared across demographic or cultural settings.

Concern 8: Address citations, formatting, and figure readability.

Please make sure you are following proper guidelines for in-line citations in APA style throughout the paper. For instance, when you are using a citation as the subject or object of a sentence, “Hasan et al., 2026” should be written as “Hasan et al. (2026).” Please also add sources for several methodological claims. For example:

“PPCA produces latent factors with both positive and negative values, making them difficult to interpret in behavioral context. NMF improves interpretability through non-negativity constraints, but does not have a probabilistic framework and can be sensitive to noise and initialization.”

Please cite sources and revise this wording carefully.

- Signed factors may be less straightforward to interpret as additive behavioral profiles, but they are not necessarily uninterpretable. Likewise, conventional NMF is often non-probabilistic, but probabilistic NMF variants do exist. It would be useful to add a sentence or two explaining the specific significance of non-negativity constraints in this

context: they can allow factors to be read as cumulative profiles rather than mixtures of positive and negative contributions.

Please be careful about punctuation, sentence structure, and repeated wording throughout the paper. A careful proofreading pass, potentially assisted by a tool such as Grammarly, would help.

Break up Figure 1 into multiple subfigures or enlarge it substantially. It is very difficult to read as currently presented because the labels are too small.

Overall: I think this is a promising work, and the relationship between the methods and the setting appears to be quite suitable. Again, I am impressed by seeing such an early-stage student researcher tackle these quite sophisticated computational methods. However, with great power comes great responsibility and care.

Before resubmission, please more clearly define the research question, explain and justify the preprocessing and likelihood choices, report the computational settings, test the robustness of the ten-factor model, qualify claims concerning stability and sparsity, improve the readability of the figures and equations, and expand the Discussion in a way that more firmly connects the results to the psychological and psychometric literature on eating-related behavior.

We would be glad to reconsider a substantially revised version of the manuscript.

Dear Editor,

Thank you for reviewing my paper and for taking the time to provide such detailed and specific feedback.

After reading all eight concerns carefully, I made a significant decision about how to revise the manuscript. Rather than trying to fix the problems within the original probabilistic non-negative matrix factorization (PNMF) framework, I substantially revised the manuscript by adopting a K-means clustering framework, which directly addresses my research question of identifying naturally occurring behavioral profiles among university students.

The reviewer's feedback helped me understand that several of the problems with my original paper were not surface-level issues I could address, they were fundamental to the method itself. The manuscript has therefore been extensively rewritten. The Introduction, Methods, Results, Discussion, Abstract, and figures have all been revised accordingly. Below we provide a point-by-point response to every reviewer comment together with references to the revised manuscript.

Reviewer Comment

Concern 1: Clarify the research question and the scope of your claims.
Response:
We agreed that the original manuscript placed too much emphasis on the computational methodology instead of the scientific question. To address this concern, we substantially revised the Introduction and clearly stated the research question near the end of the section (Please see introduction section in the paper, Line#: 82-94):

”*Can K-means clustering identify naturally occurring behavioral profiles from eating-disorder questionnaire responses collected from university students in Bangladesh, and do these profiles resemble those reported in previous studies conducted in predominantly Western populations?”*

The Abstract, Results, and Discussion were also revised so that the manuscript consistently focuses on answering this research question rather than emphasizing the machine learning algorithm itself.

Concern 2: Describe the dataset and preprocessing in substantially more detail.
Response:
The Dataset and Pre-processing section has been substantially expanded. The revised "Dataset and Pre-processing" section explains all of this step by step :

- Frequency-based responses ("Never," "Seldom," "Sometimes," "Often") were encoded as 0, 1, 2, and 3. Time-based responses ("No days" "1-12 days" "13-27 days" "Everyday") were also encoded 0-3. Both scales have a natural ordering, so this encoding preserves that ordering.

- Demographic variables (age, gender, education level, employment status, marital status, and perceived eating disorder status) were converted to numbers for processing but then excluded from the clustering entirely. They were used only afterward to characterize the clusters once formed. Only behavioral survey items were used to form the clusters, so the groups reflect eating-related behaviors rather than who the participants are.

- Behavioral variables with more than 20% missing responses were removed, leaving 50 variables. Remaining missing values were replaced with the median value of each variable.

- The 50 behavioral variables were grouped into five composite scores: Restrictive Eating (13 items), Emotional Eating (14 items), External Cue Eating (10 items), Body Image Concern (9 items), and Habitual/Loss of Control Eating (4 items). Each composite score is the average of its items.

- The five composite scores were standardized so that each one had a mean of zero and a standard deviation of one. This ensures that no single behavioral category dominates the clustering just because it happens to have a larger numerical scale.

Concern 3: Justify the use of a Poisson likelihood for ordinal and categorical survey responses. This was the most important methodological concern.

Response:
This concern helped me understand a fundamental problem with my original approach. The reviewer was correct: the Poisson distribution assumes the data represents counts of events, but my survey responses were ordinal categories, not counts. I could not find a principled justification for applying a Poisson model to this kind of data.

Rather than trying to defend an assumption I could not properly support, I chose a method that does not make this assumption at all. K-means clustering does not require any assumption about the distribution of the data. It works by calculating distances between participants based on their composite behavioral scores, which is an appropriate approach for ordinal survey data that has been averaged into composite scores. Because the primary objective of this study is to identify naturally occurring behavioral profiles rather than to develop a probabilistic latent-variable model, I substantially redesigned the methodology. The revised manuscript replaces the previous Probabilistic Non-negative Matrix Factorization (PNMF) approach with K-means clustering, an established unsupervised learning method widely used in behavioral and psychological research. This same approach has been used in published research on eating disorder survey data (García-García et al., 2021; Eck & Byrd-Bredbenner, 2021), which gave me confidence that it was a reasonable and defensible choice for my dataset.

Concern 4: Improve the explanation and reproducibility of the computational methods. Report all implementation details and fix the equation typesetting.

Response:
The reviewer pointed out that the original technical section was difficult to follow and could not be reproduced from the description alone. In the revised manuscript, the Methods section describes the K-means algorithm step by step in plain language:

(1) centroids are initialized using k-mean;
(2) each participant is assigned to the nearest centroid based on Euclidean distance;
(3) each centroid is recalculated as the mean of its assigned participants;
(4) steps 2 and 3 repeat until assignments no longer change.

The objective function is described in plain English rather than as an equation, because this avoids the typesetting problems that appeared in the original manuscript and is clearer for most readers. The concerns about variational inference, Monte Carlo sampling, the σ=1 prior, and the reparameterization trick do not apply to the revised manuscript.

Concern 5: Justify the choice of 10 latent dimensions with a sensitivity analysis.

Response:
In the revised paper, the equivalent decision is choosing K, the number of clusters. I selected K=3 using two data-driven methods, both reported in the results section:

First, the elbow method: I ran K-means for every value of K from 2 to 10 and measured how tight the groups were at each value (inertia). The inertia dropped by 277.9 points from K=2 to K=3, the largest single improvement across the entire range. After K=3, improvements became progressively smaller (202.3, 127.3, 111.1 points for K=4, 5, 6, and so on). This pattern, visible in Figure 1A, indicates that K=3 is where adding more groups stops providing meaningful improvement.

Second, the silhouette score: The highest score was at K=2 (0.2071). I chose K=3 rather than K=2 because three clusters provided distinct, interpretable behavioral profiles consistent with patterns identified in prior research, and because the elbow criterion supported it.

Both criteria are shown in Figure 1, which includes the elbow plot and silhouette scores as separately labeled subfigures.

Concern 6: Provide stronger quantitative support. Include a stability analysis and report actual numerical values rather than relying on visual inspection.

Response: The reviewer noted that the original paper claimed stability without testing it. This was a significant gap that I have addressed directly (Please see the Result section in the paper) .

The revised manuscript includes a formal stability analysis in both the Methods and Results sections. I ran K-means 100 times with different random starting points (seeds 0 through 99) while keeping everything else fixed. I then compared each result to the reference solution using the Adjusted Rand Index (ARI), which measures how similar two clustering solutions are. The results were: Average ARI: 0.996, Minimum ARI: 0.968, Maximum ARI: 1.000

These values show that the same three behavioral profiles emerged in almost every one of the 100 runs, confirming that the clusters are stable and not a product of a lucky random starting point. The Results section also reports all quantitative findings explicitly:

- Cluster sizes: 184 (33.5%), 186 (33.8%), and 180 (32.7%) participants.
- Mean behavioral scores for all five categories across all three clusters are reported in Table 1 and shown in Figure 2.
- Chi-square statistics with exact values and p-values for all five demographic variables are reported in the Demographics subsection.
- The most striking finding: eating disorder self-perception differed significantly across clusters, with 76.6%, 48.9%, and 35.6% of participants in each cluster reporting belief that they have an eating disorder.

