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Multimodal Machine-Learning Prediction of Eating-Related Psychosomatic Risk Based on Impulsivity, Interoceptive Deficits, Emotional Eating, and Body Mass Index

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A B S T R A C T

This study aimed to develop, compare, and interpret multimodal machine-learning models for predicting elevated eating-related psychosomatic risk among Mexican adults based on impulsivity, interoceptive deficits, emotional eating, and body mass index. A cross-sectional predictive study was conducted with 812 adults recruited from five metropolitan areas in Mexico. Impulsivity was assessed using the Barratt Impulsiveness Scale–11, interoceptive deficits using the corresponding subscale of the Eating Disorder Inventory–3, emotional eating using the Dutch Eating Behavior Questionnaire, and body mass index through standardized height and weight measurements. Elevated eating-related psychosomatic risk was defined as the simultaneous presence of clinically relevant disordered eating attitudes and moderate or greater somatic symptom burden. The sample was stratified into a development set of 650 participants and an independent test set of 162 participants. Logistic regression, elastic-net regression, support vector machine, random forest, extreme gradient boosting, and early- and late-fusion multimodal neural networks were evaluated using nested cross-validation. Emotional eating, interoceptive deficits, impulsivity, and body mass index were significantly and positively associated with the continuous psychosomatic-risk index. The early-fusion multimodal neural network produced the strongest test-set performance, with an ROC–AUC of .905, precision–recall AUC of .742, sensitivity of .882, specificity of .875, balanced accuracy of .879, and Brier score of .098. It significantly outperformed conventional logistic regression. Ablation analyses showed that excluding emotional eating produced the largest reduction in predictive accuracy, followed by removing interoceptive deficits and impulsivity. Body mass index alone showed limited discrimination, whereas its addition modestly improved the psychometric model. Eating-related psychosomatic risk was predicted most accurately through integration of emotional, interoceptive, behavioral, and anthropometric information, with emotional eating and interoceptive deficits representing the most influential predictors.

Keywords: *emotional eating; interoception; impulsivity; body mass index; psychosomatic risk; machine learning; eating behavior*

1. Introduction

Eating-related psychosomatic risk emerges from the interaction of cognitive, emotional, behavioral, interoceptive, and anthropometric processes that shape how individuals perceive bodily states, regulate distress, respond to food cues, and organize eating behavior. This risk cannot be reduced to the presence of a formally diagnosed eating disorder, because clinically meaningful disturbances may also appear as emotional eating, disinhibited food intake, recurrent preoccupation with eating and weight, somatic complaints, impaired awareness of hunger and satiety, or maladaptive attempts to regulate negative affect through food. Contemporary evidence indicates that eating styles are closely associated with psychological well-being and that individuals can be differentiated into profiles characterized by distinct combinations of adaptive and maladaptive eating tendencies (Serier et al., 2026). Such heterogeneity is clinically important because two people with similar body weight may differ substantially in emotional functioning, impulsive tendencies, sensitivity to internal bodily signals, and vulnerability to psychosomatic distress. A rapid review of eating-disorder risk factors likewise demonstrated that the development of disturbed eating reflects multiple interacting influences rather than a single causal pathway, including psychological, interpersonal, behavioral, biological, and sociocultural vulnerabilities (Aouad et al., 2023). Eating-related difficulties may therefore be better conceptualized as a multidimensional risk continuum extending from subclinical dysregulation to severe and persistent psychopathology. Within this continuum, the coexistence of problematic eating attitudes and somatic symptom burden may identify individuals whose eating behavior has become integrated with broader patterns of psychological distress and bodily discomfort. Detecting this combined risk before the emergence of severe impairment is especially important because eating-related psychopathology can affect social participation, occupational or academic functioning, physical health, and long-term quality of life. In adult women with anorexia nervosa, for example, eating pathology has been associated with substantial impairment in work and social adjustment as well as with broader psychopathological difficulties (Iida et al., 2023). Long-term clinical observations further indicate that treatment outcomes are influenced not only by eating symptoms but also by personality characteristics, general psychopathology, and processes occurring during treatment (Amianto et al., 2022). These findings support a risk-assessment approach that integrates multiple sources of information rather than relying exclusively on diagnostic status, body weight, or a single self-report score.

Emotional eating constitutes one of the most relevant mechanisms through which psychological distress may become translated into eating-related and somatic problems. Emotional eating refers to food consumption that is initiated or intensified by affective states rather than by physiological energy requirements. Negative emotions such as anxiety, sadness, loneliness, frustration, and boredom may increase the motivational value of palatable foods, narrow attention toward immediate relief, and weaken sensitivity to the delayed consequences of eating. A broad review of the role of emotion in food-related behavior has shown that emotional states influence food valuation, appetite, dietary choice, and decision-making through interacting cognitive, physiological, and neural pathways (Ha & Lim, 2023). Emotional eating may temporarily reduce distress or divert attention from unpleasant internal experiences, but repeated reliance on this strategy can reinforce a learned association between negative affect and food intake. A recent systematic review described this phenomenon as a process in which emotions may be experienced or interpreted as hunger, thereby blurring the distinction between affective activation and genuine physiological need (Marano et al., 2026). The decoupling of stress from eating has consequently been identified as an important translational target for restoring a healthier relationship with food and reducing the use of eating as an automatic response to psychological strain (Warren & Frame, 2025). Experimental findings also indicate that even brief mindfulness practice may reduce emotional eating by alleviating negative affect, suggesting that emotional eating is responsive to changes in emotion regulation rather than being a fixed personal characteristic (Huang et al., 2025). Mindfulness-based approaches may additionally alter visual attention and attentional bias toward food cues, although the magnitude and consistency of these effects vary across studies and intervention designs (Duffy & Attuquayefio, 2025). Emotional eating should therefore be considered both a behavioral expression of emotional dysregulation and a potential pathway connecting psychological distress with weight-related and psychosomatic outcomes.

The relevance of emotional eating becomes particularly evident in the context of obesity and weight-related distress. Emotion dysregulation has been proposed as a central process linking negative affect, maladaptive coping, loss of control over food intake, and obesity-related difficulties

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(Atwood, 2024). Individuals may eat in response to stress even when they are not physiologically hungry, and the repeated consumption of energy-dense foods under emotional conditions may contribute to weight gain, shame, self-criticism, and further emotional dysregulation. However, body mass index alone provides only an incomplete representation of this process. People within the same body mass index category may experience substantially different bodily sensations during food consumption and may differ in the degree to which those sensations guide subsequent eating decisions. Research comparing snacking experiences across body mass index levels has shown that healthy and unhealthy snack consumption is accompanied by distinguishable bodily sensations and that the perception of these sensations may vary according to weight status (Frederiksen et al., 2024). Structural modeling research has also implicated interoception in age-related obesity, suggesting that alterations in the perception and interpretation of internal bodily states may contribute to weight-related behavior across adulthood (Young & Brennan, 2023). Among candidates for bariatric surgery, patterns of disordered eating have been associated with mood-spectrum characteristics and impulsivity, emphasizing that elevated body mass index frequently coexists with complex emotional and behavioral vulnerabilities (Carmassi et al., 2026). Thus, body mass index may contribute useful anthropometric information to risk prediction, but it should not be treated as a sufficient indicator of psychosomatic or eating-related dysfunction. A multimodal framework that combines body mass index with psychological and interoceptive variables is more consistent with the heterogeneous pathways through which eating-related risk develops.

Interoception is a key construct for understanding why emotional states, bodily sensations, and eating behavior become difficult to differentiate. Interoception refers to the detection, interpretation, and integration of signals arising from within the body, including hunger, fullness, gastric activity, heartbeat, temperature, pain, tension, and autonomic arousal. Effective eating regulation requires the individual to recognize hunger, distinguish it from emotional discomfort, respond appropriately to satiety, and interpret post-consumption sensations accurately. When interoceptive processing is deficient, vague bodily arousal may be mislabeled as hunger, satiety signals may be overlooked, and emotional distress may be experienced primarily through physical symptoms. Evidence from individuals with obesity and those undergoing bariatric surgery indicates that interoceptive sensibility is meaningfully related to intuitive eating and disordered eating behavior (Joshi et al., 2024). Alexithymia and binge eating have likewise been examined in relation to both maladaptive emotion regulation and deficient interoception, with findings suggesting that difficulty identifying emotional states may coexist with reduced access to bodily information that would otherwise guide adaptive eating (Lyvers, Truncali, et al., 2022). In severe binge eaters, alexithymia and reward sensitivity may also interact with excessive exercise and other compensatory behaviors, illustrating how impaired emotional awareness can be embedded within broader patterns of behavioral dysregulation (Lyvers, Kelahroodi, et al., 2022). These relationships indicate that interoceptive deficits may not merely accompany disordered eating but may help explain why individuals have difficulty separating emotional activation from physiological appetite.

Interoceptive disturbances are also evident across multiple forms and levels of eating pathology. Time perception has been found to differ in eating disorders in relation to interoceptive awareness, suggesting that impaired access to internal states may extend beyond hunger and satiety to the broader organization of subjective experience (Meneguzzo et al., 2022). Individuals with eating disorders may also demonstrate an abnormal sense of agency, indicating disruptions in the experience of control over actions and bodily processes (Colle et al., 2023). Such disturbances may contribute to the feeling that eating behavior occurs automatically, compulsively, or outside intentional control. Among female adolescents with restrictive eating disorders and comorbid borderline personality disorder, interoceptive difficulties have been associated with self-injury and suicidal ideation, showing that altered bodily awareness may be connected to severe forms of affective and behavioral risk (Riva et al., 2025). The presence of borderline personality disorder has also been shown to influence inpatient treatment outcomes in anorexia nervosa, highlighting the clinical significance of emotion dysregulation, impulsivity, interpersonal instability, and comorbidity in the course of eating pathology (Voderholzer et al., 2021). In addition, the developmental timing of traumatic experiences may predict distorted body image among individuals with eating disorders, suggesting that bodily self-perception is shaped by both present interoceptive processing and earlier adverse experiences (Idini et al., 2024). These findings reinforce the importance of examining eating-related psychosomatic risk as a bodily

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and psychological phenomenon rather than as a narrowly nutritional problem.

Stress further complicates the relationship between interoception and eating behavior. Acute and chronic stress can alter gastrointestinal activity, autonomic arousal, appetite, reward sensitivity, and attention to food cues. A systematic review of the neural mechanisms underlying disinhibited eating concluded that stress can affect brain systems involved in reward processing, inhibitory control, and food-related decision-making, although individual responses vary according to personal and contextual factors (Giddens et al., 2023). Experimental evidence indicates that stress may modulate gastric interoception differently depending on eating traits and emotion-regulation characteristics (Kipping et al., 2026). This finding is especially relevant to psychosomatic risk because gastric sensations generated during stress may be interpreted as hunger, discomfort, fullness, or emotional disturbance depending on the individual's interoceptive accuracy and learned eating patterns. When stress-related bodily activation is misidentified as appetite, emotional eating may become more likely; when bodily sensations are experienced as threatening or confusing, somatic symptom burden may increase. Accordingly, emotional eating and interoceptive deficits may operate synergistically, with emotional distress generating bodily arousal and deficient interoception preventing the accurate interpretation of that arousal. The resulting uncertainty can promote maladaptive food intake, increased monitoring of bodily symptoms, and recurrent concern about eating, weight, or health.

Impulsivity represents another central dimension of eating-related psychosomatic vulnerability. Impulsivity is a multidimensional construct involving rapid responding, limited forethought, difficulty delaying gratification, attentional instability, and reduced inhibition of behavior. In the context of eating, impulsivity may increase sensitivity to immediately rewarding foods, weaken adherence to planned dietary intentions, and facilitate consumption before internal hunger or satiety signals have been adequately evaluated. Cross-sectional evidence has identified impulsivity as a determinant of food intake and has linked impulsive tendencies to problematic eating attitudes and behaviors (EmİRoĞLu & IŞIk, 2022). Nevertheless, different dimensions of impulsivity may not contribute equally. Non-planning impulsivity may increase the tendency to prioritize immediate emotional relief over long-term health goals, motor impulsivity may facilitate rapid eating or unplanned consumption, and attentional impulsivity may heighten distractibility and responsiveness to salient food cues. Research on cognitive impulsivity in anorexia nervosa has demonstrated associations with both eating symptoms and obsessive features, indicating that impulsivity is relevant even in restrictive conditions that may outwardly appear dominated by excessive control (Bevione et al., 2024). This apparent paradox reflects the multidimensional nature of impulsivity: individuals may rigidly control some aspects of eating while displaying cognitive inflexibility, rapid decision-making, or dysregulated behavior in other contexts. The combination of impulsivity and emotional eating may be especially consequential because negative affect can increase the motivational pull of food at the same time that impulsivity reduces the capacity to pause, evaluate bodily needs, and select an alternative coping response.

The measurement of eating behavior presents an additional methodological challenge because commonly used self-report instruments often contain overlapping psychological constructs. Measures labeled as emotional eating, external eating, uncontrolled eating, disinhibition, restraint, or food responsiveness may partly reflect shared underlying processes rather than entirely separate behaviors. A comprehensive conceptual review of self-report eating-behavior measures emphasized the need to identify the latent psychological constructs represented by these instruments and to move beyond simplistic interpretation of total scores (Dakin et al., 2025). This concern is particularly important when predicting psychosomatic risk, because aggregate scores may conceal clinically meaningful item-level patterns. Two participants with the same emotional-eating total may differ in whether eating is triggered by anxiety, sadness, anger, loneliness, or boredom. Similarly, the same total impulsivity score may reflect predominantly attentional, motor, or non-planning tendencies. Conventional regression models can estimate average linear associations among these constructs, but they may perform less effectively when risk depends on nonlinear thresholds, complex interactions, and heterogeneous combinations of features. Machine-learning methods provide a means of examining such complexity by integrating scale-level and item-level information, modeling nonlinear relationships, and estimating individual probabilities of elevated risk. Their value, however, depends on rigorous separation of training and test data, careful attention to calibration, transparent interpretation of feature contributions, and comparison with simpler statistical benchmarks.