Concern 7: Connect the results more firmly to the existing psychological literature. Revise the generalizability claims.
Response:

The reviewer asked me to explain more clearly how my clusters connect to established psychological constructs and prior research, and to be more careful about what I claimed my single-university study could show. In the revised Discussion, I connect each cluster to prior findings:

- Cluster 1 (high restrictive eating, high external food cue sensitivity) is connected to García-García et al. (2021), who identified a restrained eating group with similar characteristics using K-means. I also note that this cluster showed moderate, not high, body image concern, which may reflect a cultural difference from Western samples where restrictive eating is more often associated with body dissatisfaction. I discuss this as a finding that warrants further investigation rather than a definitive conclusion.

- Cluster 2 (low scores across all dimensions) is connected to the low-problematic eating groups identified in multiple prior studies. I am careful to note that this group should not be interpreted

as clinically healthy, it simply represents the lowest levels of the measured behaviors in this sample.

- Cluster 3 (high body image concern, high habitual eating) is connected to body-image and habit-driven profiles identified in prior research and contrasted with Cluster 1, which was driven more by intentional restriction.I also added two new references: Soodla et al. (2024), on latent profiles in eating disorders, and Yu et al. (2025), a large study that used K-means to identify three eating behavior profiles in adolescents, healthy eaters, restrictive eaters, and emotional eaters, which are directly comparable to what I found.

Regarding generalizability: I removed the statement that my dataset demonstrates eating disorders are a global issue, as the reviewer correctly noted this is too broad a claim for a single-university study. I now frame the Bangladesh setting as contributing an exploratory analysis in an underrepresented population and explicitly call for replication in future research.

Concern 8: Fix citations, formatting, and figure readability.
Response:
I have addressed all of the formatting concerns:

- All in-text citations now follow APA 7th edition format throughout. Author names are used as grammatical subjects where appropriate (e.g., "García-García et al. (2021) identified...") and parenthetical citations are used elsewhere.
- Figure 1 has been reorganized into two clearly labeled subfigures: (A) the elbow plot and (B) the silhouette scores, both with readable axis labels and titles.

- I have carefully proofread the entire manuscript, removing repeated phrases, fixing sentence structure, and replacing informal phrasing with clearer academic language.

- Methodological citations have been added where relevant, including the scikit-learn implementation used for all analysis.

I sincerely thank the Editor and Reviewer for taking the time to carefully review my manuscript and provide such thoughtful and constructive feedback. Your comments helped me improve the quality, clarity, and scientific rigor of this work. I carefully considered every suggestion and substantially revised the manuscript, including adopting a methodology that better aligns with my research question. I hope the revised manuscript and the detailed responses below satisfactorily address all of the concerns raised, and I respectfully submit it for your reconsideration.

Sincerely,
[redacted]

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

Anonymous

Abstract

Eating disorders are complex mental health conditions characterized by diverse eating-related behaviors that often co-occur. Identifying meaningful behavioral patterns in the questionnaire responses is difficult because individuals may show a combination of behaviors rather than fitting 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. The questionnaire data collected from 550 participants were preprocessed by encoding ordinal response categories, handling missing values, and grouping questionnaire items into five broader 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 optimal number of clusters was selected based on the elbow method, silhouette scores, and behavioral interpretability. Three distinct 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 highly reproducible. 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. Significantly, the pattern of body image concern observed differed from that commonly reported among Western populations, suggesting possible cultural variation in the relationships among eating-related behaviors.

Keywords:
K-means clustering, Unsupervised Machine Learning, Eating Disorders, Behavioral profiling, Cluster Analysis, Bangladesh

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 reproducible behavioral groups characterized by restrained eating, uncontrolled eating, and a low-symptom group characterized by minimal eating disorder behaviors. 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: Are the behavioral profiles identified in Western populations also observed in Bangladeshi university students? 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

An eating disorder survey dataset was analyzed to investigate eating-related behaviors among university students. 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 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.

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' perceived eating disorder status, were converted into numerical values for data processing. These

demographic 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. Behavioral variables with fewer than 80% nonmissing observations were excluded from the analysis, resulting in 50 retained behavioral variables. The missing values of other variables were replaced using the median values of those variables.

To simplify the behavioral dataset and make clustering results easier to interpret, the items in the questionnaire were grouped into five behavioral categories, depending on the eating-related behavioral construct measured by each question. Questionnaire items assessing similar behaviors were assigned to the same category based on their conceptual meaning. Specifically, items measuring food restriction or dieting behaviors were grouped under Restrictive Eating (13 questionnaire items), items measuring eating in response to emotions under Emotional Eating (14 questionnaire items), items assessing responsiveness to external food-related cues under External Cue Eating (10 questionnaire items), items describing body image and weight-related concerns under Body Image Concern (9 questionnaire items), and items assessing habitual or loss-of-control eating behaviors under Habitual/Loss-of-Control Eating (4 questionnaire items). A composite score for each behavioral category was calculated as the mean of the questionnaire items assigned to that category. This representation reduced the dimensionality of the dataset while preserving the major behavioral constructs that were assessed through the questionnaire, and the resulting five composite behavioral scores were used as the input variables for the cluster analysis.

Prior to clustering, the five composite behavioral scores were standardized using StandardScaler, which transformed each behavioral category to have a mean of zero and a standard deviation of one. This standardization ensured that each behavioral category contributed equally to the Euclidean distance calculations used by the K-means algorithm by preventing variables with larger variances from disproportionately influencing cluster assignment. 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

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. 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, each behavioral category contributed equally to the distance calculations. 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.

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 final selection of three clusters was based on examination of the elbow plot, silhouette scores, and the interpretability of the resulting behavioral profiles. The results of the cluster selection procedure are presented in the Results section.

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. The results of the stability analysis are presented in the Results section.

4. Results

Selection of the number of clusters

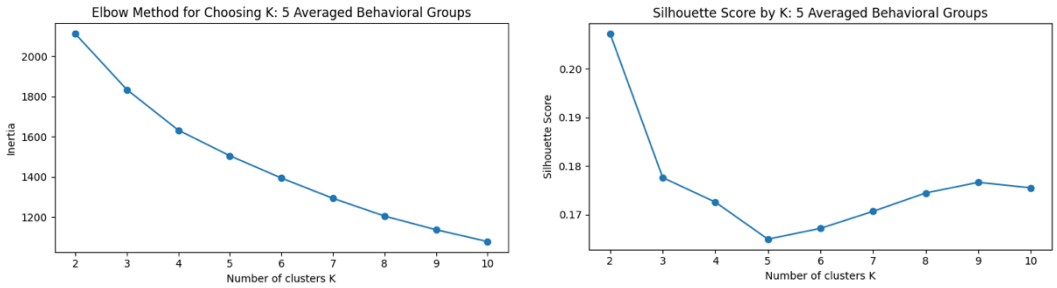
The optimal number of clusters was evaluated by fitting K-means models with values of K ranging from 2 to 10. Both the within-cluster sum of squares (inertia) and silhouette score were calculated for each value of K.

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.

To improve interpretability, the original questionnaire items were averaged into five behavioral categories before repeating the clustering analysis. From the elbow plot, there was a clear reduction in inertia after about three clusters (Figure 1A): inertia decreased from 2112.9 at K=2 to 1835.0 at K=3, a reduction of 277.9 points, with progressively smaller reductions of 202.3, 127.3, 111.1, 100.8, 88.2, 67.9, and 58.9 points for K=4 through K=10, respectively. The silhouette scores showed a substantial increase compared to the full variable analysis, with the highest value recorded for K=2 (0.2071) (Figure 1B). While the two-cluster solution produced the highest silhouette score, a three-cluster solution was selected because it corresponded with the elbow criterion, provided greater behavioral interpretability, and was consistent with previous studies that identified restrained eating, uncontrolled eating, and low-problematic behavioral profiles.

Figure 1

Selection of the number of clusters using the 5 averaged behavioral groups. (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 improved cluster separation while reducing the complexity of the behavioral data. 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 analyses were based on the five-group behavioral representation with three clusters.