A multimodal machine-learning framework is particularly appropriate when predictors represent

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qualitatively different information domains. Psychometric variables such as emotional eating, interoceptive deficits, and impulsivity describe subjective experiences and behavioral dispositions, whereas body mass index represents an anthropometric characteristic that may capture cumulative aspects of energy balance, metabolic status, and weight-related exposure. Integrating these modalities may improve prediction because body mass index can modify the expression or clinical significance of psychological vulnerabilities without replacing them. The available literature suggests that body-related interventions may improve eating-related functioning through mechanisms that extend beyond weight change. An educational intervention designed to increase food consciousness was developed to strengthen awareness of eating experiences and internal and external cues (Palazzo et al., 2021), and subsequent findings indicated that such an intervention could improve interoceptive sensitivity and the expression of exteroceptive awareness in women (Palazzo et al., 2022). Similarly, an open trial of dance movement therapy for eating disorders emphasized the therapeutic value of bodily expression and embodied experience, supporting the proposition that the body can provide clinically meaningful information that is not fully captured by verbal symptom reporting (Bastoni et al., 2023). These studies illustrate that eating-related risk is situated at the intersection of cognition, emotion, behavior, and embodied experience, thereby providing a conceptual rationale for multimodal prediction.

Despite expanding knowledge of emotional eating, impulsivity, interoception, and body mass index, these variables are frequently studied in isolation, in narrowly defined clinical groups, or through models designed primarily to test associations rather than predict individual risk. Restrictive eating disorders, binge eating, obesity, and bariatric populations have each generated important findings, but models derived from one clinical subgroup may not generalize to adults in community settings who display mixed or subthreshold patterns. Moreover, many studies emphasize eating-disorder symptom severity without simultaneously considering somatic symptom burden, even though bodily discomfort may be a major component of how psychological distress is experienced and reported. Psychosomatic risk may be especially important in settings where individuals seek medical or nutritional assistance for fatigue, pain, gastrointestinal symptoms, dizziness, sleep problems, or weight concerns without initially recognizing the role of emotional and behavioral processes. A prediction model capable of integrating psychological and anthropometric indicators could support earlier identification of individuals who warrant comprehensive evaluation rather than isolated treatment of weight, diet, or physical symptoms.

The need for culturally and contextually relevant evidence is also substantial. Eating behavior is influenced by family practices, food availability, socioeconomic conditions, urbanization, weight-related norms, stress exposure, and culturally shaped meanings of the body. Findings derived predominantly from European, North American, or specialized clinical samples cannot automatically be assumed to represent adults living in Mexico. At the same time, the psychological mechanisms identified across prior studies—including emotion-driven eating, reduced interoceptive awareness, impulsive responding, stress sensitivity, and body-related distress—provide a strong theoretical basis for investigation in a Mexican community sample. A model developed in this context should not merely maximize classification accuracy; it should also clarify the relative contribution of each predictor, determine whether anthropometric information adds value beyond psychological measures, evaluate calibration, and identify whether risk is concentrated in particular combinations of features. Explainable machine-learning procedures can address these requirements by showing how high and low feature values influence predictions at both global and individual levels.

The present study therefore aimed to develop, compare, and interpret multimodal machine-learning models for predicting elevated eating-related psychosomatic risk among Mexican adults from impulsivity, interoceptive deficits, emotional eating, and body mass index.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a cross-sectional, analytical prediction design to develop and evaluate multimodal machine-learning models for identifying eating-related psychosomatic risk based on impulsivity, interoceptive deficits, emotional eating, and body mass index. The study population consisted of adults residing in Mexico who were recruited from universities, community health centers, workplaces, and public community settings in Mexico City, Guadalajara, Monterrey, Puebla, and Querétaro. A multistage quota-based recruitment strategy was used to obtain variation in age, sex, educational background, socioeconomic status, geographic location, and body mass index. Initially, 947 individuals expressed interest in participating and were screened for eligibility. Of these individuals, 88 did not meet the inclusion criteria, 31 declined to complete the assessment after receiving information about the study, and 16 submitted questionnaires with extensive missing or inconsistent responses. Consequently, the final analytical sample consisted of exactly 812 participants.

Eligible participants were adults between 18 and 45 years of age who had resided in Mexico for at least five years, were able to read and understand Spanish, provided informed consent, and completed the anthropometric and psychological assessments required for constructing the predictive models. The selected age range was intended to capture early and middle adulthood, during which emotional eating, body-image concerns, impulsive decision-making, and weight-related psychosomatic difficulties are frequently observed. Individuals were excluded when they were pregnant, had undergone bariatric surgery during the preceding 12 months, had a medical condition that substantially interfered with the accurate assessment of body weight or appetite, demonstrated cognitive or linguistic limitations that prevented valid questionnaire completion, or submitted more than 10% missing responses across the principal study instruments. Participants receiving psychological or nutritional services were not automatically excluded because the purpose of the study was to predict risk across a heterogeneous community sample rather than to restrict the analysis to individuals without previous health-related concerns.

Data were collected through supervised in-person sessions and a secure electronic assessment platform. The same sequence of instruments, written instructions, eligibility criteria, and quality-control procedures was used in both modes of administration. Participants completing the assessment electronically attended an affiliated data-collection site for standardized measurement of height and weight. Each participant received a study identification code, and identifying information was stored separately from psychological and anthropometric data. Before participation, individuals were informed about the purpose of the research, the voluntary nature of participation, the confidentiality of their responses, and their right to discontinue the assessment without penalty. Written or electronically documented informed consent was obtained from all participants.

The required sample size was determined with consideration of both conventional predictive modeling requirements and the need to preserve an independent test set. A minimum sample of approximately 750 participants was considered necessary to provide a sufficiently large number of high-risk cases, permit stratified model development and evaluation, accommodate nonlinear associations and interactions, and produce reasonably stable estimates of discrimination and calibration. Recruitment continued until more than 800 complete and valid cases were obtained. The final sample of 812 participants was subsequently divided into a development dataset containing 650 participants and an independent test dataset containing 162 participants. The division was performed through stratified random allocation so that the proportion of participants classified as having elevated eating-related psychosomatic risk was maintained in both datasets.

2.2. Measures

A demographic and health-information form was used to record participants' age, sex, educational level, employment status, marital status, place of residence, history of psychological or nutritional treatment, current medication use, smoking status, habitual physical activity, and self-reported medical conditions. These variables were collected to describe the sample, evaluate potential selection effects, and conduct sensitivity and subgroup analyses. They were not included as primary predictors in the principal machine-learning models because the study focused specifically on the predictive contribution of impulsivity, interoceptive deficits, emotional eating, and body mass index. Supplementary models were nevertheless constructed with age and sex as adjustment variables to determine whether the performance of the primary models was robust after accounting for basic demographic characteristics.

Impulsivity was assessed using the Spanish-language version of the Barratt Impulsiveness Scale–11. This self-report instrument contains 30 statements assessing relatively stable impulsive tendencies. Participants indicate the frequency with which each statement applies to them using a four-point response format. The instrument provides a total impulsivity score and scores for attentional impulsivity, motor impulsivity, and non-planning impulsivity. Attentional impulsivity reflects difficulty sustaining attention and a tendency toward rapid cognitive shifts, motor impulsivity represents acting without sufficient deliberation, and non-planning impulsivity reflects limited future orientation and reduced consideration of long-term consequences. Higher scores indicate greater impulsivity. Both the total score and the three dimensional scores were

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retained as candidate model features because different dimensions of impulsivity may have distinct relationships with uncontrolled eating, immediate reward seeking, and difficulty maintaining planned eating behavior. Item-level responses were also retained for the neural-network and gradient-boosting models, while scale-level scores were used in the more parsimonious regression-based models.

Interoceptive deficits were measured using the Interoceptive Deficits subscale of the Eating Disorder Inventory–3. This subscale assesses difficulty recognizing and accurately interpreting internal bodily and emotional signals, including hunger, satiety, physiological arousal, and emotional activation. Participants respond to statements using the standardized response format of the inventory, and responses are scored in accordance with its established scoring procedure. Higher scores represent greater uncertainty regarding internal sensations and greater difficulty differentiating bodily states from emotional experiences. The measure was selected because disturbances in the perception of hunger and satiety may contribute to eating that is guided by external or emotional cues rather than physiological need. The total interoceptive-deficit score was entered into all predictive models, and individual item responses were made available to models capable of learning nonlinear and multidimensional response patterns.

Emotional eating was assessed using the emotional-eating subscale of the Spanish-language Dutch Eating Behavior Questionnaire. The subscale contains 13 items measuring the tendency to eat in response to diffuse emotional states and clearly identifiable emotions, such as anxiety, sadness, loneliness, irritation, boredom, or disappointment. Items are rated on a five-point scale ranging from never to very often. A mean emotional-eating score was calculated when at least 80% of the items had been completed. Higher scores indicate a stronger tendency to use food as a response to emotional distress or emotional arousal. In addition to the overall score, item-level responses were retained to allow the machine-learning models to distinguish between emotional-eating patterns associated with different affective conditions. This approach enabled the models to capture information that might be obscured when emotional eating is represented by a single aggregate score.

Body mass index constituted the anthropometric modality of the prediction framework. Body weight was measured to the nearest 0.1 kilogram using a calibrated digital scale, with participants wearing light clothing and no shoes. Height was measured to the nearest 0.1 centimeter using a portable stadiometer, with the participant standing upright, barefoot, and with the head positioned in the Frankfurt horizontal plane. Two measurements were obtained for both weight and height. When the two measurements differed by more than 0.2 kilograms for weight or 0.5 centimeters for height, a third measurement was performed, and the mean of the two closest values was used. Body mass index was calculated by dividing body weight in kilograms by the square of height in meters. The continuous body mass index value was used as the principal anthropometric predictor. Body mass index categories were generated only for descriptive and sensitivity analyses because categorization can reduce information and obscure nonlinear relationships. Implausible anthropometric values were verified against the original measurement record before analysis and were treated as missing only when a recording or measurement error could not be resolved.

Eating-related psychosomatic risk, which constituted the prediction outcome, was operationalized through the combined assessment of disordered eating attitudes and somatic symptom burden. Disordered eating attitudes were evaluated using the Eating Attitudes Test–26. The instrument consists of 26 items addressing dieting behavior, food preoccupation, oral control, fear of weight gain, and behavioral features associated with disturbed eating. Responses were scored using the conventional scoring method, and a total score of 20 or higher was considered indicative of clinically relevant eating-related concern requiring further assessment. The measure was used as a screening instrument rather than as a diagnostic tool.

Somatic symptom burden was assessed using the Patient Health Questionnaire–15. The questionnaire evaluates the extent to which participants have been bothered by common physical symptoms, including gastrointestinal complaints, fatigue, pain, dizziness, sleep-related difficulties, and cardiopulmonary sensations. Each item is rated from zero to two, and the responses are summed to produce a total score. A score of 10 or higher was considered indicative of at least moderate somatic symptom burden. Participants were classified as having elevated eating-related psychosomatic risk when they simultaneously obtained an Eating Attitudes Test–26 score of 20 or higher and a Patient Health Questionnaire–15 score of 10 or higher. This combined definition was used to distinguish individuals whose problematic eating attitudes co-occurred with a meaningful level of bodily distress from those presenting with isolated eating concerns or isolated somatic symptoms. The resulting binary variable served as the primary outcome for the classification models. A continuous risk index was also calculated by standardizing the total scores of the two outcome instruments and averaging the standardized values. This index was used in supplementary regression analyses to determine whether the identified predictors were also capable of estimating risk severity across the full distribution of scores.

All psychological instruments were administered in Spanish. Established Spanish versions were used when available, and the wording was reviewed by two bilingual psychologists and one Mexican clinical nutrition specialist to ensure cultural and linguistic suitability for the target population. A pilot assessment involving 35 adults who were not included in the final sample was conducted to examine clarity, administration time, technical functioning, and participant comprehension. Internal consistency was evaluated in the final sample using McDonald's omega and Cronbach's alpha. Coefficients of .70 or higher were interpreted as acceptable for research purposes, although decisions regarding feature retention were based on conceptual relevance and predictive performance rather than reliability coefficients alone.

Several data-quality procedures were implemented before model development. Electronic questionnaires included mandatory responses for core items, range restrictions, and embedded attention checks. In-person questionnaires were reviewed for omissions before participants left the assessment setting. Records were examined for duplicate identification codes, identical response patterns, incompatible demographic responses, unrealistically short completion times, and repeated failures on attention-check items. Records showing clear evidence of careless or automated responding were excluded before the dataset was divided into development and test subsets. These procedures were completed without examining participants' final risk classifications to reduce the possibility of outcome-informed data cleaning.

2.3. Data Analysis

Data analysis was conducted using a combined statistical and machine-learning framework. Preliminary analyses included examination of score distributions, missingness patterns, central tendency, dispersion, skewness, kurtosis, and potential floor or ceiling effects. Continuous variables were summarized using means and standard deviations when their distributions were approximately symmetrical and medians and interquartile ranges when substantial asymmetry was present. Categorical variables were summarized using frequencies and percentages. Differences between participants retained in the analysis and those excluded because of incomplete data were examined when sufficient information was available. Associations among impulsivity, interoceptive deficits, emotional eating, body mass index, eating attitudes, and somatic symptoms were initially explored using Pearson or Spearman correlation coefficients, depending on variable distributions. These analyses were descriptive and were not used to preselect predictors for the primary machine-learning models.