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

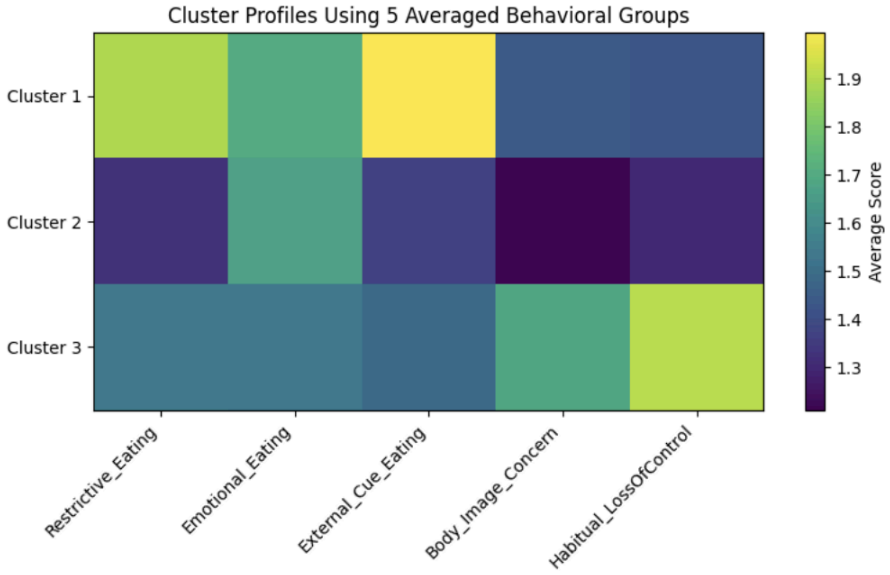
Average behavioral scores across the five behavioral categories for each identified cluster.

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

Figure 2

Heatmap showing the average behavioral scores for the five behavioral categories across the three identified clusters.



Distinct behavioral differences 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 was the one that had the lowest scores on almost all behavioral categories, suggesting comparatively fewer problematic eating behaviors. 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. In each cluster, there is a distinct pattern of average behavioral scores, suggesting that individuals showed variance across several behavioral dimensions instead of one continuous scale of eating-related behaviors.

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.

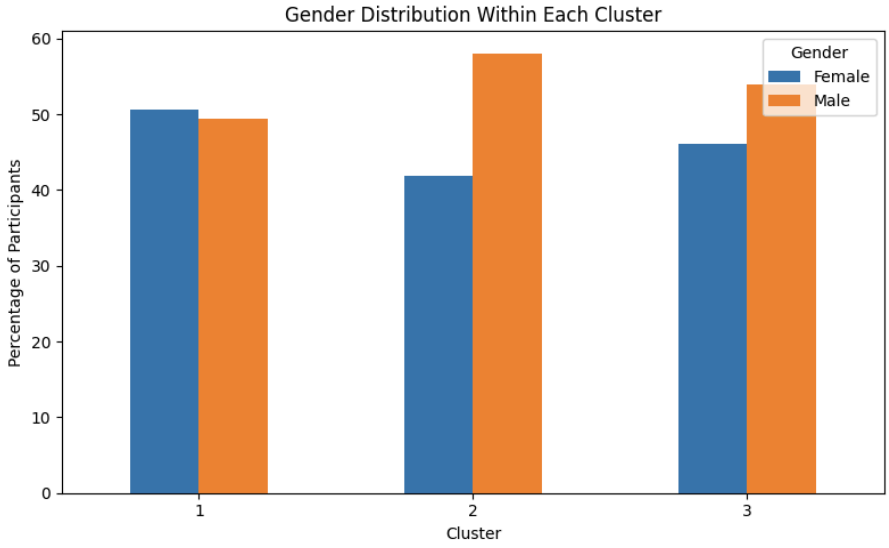
Gender

Gender distributions were relatively similar across the three behavioral profiles (Figure 3). Cluster 1 contained nearly equal

proportions of females (50.5%) and males (49.5%). Cluster 2 included a greater proportion of males (58.1%) than females (41.9%), while Cluster 3 consisted of 53.9% males and 46.1% females. No significant difference in gender distribution was observed across clusters (χ^2 (2, N = 550) = 2.76, p = .252).

Figure 3

Gender distribution within each identified behavioral cluster

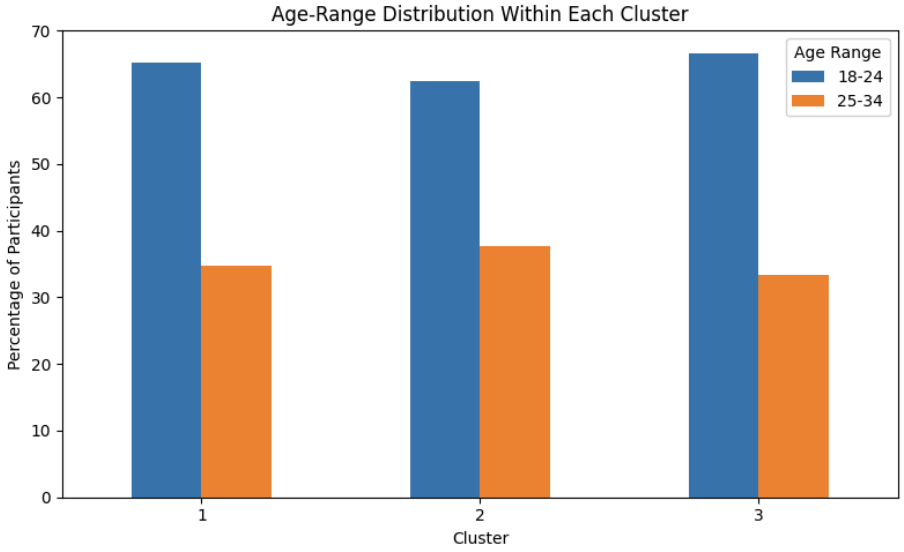


Age

Participants aged 18- 24 years were the majority among all behavioral profiles (Figure 4). These individuals made up anywhere from 62.4 to 66.7 percent of the participants in all three clusters, while participants aged 25–34 represented the other third in each cluster. Age range did not differ significantly across the three clusters (χ^2 (2, N = 550) = 0.77, p = .680).

Figure 4

Age-range distribution within each cluster

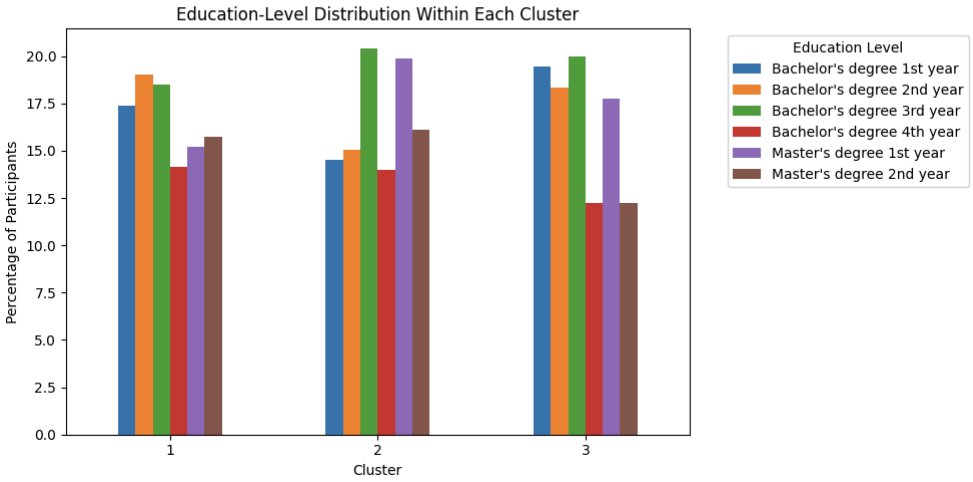


Educational level

Educational distribution was quite similar for the three clusters (Figure 5). Participants with a bachelor's degree made up the biggest proportion of the educational categories within all behavioral clusters, while those with a master's degree represented smaller proportions. There was little difference among the clusters. Education level showed no significant difference across clusters (χ^2 (10, N = 550) = 5.07, p = .887).

Figure 5

Educational-level distribution within each cluster



Employment and Marital Status

Employment status as well as marital status was similarly distributed between the three behavioral profiles. Students comprised the majority in the employment category within each cluster, whereas single participants were the majority in the marital status category. Overall, there were no significant differences between the clusters in terms of employment and marital status.

Demographic characteristics overall showed much less variance than did behavioral characteristics, suggesting that the clustering solution primarily reflected differences in eating-related behaviors rather than demographic composition. Chi-square tests confirmed that neither employment status (χ^2 (6, N = 550) = 5.32, p = .503) nor marital status (χ^2 (4, N = 550) = 5.20, p = .268) differed significantly across the three clusters.

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. In contrast to the five demographic variables, eating disorder self-perception was the only measured characteristic that differed significantly across the identified behavioral profiles.

Stability Analysis

The robustness 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 distinct behavioral profiles generated

were reproducible and were not substantially influenced by random centroid initialization.

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 distinct behavioral profiles emerged, suggesting that eating-related behaviors within this population can be organized into distinct behavioral patterns using an unsupervised learning approach. Furthermore, the stability analysis indicated that these behavioral profiles were highly reproducible across repeated clustering analyses, supporting the stability and robustness of the identified cluster solution.

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 low-symptom group characterized by minimal eating disorder behaviors. The participants who were assigned to this cluster exhibited the lowest average scores in almost all behavioral categories such as Restrictive Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating, whereas the score for Emotional Eating was fairly moderate. These results suggest that the participants in this cluster reported comparatively few eating disorder-related behaviors across the measured domains. Since the clustering analysis was an exploratory one based on only questionnaire results, this particular profile cannot be seen as an indicator of the lack of eating disorder risk or the presence of a clinically healthy group. Rather, it represents the group with the lowest overall levels of eating disorder-related behaviors within the present sample.

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 important contribution made by the current study is its focus on university students from Bangladesh, a population that remains underrepresented in quantitative eating disorder research. Most of the clustering studies have been carried out among Western samples, while very few studies have been done investigating eating-related behavioral patterns related to eating disorders among South Asian populations. While the current study has found behavioral profiles that are quite similar to those seen in previous studies, some differences have been noticed. In particular, Cluster 1 has relatively higher restrictive eating behavior scores even when the Body Image Concern score is moderate. This observation suggests that restrictive eating behaviors within this population may not always be associated with the greatest levels of body image dissatisfaction. Cultural, environmental, or social influences may therefore contribute differently to eating-related behaviors than has been reported in predominantly Western populations. As the factors mentioned above were not assessed in the current study, further studies are needed to better understand the difference.

The stability analysis further supported the identified behavioral profiles. 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 reproducible despite different centroid initializations. Based on the high average ARI score, along with the low variance between the minimum and maximum ARI scores, it suggests that the three identified behavioral profiles represent stable patterns within the dataset rather than clusters produced by random initialization. The fact that the solution is reproducible further supports the robustness of the final clustering solution.

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, alongside the absence of significant demographic differences across clusters, suggests that eating disorder self-awareness in this sample was more closely associated with behavioral patterns than with demographic characteristics. This finding supports the potential relevance of behavioral profiling as an exploratory tool for understanding variation in eating disorder recognition within university populations.

From the demographic analyses, there appeared to be very minimal differences between the clusters based on gender, age group, education level, employment, and marital status. The participants belonging to the age group of 18-24 years comprised the majority of all behavioral profiles, since this study was conducted among the population of the university. Similarly, there seemed to be minimal differences in the distribution of gender, education, employment, and marital status among the three behavioral clusters identified. These findings suggest that the behavioral profiles primarily reflected variation in eating-related behaviors rather than demographic characteristics.

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. 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 distinct behavioral profiles in university students by using the data from an eating disorder questionnaire. The three identified clusters captured distinct patterns of eating-related behaviors, but at the same time, they were highly stable across repeated analyses. By applying clustering analysis to a relatively unexplored Bangladeshi population and showing a robust clustering solution, 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 people into clusters according to similarities in their eating-related behavioral patterns.

Three distinct behavioral profiles emerged from the analysis that differed across Restrictive Eating, Emotional Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating. Selection of the cluster solution was done based on the elbow criterion and silhouette scores, and the resulting profiles were highly reproducible across repeated clustering analyses, indicating high stability. Eating disorder self-perception also differed significantly across clusters (χ^2 (2, N = 550) = 64.47, p < .001), suggesting that identified behavioral profiles were significantly associated with participants' self-perceptions of their eating disorder status. Additionally, 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 Kaggle and is based on the dataset introduced by Hasan et al. The dataset contains responses from 550 university students at Daffodil International University in Bangladesh, collected between August and November 2024.

Dataset repository:
https://www.kaggle.com/datasets/jocelyndumlao/neurobehavioral-factors-in-eating-disorders-study/data

The figures and analyses presented in this study were generated using this publicly available resource.

Mentor Contribution Statement

Mentor 1 provided instruction and guidance on the K-means clustering framework and the data analysis approach, including preprocessing, cluster selection, and stability analysis.

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

This is an interesting and potentially valuable study using k-means clustering to examine eating-related behavioral profiles among university students in Bangladesh. The introduction is particularly strong: it clearly establishes the importance of eating disorders, explains the value of unsupervised learning for identifying patterns that may not fit predefined diagnostic categories, and motivates the need to extend this work beyond predominantly Western populations.

My main concerns relate to several analytical choices that strongly shape the results but are not sufficiently justified or validated. **I recommend acceptance with major revisions.**

1. **The five behavioral categories need more justification**

My biggest concern is the decision to reduce the questionnaire items into five subjective categories, and then perform the primary analysis on those 5 averages. This seems at odds with the motivation for using unsupervised learning: namely to allow the patterns to emerge from higher-dimensional data without imposing predefined structure. More importantly, there is currently little data or evidence presented by the authors showing that these five categories are valid or preferable to other possible groupings.

Please expand Section 2 to explain which questions were assigned to each category, provide representative examples, explain how the categories were selected, and provide evidence that the items within each category measure a coherent construct. A complete item to category table should be included in the appendix.

Similarly, please clarify how many questions were excluded for having less than 80% nonmissing data and why 80% was chosen as the threshold.

The manuscript should also provide stronger evidence for using the five-category solution instead of the 50-variable analysis. The variable-level clustering has very low silhouette scores, whereas separation improves after the questions are grouped. Could the variable-level data itself be used to validate the proposed categories? For example, through factor analysis, PCA, or clustering of questionnaire items? Even if the 5 conceptual categories are retained, some empirical validation would make the downstream results much more convincing.

2. **The 3-cluster solution is not yet fully convincing**

The paper describes 3 distinct profiles, but the highest silhouette score occurs at k=2, not k=3. I recommend directly comparing the 2 and 3 cluster solutions. What is gained from k=3 over k=2, and do the results change substantively under k=2?

I would also avoid circular reasoning when relying on similarity to previous 3-cluster studies when selecting k=3 and then presenting the similarity as evidence that the Bangladeshi sample reproduces Western patterns. Because one of the goals is to test whether previously observed

profiles appear in Bangladesh, the cluster selection process should be more independent of that expectation.
Finally, the high ARI across random seeds is is useful evidence that k-means reliably converges to the same solution, but it doesn't mean the clusters would reproduce in another sample. A bootstrap or participant subsampling analysis would provide stronger evidence for stability. Otherwise, I suggest narrowing the claims that the clusters are "robust" or "distinct".

3. **The relationship between the clusters and eating-disorder risk needs clearer interpretation**

The non-clinical university sample is an interesting contribution, but the cluster means in Table 1 are generally below the midpoint of the response scale, while the percentage of participants reporting that they believe they have an eating disorder is surprisingly high.

I would like to better understand how these findings fit together. Please describe the eating-disorder self-perception question and its response options in the dataset section, since this variable becomes an important finding later in the paper.

I also think the analysis would benefit from examining participants with more clearly elevated behavioral responses. For example, the authors could report the percentage within each cluster who score above the scale midpoint on multiple items or domains, or who select the highest response category on multiple questions. This would help distinguish differences among generally low-scoring participants from profiles that may reflect more meaningful eating-disorder risk.

Additional comments

- For the demographic analysis, consider reporting the distribution of cluster membership within each demographic group rather than demographic composition within each cluster. This would make demographic comparisons easier since the distributions differ across groups.
- I would also temper the conclusion that demographics are unrelated to the behavioral profiles, given that this is a fairly homogenous university sample, particularly in age, education, employment, and marital status.
- Finally, I found the cultural discussion very interesting but somewhat underdeveloped. The observation that restrictive eating might occur without especially high body-image concern could be important, but would benefit from a more thorough exploration of existing literature on eating disorders and body image in Bangladesh or South Asia.

Recommendation

Accept with major revisions.