Before model development, the complete dataset was randomly divided into a development set of 650 participants and an independent test set of 162 participants. Stratification was based on the binary eating-related psychosomatic risk outcome. The independent test set was isolated before preprocessing, feature selection, hyperparameter tuning, or threshold determination and was used only once for final performance evaluation. All preprocessing procedures were estimated exclusively from the development data and then applied to the test data. This procedure was adopted to prevent information leakage and optimistic estimation of model performance.

Missing predictor values were examined separately within the development and test datasets. Participants with more than 10% missing data across the principal instruments had already been excluded. Remaining missing continuous values were imputed using the median calculated within each training fold, while missing categorical adjustment variables were imputed using the most frequent category within the same fold. Continuous predictors were standardized using the training-fold mean and standard deviation for algorithms sensitive to variable scale, including logistic regression, support vector machines, and neural networks. Tree-based models were fitted using the original continuous scale because they did not require standardization. Psychometric total scores were calculated according to instrument-specific rules before model development. Item-level data were standardized only after data splitting. No imputation or scaling parameter was estimated from the independent test set.

The principal predictive features were the total and dimensional scores of impulsivity, the interoceptive-deficit score, the emotional-eating score, and continuously measured body mass index. For algorithms designed to handle higher-dimensional inputs, item-level responses from the impulsivity, interoceptive-deficit, and emotional-eating instruments were also included. This produced two levels of

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representation: a parsimonious construct-level feature set and an expanded item-level feature set. Polynomial terms and pairwise interactions among the four principal constructs were considered in the penalized regression models, while nonlinear algorithms were permitted to learn interactions directly. Body mass index was entered as a continuous variable, and a quadratic body mass index term was included in selected models to account for the possibility that psychosomatic risk increased at both low and high body mass index values.

A conventional multivariable logistic regression model was first fitted as a clinical benchmark. The benchmark model included impulsivity, interoceptive deficits, emotional eating, and body mass index as continuous predictors. Elastic-net penalized logistic regression was then evaluated to manage correlated psychometric features and reduce overfitting. Additional candidate algorithms included a support vector machine with a radial-basis-function kernel, random forest, gradient-boosted decision trees, extreme gradient boosting, and a multilayer perceptron neural network. The algorithms were selected to represent linear, nonlinear, ensemble, kernel-based, and neural prediction approaches. Class-weighted loss functions were applied when the elevated-risk group was less frequent than the comparison group. Synthetic oversampling was not used in the primary analysis because generating artificial psychometric profiles could reduce clinical interpretability. A sensitivity analysis using oversampling within the training folds was conducted to determine whether alternative handling of class imbalance materially changed model performance.

The multimodal model was designed to process psychometric and anthropometric information through separate computational pathways. The psychometric pathway received the impulsivity, interoceptive-deficit, and emotional-eating features, whereas the anthropometric pathway received continuous body mass index and its derived nonlinear term. Within the neural architecture, the psychometric inputs were processed through two fully connected layers with rectified linear activation, batch normalization, and dropout regularization. The anthropometric inputs were processed through a smaller fully connected layer. The representations generated by the two pathways were subsequently concatenated and entered into a fusion layer that produced the predicted probability of elevated eating-related psychosomatic risk through a sigmoid output function. An early-fusion model, in which all features were entered simultaneously into a single algorithm, and a late-fusion model, in which separate psychometric and anthropometric predictions were combined, were evaluated. Comparison of these approaches made it possible to determine whether modality-specific representation improved prediction beyond simple aggregation of all variables.

Hyperparameters were optimized within the development dataset using nested stratified cross-validation. The outer loop consisted of five folds and was used to estimate model generalizability during model selection. The inner loop also consisted of five folds and was used for hyperparameter optimization. The optimized parameters included the regularization strength and mixing ratio for elastic-net regression; kernel width and penalty parameters for the support vector machine; the number and depth of trees, minimum node size, and number of candidate variables for random forest; learning rate, tree depth, subsampling ratio, number of estimators, and regularization parameters for gradient-boosting models; and the number of hidden units, dropout rate, learning rate, batch size, and regularization strength for the neural network. Hyperparameter combinations were selected according to the mean area under the receiver operating characteristic curve across the inner validation folds. Random-search optimization was used for models with large hyperparameter spaces, while grid search was used for models with a limited number of parameters.

The area under the receiver operating characteristic curve was specified as the primary measure of predictive discrimination. Secondary performance measures included the area under the precision–recall curve, sensitivity, specificity, positive predictive value, negative predictive value, F1 score, balanced accuracy, and overall classification accuracy. Because the intended application was risk screening rather than diagnosis, the final probability threshold was selected within the development dataset to maximize the Youden index while maintaining a sensitivity of at least .80 whenever possible. The selected threshold was fixed before application to the independent test dataset. Calibration was evaluated using the Brier score, calibration intercept, calibration slope, and graphical comparison of predicted and observed probabilities. Ninety-five percent confidence intervals for test-set performance measures were calculated using 2,000 stratified bootstrap samples. Differences between the areas under the receiver operating characteristic curves of the best-performing models were evaluated using an appropriate paired comparison procedure.

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The incremental contribution of each information modality was examined through ablation analyses. A psychometric-only model was fitted using impulsivity, interoceptive deficits, and emotional eating; an anthropometric-only model was fitted using body mass index; and a complete multimodal model was fitted using both psychometric and anthropometric information. The performance of these models was compared to determine whether body mass index improved prediction beyond psychological measures and whether psychological features substantially improved prediction beyond body mass index alone. Additional ablation analyses removed one psychological construct at a time from the complete model. A meaningful reduction in discrimination, precision–recall performance, or calibration after removal of a construct was interpreted as evidence that the construct contributed unique predictive information.

Model interpretation was conducted using permutation importance and Shapley additive explanation values. Global Shapley values were used to rank the overall contribution of impulsivity, interoceptive deficits, emotional eating, body mass index, and their constituent features. Local explanations were generated for selected participants to illustrate how combinations of risk and protective characteristics influenced individual predictions. Partial-dependence and accumulated-local-effect analyses were used to examine nonlinear associations between continuous predictors and predicted risk. Particular attention was given to possible interaction patterns involving emotional eating and impulsivity, interoceptive deficits and emotional eating, and body mass index and emotional eating. Interpretations were restricted to predictive associations and were not presented as evidence of causal effects.

Model robustness was assessed through several sensitivity analyses. The analyses were repeated using the continuous psychosomatic-risk index as the outcome, with mean absolute error, root mean squared error, and explained variance used as performance measures. Models were also refitted after adjustment for age and sex and after exclusion of participants who reported current psychological, psychiatric, or nutritional treatment. Subgroup performance was examined across sex, age categories, geographic recruitment sites, and body mass index groups when subgroup sizes were adequate. Differences in sensitivity, specificity, calibration, and false-negative rates were evaluated to identify potential performance disparities. Any subgroup results based on small numbers of elevated-risk cases were interpreted cautiously.