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

Recommendation: Accept with major revisions

Overall Comments: This paper applies K-means clustering to a dataset of surveys on eating habits of university students in Bangladesh. It is an important area of study and well-motivated with a thorough literature review. The method chosen is appropriate and the results align with previous research on different eating behavior profiles. An additional strength is the stability analysis. Given this, I think this paper is acceptable for publication after major revisions. More background needs to be included about the dataset and the methods used, with appropriate motivation or references. I recommend that the results section is significantly restructured: The paper needs a "Table 1" summarizing the cohort and also displaying statistics of the demographics for the different clusters found (currently the paper uses bar charts which are not effective for identifying trends or rigorous for identifying statistical associations). In addition, the analysis of the behavioral categories across clusters needs to be expanded, or else clarified that it is purely descriptive and no statistical conclusions can be drawn.

Domains for Evaluation:

- Originality & Significance – *Good:* K-means clustering is a well-established method which appears to have been applied to similar dataests before, but here it is novel to apply it to this large dataset from a unique population. The introduction properly motivates the need to study this topic for non-Western cohorts.
- Clarity & Structure – *Needs Improvement:* The introduction and methods sections are well-organized. However, the results section could use significant re-arrangement to more closely follow the standard for scientific research. See specific comments below. As an overall comment, the introduction, discussion, and conclusion sections could be shortened in length (e.g. repeating the results on self-perception in multiple places).
- Use of Evidence & Research Methods – *Good:* The methods are rigorous with clear justificiation at each step. There are a few places that could use elaboration, as noted below. The K-means clustering method is strengthed by the selection of K by two methods and the stability analysis.
- Engagement with Literature – *Excellent:* The introduction appropriately motivates the research question using relevant papers. The discussion explicitly compares the identified clusters to those noted in other studies.
- Grammar & Language – *Good:* The writing is generally clear and professional throughout.

Major Changes:

- Dataset background: Since the author did not collect the data as part of this study, the source should be cited in the main text of the paper (not just the data availability statement). I would like more detail about the dataset and the study that used it first.

Was there any info about the response rate? Were any participants excluded? Did the original survey designated the behaviorial groupings, or is this something the author did for the current analysis? Including an example question from each behavioral category could be useful.

- The information displayed in Figures 3, 4, 5 would be better displayed in table format with the exact values printed. I recommend combining this info with Table 1 to create an overall summary of the demographics (commonly done as “Table 1” in scientific papers). Columns are the three clusters and an additional “Overall” column to show the distribution of demographics for the entire cohort. An additional column can display the p-value for the comparison between clusters.
- The methods section should be expanded to include more background description of the K-means clustering method and cluster selection process. Imagine you’re writing for another high school student who is not familiary with this method. Explain at a high level and/or give citations for other references to learn. The current section is a good start, but some methods could be elaborated. E.g., what is the k-means++ initialization method? What is silhouette score?
- What is the maximum score in each behavioral category? It is not clear to me based on how this is described. Since it is categorical responses, it would be more appropriate to report as percentages instead of the average score (i.e. X% score 0, Y% score 1) and in this case the heat map is not the best visaulization.
- Comparison of behavioral categories: Why was there no statistical test to evaluate differences in behavioral categories amongst the clusters? Table 1 and Figure 1 display means, but this is all exploratory/descriptive. Either test if there are significant differences, or make it very clear throughout (and in the discussion) that all conclusions are from an exploratory analysis.
- Consider reporting effect sizes alongside the chi-square tests for demographics. Given the sample size, it would strengthen the demographic comparisons to report an effect size measure (e.g., Cramer's V) in addition to the chi-square statistics and p-values, since statistical significance alone does not indicate the practical size of an association.

Minor Suggestions:

- In the abstract, the phrase “the questionnaire” responses is used in the second sentence before introducing the questionnaire. I think this sentence could be deleted entirely and overall the abstract tightened up.
- Tools used such as StandardScaler should have a citation.

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

Anonymous

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 broader 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 distinct 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 was 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. Significantly, the pattern of body image concern observed differed from that commonly reported among Western populations, highlighting an area for further cross-cultural investigation.

Keywords:
K-means clustering, Unsupervised Machine Learning, Eating Disorders, Behavioral profiling, Cluster Analysis, Bangladesh

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 reproducible behavioral groups characterized by restrained eating, uncontrolled eating, and a low-symptom group characterized by minimal eating disorder behaviors. 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: Are the behavioral profiles identified in Western populations also observed in Bangladeshi university students? 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 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. This representation reduced the dimensionality of the dataset while preserving the major behavioral constructs that were assessed through the questionnaire, and the resulting five composite behavioral scores were used as the input variables for the cluster analysis.

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 ensured that each behavioral category contributed equally to the Euclidean distance calculations used by the K-means algorithm by preventing variables with larger variances from disproportionately influencing cluster assignment. 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

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, each behavioral category contributed equally to the distance calculations. 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.

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. The final cluster solution was chosen based on these

quantitative measures along with the additional behavioral structures captured by each solution. The results of this comparison are presented in the Results section.

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

Selection of the number of clusters

The optimal 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.

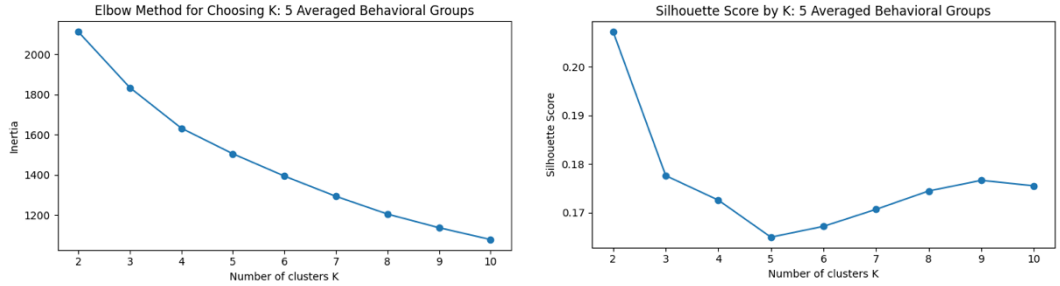
The clustering analysis was then repeated using the five composite behavioral categories. The inertia curve again suggested an elbow around K=3 (Figure 1A), with inertia decreasing from 2112.9 at K=2 to 1835.0 at K=3. In contrast, the silhouette score was highest at K=2 (0.2071), compared with 0.1776 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 retained 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.

Figure 1

Selection of the number of clusters using the 5 averaged behavioral groups. (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 improved cluster separation while reducing the complexity of the behavioral data. 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 analyses were based on the five-group behavioral representation with three clusters.

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 have a more interpretable characterization of behavioral elevation in each cluster, the proportion of participants with scores greater than the scale midpoint (>1.5) on each behavioral category was analyzed. 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 elevated responses across individual and multiple behavioral categories.

To evaluate whether the observed differences in behavioral scores across clusters were statistically significant, 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 results confirm that the three behavioral clusters differed significantly across all measured behavioral domains.

Figure 2

Radar chart showing the mean composite behavioral scores across the five behavioral categories for the three identified clusters. Composite scores range from 0 to 3.



Distinct behavioral differences 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 was the one that had the lowest scores on almost all

behavioral categories, suggesting comparatively fewer problematic eating behaviors. 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. In each cluster, there is a distinct pattern of average behavioral scores, suggesting that individuals showed variance across several behavioral dimensions instead of one continuous scale of eating-related behaviors.

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. 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.

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%)		

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.

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. In contrast to the five demographic variables, eating disorder self-perception was the only measured characteristic that differed significantly across the identified behavioral profiles.

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 distinct behavioral profiles emerged, suggesting that eating-related behaviors within this population can be organized into distinct behavioral patterns using an unsupervised learning approach. Furthermore, the stability analysis indicated that these behavioral profiles were highly stable across different random centroid initializations within the present dataset, supporting the stability of the identified cluster solution.

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.

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 low-symptom group characterized by minimal eating disorder behaviors. The participants who were assigned to this cluster exhibited the lowest average scores in almost all behavioral categories such as Restrictive Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating, whereas the score for Emotional Eating was fairly moderate. These results suggest that the participants in this cluster reported comparatively few eating disorder-related behaviors across the measured domains. Since the clustering analysis was an exploratory one based on only questionnaire results, this particular profile cannot be seen as an indicator of the lack of eating disorder risk or the presence of a clinically healthy group. Rather, it represents the group with the lowest overall levels of eating disorder-related behaviors within the present sample.

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. However, it suggests that assessment tools and conceptual frameworks developed primarily in Western contexts may not fully capture the range of eating-disorder presentations relevant to Bangladeshi university populations and supports further research examining culturally sensitive approaches in this setting.