All conventional statistical tests were two-sided, and a probability level below .05 was considered statistically significant. Statistical significance was not used as the principal criterion for selecting machine-learning predictors or models. Model selection was based on out-of-sample discrimination, precision–recall performance, calibration, clinical screening utility, stability across cross-validation folds, and interpretability. A fixed random seed was used for data splitting, cross-validation, and model initialization to support computational reproducibility. The final analytical workflow preserved the independent test dataset, conducted all preprocessing within resampling folds, and reported both predictive accuracy and calibration to reduce the risk of overfitting and provide a realistic estimate of the model’s performance in Mexican adults.

3. Findings and Results

The final sample consisted of 812 adults recruited from five metropolitan areas of Mexico. Participants ranged in age from 18 to 45 years, with a mean age of 29.74 years and a standard deviation of 7.56 years. Of the participants, 478 were women, representing 58.9% of the sample, and 334 were men, representing 41.1%. Regarding age distribution, 257 participants, or 31.7%, were between 18 and 24 years of age, 322 participants, or 39.7%, were between 25 and 34 years of age, and 233 participants, or 28.7%, were between 35 and 45 years of age. A total of 461 participants, corresponding to 56.8% of the sample, were single; 285 participants, or 35.1%, were married or cohabiting; and 66 participants, or 8.1%, were separated, divorced, or widowed. In terms of educational attainment, 128 participants, or 15.8%, had completed secondary education or a lower level, 247 participants, or 30.4%, had completed upper-secondary education, 345 participants, or 42.5%, held or were completing a university degree, and 92 participants, or 11.3%, had postgraduate education. The geographic distribution included 237 participants from Mexico City, 168 from Guadalajara, 151 from Monterrey, 137 from Puebla, and 119 from Querétaro, representing 29.2%, 20.7%, 18.6%, 16.9%, and 14.7% of the sample, respectively.

The participants’ mean body mass index was 26.42 kg/m², with a standard deviation of 5.31 kg/m² and a range from 16.83 to 43.76 kg/m². According to conventional body mass index categories, 32 participants, or 3.9%, were classified as underweight, 316 participants, or 38.9%, were within the normal-weight range, 282 participants, or 34.7%, were classified as overweight, and 182 participants, or 22.4%, met the criterion for obesity. A total of 105 participants, representing 12.9% of the sample, reported currently receiving psychological, psychiatric, nutritional, or weight-management services. Based on the predefined screening criteria, 234 participants, or 28.8%, obtained an Eating Attitudes Test–26 score of 20 or higher, while 281 participants, or 34.6%, obtained a Patient Health Questionnaire–15 score of 10 or higher. A total of 173 participants, corresponding to 21.3% of the complete sample, simultaneously met both criteria and were therefore classified as having elevated eating-related psychosomatic risk. The remaining 639 participants, or 78.7%, were classified as not having elevated combined risk. Stratified allocation resulted in 139 elevated-risk cases among the 650 participants in the development dataset and 34 elevated-risk cases among the 162 participants in the independent test dataset. The corresponding prevalence rates were 21.4% and 21.0%, indicating that the outcome distribution was effectively preserved during data splitting. No statistically significant differences were observed between the development and test datasets in age, sex distribution, body mass index, impulsivity, interoceptive deficits, emotional eating, eating-attitude scores, somatic symptom burden, or prevalence of elevated psychosomatic risk, with all probability values exceeding .10.

Table 1

Descriptive Statistics, Internal Consistency, and Correlations Among the Principal Study Variables

Variable	Mean	SD	McDonald's ω	1	2	3	4	5	6	7
1. Total impulsivity	63.84	10.92	.88	—						
2. Interoceptive deficits	12.76	5.81	.86	.42	—					
3. Emotional eating	2.63	0.89	.92	.47	.53	—				
4. Body mass index	26.42	5.31	—	.18	.16	.27	—			
5. Disordered eating attitudes	14.88	10.37	.90	.49	.61	.64	.29	—		
6. Somatic symptom burden	7.92	4.76	.87	.38	.49	.46	.22	.55	—	
7. Continuous psychosomatic-risk index	0.00	0.82	—	.52	.66	.68	.31	.88	.87	—

As shown in Table 1, the psychological measures demonstrated satisfactory to excellent internal consistency, with McDonald's omega coefficients ranging from .86 for interoceptive deficits to .92 for emotional eating. The mean total impulsivity score was 63.84, indicating considerable individual variability in attentional, motor, and non-planning impulsive tendencies. The mean interoceptive-deficit score was 12.76, while the mean emotional-eating score was 2.63 on the five-point response scale. The mean Eating Attitudes Test–26 score of 14.88 was below the conventional screening threshold at the sample level, although the relatively large standard deviation of 10.37 indicated that a substantial subgroup reported clinically relevant eating-related concerns. The mean somatic symptom score was 7.92, corresponding to a generally mild level of symptom burden across the entire sample, with considerable variation between participants.

All principal predictors were positively associated with both components of eating-related psychosomatic risk. Emotional eating showed the strongest association with the continuous psychosomatic-risk index, $r = .68$, $p < .001$, followed closely by interoceptive deficits, $r = .66$, $p < .001$. Total impulsivity was moderately associated with the continuous risk index, $r = .52$, $p < .001$, whereas body mass index demonstrated a smaller but still statistically significant association, $r = .31$, $p < .001$. Emotional eating was strongly associated with disordered eating attitudes, $r = .64$, $p < .001$, and moderately associated with somatic symptom burden, $r = .46$, $p < .001$. Interoceptive deficits were also strongly related to disordered eating attitudes, $r = .61$, $p < .001$, and moderately related to somatic symptom burden, $r = .49$, $p < .001$. The correlation between disordered eating attitudes and somatic symptom burden was .55, $p < .001$, supporting the conceptual distinction between the two outcome dimensions while demonstrating meaningful co-occurrence. Correlations among the predictors ranged from .16 to .53. The largest predictor correlation was observed between interoceptive deficits and emotional eating, $r = .53$, $p < .001$, but none of the associations approached a level suggesting problematic redundancy. The comparatively weak correlations between body mass index and the psychological predictors indicated that the anthropometric modality contributed information that was related to, but not interchangeable with, the psychometric modality.

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Table 2

Performance of Candidate Classification Models in the Independent Test Dataset

Model	ROC–AUC (95% CI)	PR–AUC	Sensitivity	Specificity	PPV	NPV	F1 Score	Balanced Accuracy	Brier Score
Conventional logistic regression	.801 (.718–.876)	.568	.765	.805	.510	.928	.612	.785	.151
Elastic-net logistic regression	.838 (.765–.903)	.621	.794	.836	.563	.939	.659	.815	.137
Support vector machine	.859 (.794–.916)	.658	.824	.844	.583	.947	.683	.834	.125
Random forest	.872 (.808–.928)	.672	.794	.859	.600	.940	.684	.827	.119
Extreme gradient boosting	.893 (.835–.944)	.714	.853	.867	.630	.957	.725	.860	.106
Early-fusion multimodal neural network	.905 (.850–.952)	.742	.882	.875	.652	.966	.750	.879	.098
Late-fusion multimodal model	.897 (.839–.946)	.731	.853	.883	.659	.958	.744	.868	

Table 2 presents the performance of the candidate algorithms in the previously unseen independent test dataset. The conventional logistic regression model produced an ROC–AUC of .801, indicating acceptable discrimination between participants with and without elevated eating-related psychosomatic risk. At the prespecified threshold, this model correctly identified 26 of the 34 elevated-risk participants, producing a sensitivity of .765. It correctly classified 103 of the 128 participants without elevated risk, resulting in a specificity of .805. Its positive predictive value was .510, indicating that approximately half of the participants classified as high risk by the conventional regression model actually met the combined risk criterion. Its negative predictive value was substantially higher at .928, demonstrating that a low-risk prediction was generally reliable. Nevertheless, the model’s Brier score of .151 indicated that the accuracy of its predicted probabilities was inferior to that of the more complex algorithms.

Penalization improved the performance of logistic regression. The elastic-net model achieved an ROC–AUC of .838 and a precision–recall area of .621. Its sensitivity was .794, specificity was .836, and balanced accuracy was .815. The improvement suggested that shrinkage of weak or redundant item-level coefficients was useful when the psychometric features were modeled simultaneously. The support vector machine produced a further increase in discrimination, with an ROC–AUC of .859 and a precision–recall area of .658. It identified 28 of the 34 elevated-risk participants and correctly classified 108 of the 128 participants without elevated risk. Its negative predictive value of .947 indicated that fewer than 6% of participants classified as low risk were false-negative cases.

The random forest model achieved an ROC–AUC of .872 and the highest specificity among the single-algorithm models other than the multimodal fusion approaches. However, its sensitivity of .794 was lower than that of the support vector machine and the boosting-based models. Extreme gradient boosting showed stronger overall performance, with an ROC–AUC of .893, a precision–recall area of .714, sensitivity of .853, specificity of .867, and balanced accuracy of .860. This model correctly identified 29 of the 34 elevated-risk participants and 111 of the 128 participants without elevated risk. Its Brier score of .106 also indicated more accurate predicted probabilities than those produced by the regression, support vector machine, and random forest models.

The early-fusion multimodal neural network demonstrated the strongest overall test-set performance. Its ROC–AUC was .905, with a 95% confidence interval ranging from .850 to .952, and its precision–recall area was .742. The model correctly identified 30 of the 34 elevated-risk participants, corresponding to a sensitivity of .882, and correctly classified 112 of the 128 participants without elevated risk, corresponding to a specificity of .875. The resulting positive predictive value was .652, meaning that almost two thirds of participants classified as elevated risk met the combined outcome criterion. The negative predictive value was .966, indicating that only 4 of the 116 participants classified as low risk were actually elevated-risk cases. The model’s F1 score was .750, its balanced accuracy was .879, and its Brier score was .098. These results indicated that the early-fusion architecture provided the most favorable combination of discrimination, sensitivity, specificity, class-sensitive accuracy, and probability calibration.

The late-fusion model produced performance that was closely comparable to that of the early-fusion model, with an ROC–AUC of .897 and a precision–recall area of .731. Its specificity of .883 and positive predictive value of .659 were marginally higher than those of the early-fusion model, but its sensitivity was lower at .853. Thus, the late-fusion model generated fewer false-positive classifications but missed one additional elevated-risk participant. Pairwise comparison of receiver operating characteristic areas showed that the early-fusion model significantly outperformed conventional logistic regression, p = .008, and elastic-net logistic regression, p = .029. Its advantage over extreme gradient boosting was smaller and did not reach statistical significance, p = .371. Considering the screening-oriented objective of the study, the early-fusion model was retained as the final model because it achieved the highest sensitivity, highest ROC–AUC, highest precision–recall area, highest F1 score, and lowest Brier score.

Calibration analysis further supported the performance of the final model. The early-fusion neural network produced a calibration intercept of 0.04 and a calibration slope of 0.96 in the independent test dataset. These values were close to the ideal values of zero and one, respectively, suggesting limited systematic overestimation or underestimation of risk. Participants assigned predicted probabilities below .20 had an observed elevated-risk prevalence of 5.1%, whereas participants assigned probabilities between .20 and .49 had an observed prevalence of 24.6%. Among participants with predicted probabilities between .50 and .74, the observed prevalence was 59.3%, and among those with predicted probabilities of .75 or higher, the observed prevalence was 81.8%. This progressive increase in observed risk across probability intervals indicated that the model's predicted probabilities had meaningful clinical ordering and could potentially be used for graded screening rather than only binary classification.

Table 3

Modality Contribution and Feature-Ablation Performance of the Final Predictive Framework

Predictor Configuration	ROC–AUC (95% CI)	Change in ROC–AUC	PR–AUC	Sensitivity	Specificity	Balanced Accuracy	Brier Score
Body mass index only	.664 (.566–.759)	−.241	.346	.647	.648	.648	.184
Psychometric predictors only	.892 (.834–.942)	−.013	.721	.853	.867	.860	.105
Complete multimodal model	.905 (.850–.952)	Reference	.742	.882	.875	.879	.098
Complete model without impulsivity	.887 (.827–.938)	−.018	.700	.824	.867	.846	.111
Complete model without interoceptive deficits	.874 (.810–.930)	−.031	.681	.824	.852	.838	.117
Complete model without emotional eating	.858 (.790–.918)	−.047	.643	.794	.844	.819	.126
Complete model without body mass index	.892 (.834–.942)	−.013	.721	.853	.867	.860	.105

The modality comparison and ablation findings presented in Table 3 demonstrated that body mass index alone had limited predictive capacity. The body mass index-only model produced an ROC–AUC of .664 and a precision–recall area of .346. Its sensitivity and specificity were both approximately .65, and its Brier score of .184 indicated relatively weak probability accuracy. Although this performance exceeded chance prediction, it was substantially lower than that of models incorporating psychological variables. The finding indicated that anthropometric status alone was insufficient for accurately distinguishing individuals whose disturbed eating attitudes co-occurred with moderate or severe somatic symptom burden.

The psychometric-only model, which included impulsivity, interoceptive deficits, and emotional eating but excluded body mass index, achieved an ROC–AUC of .892, a precision–recall area of .721, and a balanced accuracy of .860. Its performance was therefore substantially stronger than that of the body mass index-only model. Adding body mass index to the psychological predictors increased the ROC–AUC from .892 to .905 and reduced the Brier score from .105 to .098. The improvement in discrimination was modest in absolute magnitude, but the complete multimodal model correctly identified one additional elevated-risk participant and one additional non-risk participant compared with the psychometric-only model. These results suggested that most of the model's predictive capacity was derived from the psychometric measures, while body mass index provided a smaller but nonredundant contribution that improved final classification and calibration.