The stability analysis further supported the identified behavioral profiles. 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, while the Kruskal-Wallis tests confirm statistically significant differences across clusters, all behavioral comparisons remain exploratory in nature and do not support causal conclusions. 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 distinct behavioral 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 distinct behavioral profiles emerged 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 figures and analyses presented in this study were generated using this publicly available resource.

Mentor Contribution Statement

Mentor 1 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	Restrictive Eating	Never (0); Seldom (1); Sometimes (2);	0	3

			Control		Often (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 like 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

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 Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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 Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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: seeing your shape in the mirror, in a shop window reflection, while undressing or taking a bath or shower)?	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3

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 crave them?	Section F: Reward Processing/Habit Formation	Habitual/Loss-of-Control Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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

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

Anonymous

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 broader 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 distinct 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 was 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. Significantly, the pattern of body image concern observed differed from that commonly reported among Western populations, highlighting an area for further cross-cultural investigation.

Keywords:
K-means clustering, Unsupervised Machine Learning, Eating Disorders, Behavioral profiling, Cluster Analysis, Bangladesh

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 reproducible behavioral groups characterized by restrained eating, uncontrolled eating, and a low-symptom group characterized by minimal eating disorder behaviors. 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: Are the behavioral profiles identified in Western populations also observed in Bangladeshi university students? 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 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. This representation reduced the dimensionality of the dataset while preserving the major behavioral constructs that were assessed through the questionnaire, and the resulting five composite behavioral scores were used as the input variables for the cluster analysis.

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 ensured that each behavioral category contributed equally to the Euclidean distance calculations used by the K-means algorithm by preventing variables with larger variances from disproportionately influencing cluster assignment. 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

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, each behavioral category contributed equally to the distance calculations. 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.

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. The final cluster solution was chosen based on these

quantitative measures along with the additional behavioral structures captured by each solution. The results of this comparison are presented in the Results section.

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

Selection of the number of clusters

The optimal 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.

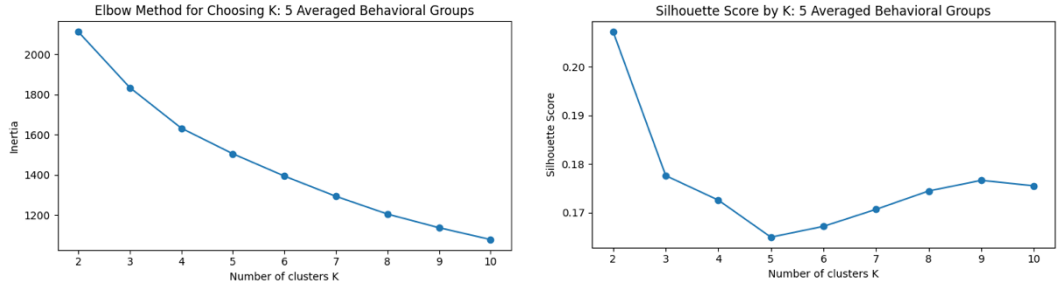
The clustering analysis was then repeated using the five composite behavioral categories. The inertia curve again suggested an elbow around K=3 (Figure 1A), with inertia decreasing from 2112.9 at K=2 to 1835.0 at K=3. In contrast, the silhouette score was highest at K=2 (0.2071), compared with 0.1776 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 retained 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.

Figure 1

Selection of the number of clusters using the 5 averaged behavioral groups. (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 improved cluster separation while reducing the complexity of the behavioral data. 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 analyses were based on the five-group behavioral representation with three clusters.

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 have a more interpretable characterization of behavioral elevation in each cluster, the proportion of participants with scores greater than the scale midpoint (>1.5) on each behavioral category was analyzed. 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 elevated responses across individual and multiple behavioral categories.

To evaluate whether the observed differences in behavioral scores across clusters were statistically significant, 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 results confirm that the three behavioral clusters differed significantly across all measured behavioral domains.

Figure 2

Radar chart showing the mean composite behavioral scores across the five behavioral categories for the three identified clusters. Composite scores range from 0 to 3.



Distinct behavioral differences 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 was the one that had the lowest scores on almost all

behavioral categories, suggesting comparatively fewer problematic eating behaviors. 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. In each cluster, there is a distinct pattern of average behavioral scores, suggesting that individuals showed variance across several behavioral dimensions instead of one continuous scale of eating-related behaviors.

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. 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.

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%)		

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.

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. In contrast to the five demographic variables, eating disorder self-perception was the only measured characteristic that differed significantly across the identified behavioral profiles.

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 distinct behavioral profiles emerged, suggesting that eating-related behaviors within this population can be organized into distinct behavioral patterns using an unsupervised learning approach. Furthermore, the stability analysis indicated that these behavioral profiles were highly stable across different random centroid initializations within the present dataset, supporting the stability of the identified cluster solution.

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.

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 low-symptom group characterized by minimal eating disorder behaviors. The participants who were assigned to this cluster exhibited the lowest average scores in almost all behavioral categories such as Restrictive Eating, External Cue Eating, Body Image Concern, and Habitual/Loss-of-Control Eating, whereas the score for Emotional Eating was fairly moderate. These results suggest that the participants in this cluster reported comparatively few eating disorder-related behaviors across the measured domains. Since the clustering analysis was an exploratory one based on only questionnaire results, this particular profile cannot be seen as an indicator of the lack of eating disorder risk or the presence of a clinically healthy group. Rather, it represents the group with the lowest overall levels of eating disorder-related behaviors within the present sample.

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. However, it suggests that assessment tools and conceptual frameworks developed primarily in Western contexts may not fully capture the range of eating-disorder presentations relevant to Bangladeshi university populations and supports further research examining culturally sensitive approaches in this setting.

The stability analysis further supported the identified behavioral profiles. 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, while the Kruskal-Wallis tests confirm statistically significant differences across clusters, all behavioral comparisons remain exploratory in nature and do not support causal conclusions. 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 distinct behavioral 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 distinct behavioral profiles emerged 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 figures and analyses presented in this study were generated using this publicly available resource.

Mentor Contribution Statement

Mentor 1 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 like 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
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 Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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 Processing	External Cue Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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: seeing your shape in the mirror, in a shop window reflection, while undressing or	Section E: Body Image Processing	Body Image Concern	No days (0); 1-12 days (1); 13-27 days (2); Every day (3)	0	3

		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 crave them?	Section F: Reward Processing/Habit Formation	Habitual/Loss-of-Control Eating	Never (0); Seldom (1); Sometimes (2); Often (3)	0	3
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

Response to Reviewers

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

Dear Editor and Reviewers,

Thank you for the constructive evaluation of my manuscript. I appreciate the reviewers' positive assessment of the study's motivation and their thoughtful comments and suggestions for improving the quality and clarity of my work. I have carefully considered all comments and have substantially revised the manuscript accordingly. My point-by-point responses are provided below.

Response to Reviewer 1

Comment: The five behavioral categories need more justification

My biggest concern is the decision to reduce the questionnaire items into five subjective categories, and then perform the primary analysis on those 5 averages. This seems at odds with the motivation for using unsupervised learning: namely to allow the patterns to emerge from higher-dimensional data without imposing predefined structure. More importantly, there is currently little data or evidence presented by the authors showing that these five categories are valid or preferable to other possible groupings.

Please expand Section 2 to explain which questions were assigned to each category, provide representative examples, explain how the categories were selected, and provide evidence that the items within each category measure a coherent construct. A complete item to category table should be included in the appendix.

Similarly, please clarify how many questions were excluded for having less than 80% nonmissing data and why 80% was chosen as the threshold. The manuscript should also provide stronger evidence for using the five-category solution instead of the 50-variable analysis. The variable-level clustering has very low silhouette scores, whereas separation improves after the questions are grouped. Could the variable-level data itself be used to validate the proposed categories? For example, through factor analysis, PCA, or clustering of questionnaire items? Even if the 5 conceptual categories are retained, some empirical validation would make the downstream results much more convincing.

Response: Thank you for this comment. We extended the "*Dataset and Preprocessing*" section to clarify how the 50 behavioral items were grouped into 5 categories according to the behavioral constructs represented by Sections B through F of the original questionnaire and the content of the individual items. In addition, we included *Appendix Table A1*, which provides the complete item-to-category mapping, original survey section, response scale, and scoring information for all 50 behavioral items. We also clarified that all 50 behavioral items had complete responses across 550 participants, so no items were excluded for missing data. The 80% nonmissing threshold is a commonly used convention in survey data analysis. Since all 50

items had complete data, this criterion did not result in any exclusions and was therefore removed from the revised methodology. We therefore removed this unnecessary filtering criterion from the revised methodology and noted that all 50 behavioral items were retained.

Comment: The 3-cluster solution is not yet fully convincing

The paper describes 3 distinct profiles, but the highest silhouette score occurs at k=2, not k=3. I recommend directly comparing the 2 and 3 cluster solutions. What is gained from k=3 over k=2, and do the results change substantively under k=2?

I would also avoid circular reasoning when relying on similarity to previous 3-cluster studies when selecting k=3 and then presenting the similarity as evidence that the Bangladeshi sample reproduces Western patterns. Because one of the goals is to test whether previously observed profiles appear in Bangladesh, the cluster selection process should be more independent of that expectation.

Finally, the high ARI across random seeds is useful evidence that k-means reliably converges to the same solution, but it doesn't mean the clusters would reproduce in another sample. A bootstrap or participant subsampling analysis would provide stronger evidence for stability. Otherwise, I suggest narrowing the claims that the clusters are "robust" or "distinct".

Response: Thank you for your comment. We adjusted our cluster selection analysis to compare K=2 and K=3 directly, rather than choose K=3 based on interpretation. Although K=2 had a higher silhouette score (0.2071 compared to 0.1776 for K=3), the direct comparison showed that K=2 primarily separated participants according to overall behavioral response levels. In contrast, K=3 captured additional differences in the patterns of responses across the five behavioral categories. We also analyzed how the participant assignments changed between the two solutions. The reason for and procedure for this comparison have been added in the Materials and Methods, *"Selection of the number of clusters"* section, and the numerical and behavioral comparison has been added in the Results, *"Selection of the number of clusters"* section. A brief interpretation was also added in the Discussion.

We modified the rationale for selecting our clusters so that similarity to previously reported three cluster solutions was no longer evidence for selecting K=3. Rather, the final selection was based on the elbow and silhouette results combined with a direct comparison of the behavioral structure and participant assignments produced by K=2 and K=3. Comparison with previous literature is saved for interpretation in the Discussion.

Lastly, we clarified that the high ARI values are an indication of stability across different random centroid initializations within the present dataset, instead of reproducibility across independent samples. We therefore narrowed claims of robustness and reproducibility and suggested bootstrap or participant subsampling analyses and independent sample validation for further studies in the discussion section.

Comment: The relationship between the clusters and eating-disorder risk needs clearer interpretation

The non-clinical university sample is an interesting contribution, but the cluster means in Table 1 are generally below the midpoint of the response scale, while the percentage of participants reporting that they believe they have an eating disorder is surprisingly high.

I would like to better understand how these findings fit together. Please describe the eating-disorder self-perception question and its response options in the dataset section, since this variable becomes an important finding later in the paper.

I also think the analysis would benefit from examining participants with more clearly elevated behavioral responses. For example, the authors could report the percentage within each cluster who score above the scale midpoint on multiple items or domains, or who select the highest response category on multiple questions. This would help distinguish differences among generally low-scoring participants from profiles that may reflect more meaningful eating-disorder risk.

Response:

Thank you for this perceptive observation. The reviewer has identified an apparent tension in the results that deserves a clearer explanation. I have addressed both requests, describing the ED self-perception item in the Dataset section and adding above-midpoint analysis to the Results section.

I have added the following to the *"Dataset and Pre-processing section"*: "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 apparent contradiction between moderate cluster means and high ED self-perception rates is resolved when the composite scores are examined more carefully. Composite scores average across all items within a category, including items on which a student scores low, which naturally pulls the mean toward the center of the scale even when some behaviors are strongly elevated. The above-midpoint analysis, which I have added to the Results section, clarifies this directly.

In Cluster 1, 98.9% of participants scored above the scale midpoint on Restrictive Eating and 98.4% on External Cue Eating, meaning that nearly every student in this cluster showed elevated scores on these two domains, even though the composite mean of 1.89 and 2.00 appears moderate on a 0–3 scale. Additionally, 90.8% of Cluster 1 participants scored above the midpoint on three or more behavioral domains simultaneously, and 50.5% scored above the midpoint on four or more domains. It is this breadth of elevated behavioral responding, high restriction and high external cue sensitivity occurring together, that likely drives the high ED self-perception rate of 76.6% in this cluster.

In Cluster 3, 72.8% of 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 domains simultaneously. This sustained multi-domain elevation corresponds to a 35.6% ED self-perception rate, lower than Cluster 1 but substantially higher than would be expected if behavioral scores were uniformly low.

In contrast, Cluster 2 showed an above-midpoint rate of 66.7% for Emotional Eating, while rates for the other four behavioral domains ranged from 11.8% to 29.0%, and only 18.8% of Cluster 2 participants scored above the midpoint on three or more domains simultaneously. This group's 48.9% ED self-perception rate is notably higher than its behavioral profile might predict, which I have acknowledged in the Discussion as a finding that warrants further investigation, possibly reflecting subjective distress or awareness of disordered eating patterns not fully captured by the composite scores.

These additions can be found in the Dataset and Pre-processing section and the Results section ("Behavioral profiles identified by K-means clustering," new paragraph following Table 1).

Comment: Demographic analysis

For the demographic analysis, consider reporting the distribution of cluster membership within each demographic group rather than demographic composition within each cluster. This would make demographic comparisons easier since the distributions differ across groups.

Response:
Thank you for this helpful suggestion. We revised the demographic analysis to report the distribution of cluster membership within each demographic group rather than the demographic composition within each cluster. We also replaced the previous demographic figures with a single summary table (Table 2) reporting exact counts and percentages for the overall sample and each of the three behavioral clusters, together with the corresponding chi-square *p*-values and Cramér's *V* effect sizes.

I have revised the discussion of the demographic findings accordingly. The original conclusion, that demographic variables are unrelated to behavioral profiles, was too strong given the composition of the sample. The dataset is relatively homogeneous: 64.7% of participants were aged 18–24, all participants were university-enrolled, 44.0% identified as students in terms of employment status, and 37.8% were single. When a sample has limited variation on demographic characteristics, statistical tests comparing groups may have reduced power to detect associations even if those associations exist in more diverse populations.

I have added the following to the Results section: The finding that no demographic variable differed significantly across clusters should be interpreted with caution. This university sample is relatively homogeneous in age (64.7% aged 18–24), education (all university-enrolled), employment status (44.0% students), and marital status (37.8% single). The limited

demographic variability may reduce the statistical power to detect associations between demographic characteristics and behavioral profiles. Studies that include more demographically diverse samples, spanning wider age ranges, varied educational backgrounds, and different employment contexts, would be needed to draw stronger conclusions about the relationship between demographic factors and eating-related behavioral profiles.

I have also revised the Discussion to replace the original conclusion with more cautious language: rather than stating that demographics are unrelated to behavioral profiles, the revised text states that no significant demographic differences were observed within this particular sample, and notes that replication in more diverse populations is needed before broader conclusions can be drawn.

Comment: Interpretation of demographic differences

I would also temper the conclusion that demographics are unrelated to the behavioral profiles, given that this is a fairly homogenous university sample, particularly in age, education, employment, and marital status.

Response:
The reviewer is correct that concluding demographics are unrelated to behavioral profiles is too strong a claim given the composition of this sample. The dataset is drawn from a single university and is relatively homogeneous: 64.7% of participants were aged 18–24, all were university-enrolled, 44.0% identified as students in terms of employment, and 37.8% were single. When a sample has limited variation on a characteristic, statistical tests comparing groups on that characteristic have reduced power to detect associations, even if those associations would emerge in a more diverse population. The limited demographic variability may therefore reduce the statistical power to detect associations, meaning that the non-significant results should not be interpreted as evidence that demographic associations would also be absent in more diverse populations. We revised both the Results and Discussion sections to reflect this more cautious interpretation.

Comment: Cultural discussion

Finally, I found the cultural discussion very interesting but somewhat underdeveloped. The observation that restrictive eating might occur without especially high body-image concern could be important, but would benefit from a more thorough exploration of existing literature on eating disorders and body image in Bangladesh or South Asia.

Response:

I agree that the original cultural discussion did not do it justice. I have substantially expanded this section with reference to existing literature on eating disorders and body image in Bangladesh and South Asia.

The revised Discussion now frames the observation, high restrictive eating in Cluster 1 without correspondingly high body image concern, within existing literature on cultural differences in eating disorder presentations in South Asian populations. Specifically:

First, I have referenced the narrative review of eating disorders in Bangladesh by Banna et al. (2025), which synthesized 10 studies conducted between 2015 and 2023 and found that the rate of eating disorder risk among Bangladeshi university students ranged from 20.4% to 38%, with sociocultural and individual psychological factors among those associated with eating disorder risk. This review also highlighted the limited research on eating disorders in Bangladesh and called for culturally sensitive approaches to assessment.

Second, I have referenced literature on non-fat-phobic anorexia nervosa in South Asian populations. Research among British South Asian adolescents has documented restrictive eating presentations involving less fat phobia and weight preoccupation than among matched White English participants (Tareen et al., 2005). The pattern observed in Cluster 1, relatively high restrictive eating without correspondingly high body image concern, may warrant further investigation in relation to these previously documented cultural differences.

Third, I have cited broader research on cultural differences in eating disorder presentations, particularly within British South Asian communities (Cini et al., 2024). This literature suggests that the presentation and cultural understanding of eating disorders may differ across sociocultural contexts. These findings provide useful context for considering whether the relationship between restrictive eating and body image concern may vary across populations.

The revised Discussion presents these connections explicitly while being careful to frame the observation as exploratory and requiring replication, consistent with the non-clinical and cross-sectional nature of the dataset. The expanded cultural discussion now includes three new citations: Banna et al. (2025), Tareen et al. (2005), and Cini et al. (2024).

Response to Reviewer 2

Comment: Dataset background

Since the author did not collect the data as part of this study, the source should be cited in the main text of the paper (not just the data availability statement). I would like more detail about the dataset and the study that used it first. Was there any info about the response rate? Were any participants excluded? Did the original survey designated the behavioral groupings, or is this something the author did for the current analysis? Including an example question from each behavioral category could be useful.

Response: Thank you for this comment. We expanded the Dataset and Preprocessing section to give additional background about the dataset, such as the source, study population, data-collection period, and survey administration. We also added citations to the original dataset and its associated study in the main text and clarified that all 550 responses were retained for the analysis. Both the original Mendeley dataset (Hasan et al., 2025) and the associated study (Hasan et al., 2026) have been cited in the text, along with the information that all 550 questionnaires were included in the present analysis. Additionally, we elaborated on the explanation of how the 50 behavioral items were organized into five composite behavioral categories based on the original questionnaire structure and item content. The complete mapping of all 50 behavioral items to their assigned behavioral categories and original questionnaire sections, along with their response scales, is now provided in Appendix Table A1.

Comment: Demographic results and Table 1

The information displayed in Figures 3, 4, 5 would be better displayed in table format with the exact values printed. I recommend combining this info with Table 1 to create an overall summary of the demographics (commonly done as "Table 1" in scientific papers). Columns are the three clusters and an additional "Overall" column to show the distribution of demographics for the entire cohort. An additional column can display the p-value for the comparison between clusters.

Response: Thank you for this feedback. Figure 3 to 5 have been replaced by a demographic summary table (table 2) that reports exact n (%) values for gender, age range, education level, employment status, and marital status for the overall sample and each of the three clusters. The table also reports the p-value and Cramer's V for each demographic comparison.

Comment: Expand the description of K-means clustering and cluster selection

The methods section should be expanded to include more background description of the K-means clustering method and cluster selection process. Imagine you're writing for another high school student who is not familiar with this method. Explain at a high level and/or give citations for other references to learn. The current section is a good start, but some methods could be elaborated. E.g., what is the k-means++ initialization method? What is silhouette score?

Response: Thank you for this suggestion. We have extended the Materials and Methods section to provide a clearer description of the K-means clustering process, including how participants are assigned to clusters and how centroids are updated. In addition, we have added explanations for k-means++ initializations and silhouette scores along with appropriate references to Arthur and Vassilvitskii (2007), Rousseeuw (1987), and Pedregosa et al. (2011).

Comment: Behavioral category scores and visualization

What is the maximum score in each behavioral category? It is not clear to me based on how this is described. Since it is categorical responses, it would be more appropriate to report as

percentages instead of the average score (i.e. X% score 0, Y% score 1) and in this case the heat map is not the best visualization.

Response: Thank you for this comment. We clarified in the Dataset and Preprocessing section that individual behavior items were encoded from 0-3 and that the mean-based composite scores therefore also ranged from 0-3, with a maximum possible score of 3 for each behavioral category.

Regarding the suggestion to report percentages in the format of X% score 0, Y% score 1: this approach is well-suited to single categorical items, where each participant has one response value. However, our five behavioral categories are each composed of 4 to 14 individual items, and each participant's composite score is the mean of those items rather than a single categorical response. Reporting the full response distribution at the item level would require over 200 cells across five categories, four response levels, and three clusters, which is impractical for the main text and would make the results harder rather than easier to interpret. The above-midpoint analysis, reporting the proportion of participants within each cluster scoring above 1.5 on each behavioral category, serves the same interpretive purpose as percentage-based reporting while remaining concise and directly comparable across categories and clusters.

To provide this percentage-based characterization of behavioral elevation, we added an above-midpoint analysis to the Results section reporting the proportion of participants within each cluster scoring above the scale midpoint (>1.5) on each behavioral category and across multiple categories simultaneously. For example, 98.9% of Cluster 1 participants scored above the midpoint on Restrictive Eating, and 90.8% scored above the midpoint on three or more categories simultaneously, providing a clear picture of the breadth and intensity of behavioral elevation within each profile (See Results Line# 234).

Finally, the original heatmap was changed to a radar chart to better visualize the relative patterns of mean composite scores across the five behavioral categories for the three clusters.The radar chart makes it easier to see the distinct behavioral shape of each cluster at a glance, while the above-midpoint percentages in the Results section provide the numerical characterization the reviewer requested.

Comment: Comparison of behavioral categories

Why was there no statistical test to evaluate differences in behavioral categories amongst the clusters? Table 1 and Figure 1 display means, but this is all exploratory/descriptive. Either test if there are significant differences, or make it very clear throughout (and in the discussion) that all conclusions are from an exploratory analysis.

Response: The reviewer is correct that the original manuscript presented only descriptive means without statistical confirmation that the differences across clusters were non-random. I have addressed this directly by adding Kruskal-Wallis tests for all five behavioral categories.The Kruskal-Wallis test is a non-parametric statistical test that evaluates whether three or more

groups differ significantly on a given measure. It is appropriate here because the behavioral composite scores are derived from ordinal survey responses (Never=0, Seldom=1, Sometimes=2, Often=3), and the test does not assume a normal distribution.

Results showed statistically significant differences across the three clusters for all five behavioral 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 results confirm that the behavioral differences across clusters are statistically significant and not attributable to random variation.

I have also added a sentence to the Discussion Limitations section clarifying the exploratory nature of the analysis: "While the Kruskal-Wallis tests confirm statistically significant differences across clusters, all behavioral comparisons remain exploratory in nature and do not support causal conclusions." These additions can be found in the Results section ("Behavioral profiles identified by K-means clustering") and the Discussion ("Limitations and future directions").

Comment: Effect sizes for demographic comparisons

Consider reporting effect sizes alongside the chi-square tests for demographics. Given the sample size, it would strengthen the demographic comparisons to report an effect size measure (e.g., Cramer's V) in addition to the chi-square statistics and p-values, since statistical significance alone does not indicate the practical size of an association.

Response: Thank you for this suggestion. I have added Cramér's V as an effect-size measure alongside the chi-square tests for all demographic comparisons in Table 2. The results showed small associations between cluster membership and all five demographic variables: gender, $\chi^2(2, N = 550) = 2.76$, $p = .252$, Cramér's $V = .071$; age range, $\chi^2(2, N = 550) = 0.77$, $p = .680$, Cramér's $V = .037$; education level, $\chi^2(10, N = 550) = 5.07$, $p = .887$, Cramér's $V = .068$; employment status, $\chi^2(6, N = 550) = 5.32$, $p = .503$, Cramér's $V = .070$; and marital status, $\chi^2(4, N = 550) = 5.20$, $p = .268$, Cramér's $V = .069$. Reporting Cramér's V alongside the chi-square statistics provides an estimate of the magnitude of these associations in addition to their statistical significance.

Comment: Abstract

In the abstract, the phrase "the questionnaire" responses is used in the second sentence before introducing the questionnaire. I think this sentence could be deleted entirely and overall the abstract tightened up.

Response: Thank you for this suggestion. The abstract was revised and tightened through removal of the reference to "the questionnaire" prior to its introduction, updating the description of the cluster-selection process, and revising statements that overstated the stability and cultural findings.

Comment: Citation for analytical tools

Tools used such as StandardScaler should have a citation.

Response: Thank you for this comment. We have included a citation to Pedregrosa et al. (2011) for the scikit-learn library used for preprocessing and analysis, including StandardScaler and K-means clustering.