Removal of emotional eating produced the largest reduction in predictive performance. When emotional-eating variables were excluded, the ROC–AUC decreased from .905 to .858, the precision–recall area decreased from .742 to .643, and balanced accuracy declined from .879 to .819. Sensitivity also decreased from .882 to .794, indicating that omission of emotional eating resulted in three additional

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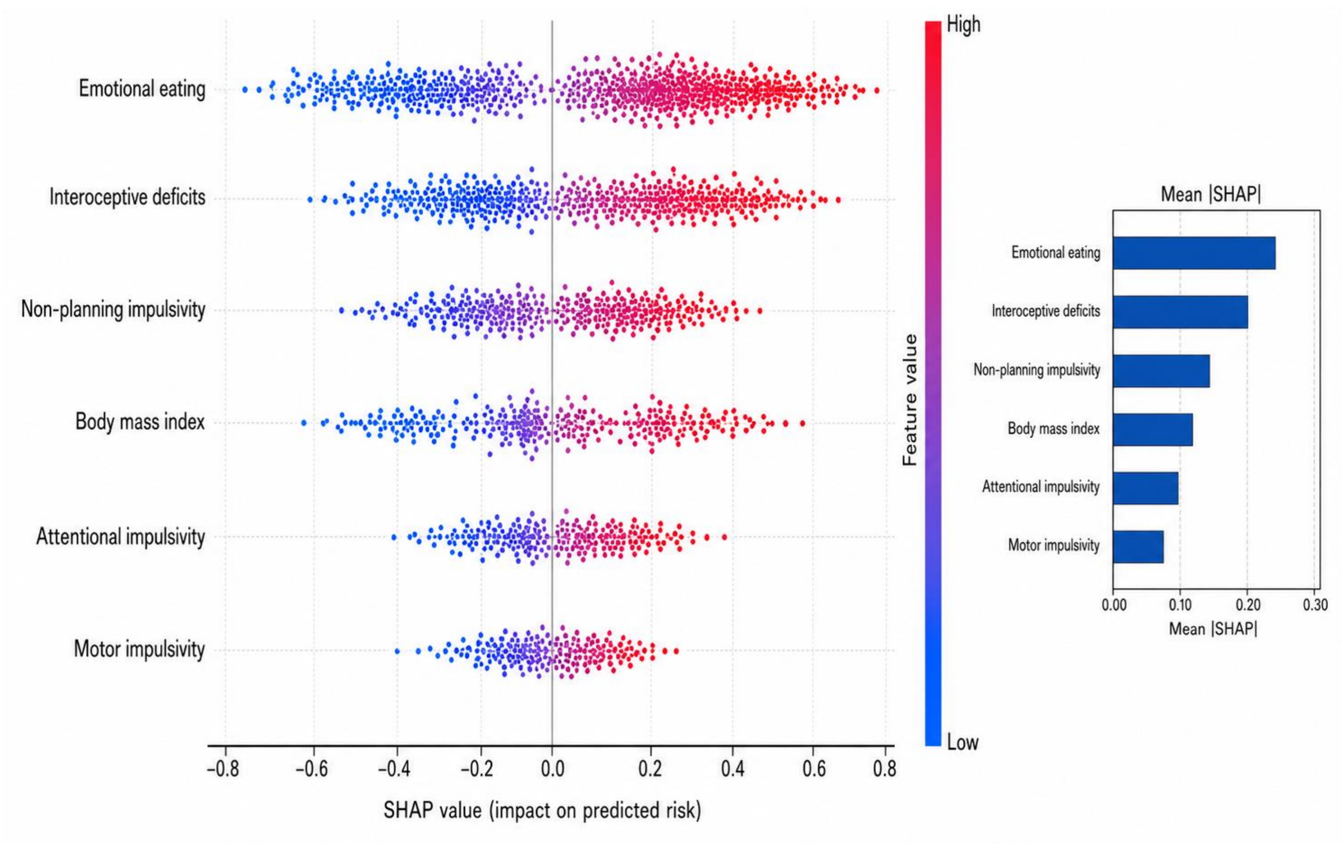
false-negative cases. The Brier score increased from .098 to .126, showing that emotional-eating information contributed not only to discrimination but also to the accuracy of predicted probabilities. This pattern identified emotional eating as the most influential predictor domain in the multimodal framework.

Removal of interoceptive deficits produced the second-largest performance reduction. The corresponding ROC–AUC declined to .874, and the precision–recall area declined to .681. Sensitivity fell to .824, specificity fell to .852, and the Brier score increased to .117. This finding indicated that difficulty identifying and interpreting internal bodily and emotional signals provided information that could not be fully replaced by emotional eating, impulsivity, or body mass index. Removing impulsivity resulted in a smaller but still meaningful reduction, with an ROC–AUC of .887 and a precision–recall area of .700. The decrease in sensitivity from .882 to .824 suggested that impulsivity was particularly useful for identifying a subset of elevated-risk participants whose risk might not have been fully represented by emotional-eating or interoceptive-deficit scores alone.

The smallest reduction occurred when body mass index was removed from the complete model. The ROC–AUC decreased by .013, and the Brier score increased by .007. Although this decrement was smaller than those associated with removing the psychological constructs, it was consistent across discrimination, sensitivity, specificity, and calibration measures. Taken together, the ablation analyses demonstrated that the multimodal framework performed best when all four predictor domains were retained. Emotional eating provided the greatest unique predictive contribution, followed by interoceptive deficits and impulsivity, while body mass index supplied a smaller complementary contribution that improved the overall stability and precision of the final model.

Figure 1

Shapley Additive Explanation Summary of the Final Early-Fusion Multimodal Model



The model-interpretation analysis summarized in Figure 1 confirmed that emotional eating was the dominant contributor to individual risk predictions. The overall emotional-eating score had the largest mean absolute Shapley value, followed by interoceptive deficits, non-planning impulsivity, body mass index, attentional impulsivity, and motor impulsivity. Higher emotional-eating scores consistently shifted model predictions toward the elevated-risk category. The relationship was not entirely linear. Predicted risk increased gradually at emotional-eating scores below approximately 2.50 but rose more sharply when scores exceeded approximately 3.00. Participants with emotional-eating scores above 3.50 showed the largest positive contributions to predicted risk, particularly when elevated emotional eating occurred together with high interoceptive-deficit scores.

Interoceptive deficits demonstrated a similarly directional but somewhat more gradual association with model predictions. Scores below approximately 8 were generally associated with lower predicted risk, whereas scores above approximately 15 increasingly shifted predictions toward elevated psychosomatic risk. The strongest positive contributions were observed among participants who reported substantial difficulty distinguishing hunger, satiety, emotional activation, and nonspecific bodily discomfort. Interaction analysis showed that the combination of elevated interoceptive deficits and elevated emotional eating generated a greater increase in predicted risk than would have been expected from either variable considered independently. This interaction suggested that emotional eating was especially predictive when participants also had difficulty accurately interpreting internal physiological and emotional signals.

Among the impulsivity dimensions, non-planning impulsivity made the greatest contribution to prediction. High non-planning scores increased predicted risk, particularly among participants with elevated emotional eating. Attentional impulsivity also contributed positively, with higher risk observed among individuals reporting difficulty maintaining cognitive focus and resisting intrusive or rapidly changing impulses. Motor impulsivity had a smaller overall contribution but remained informative for a subgroup characterized by immediate behavioral responding and high emotional-eating scores. The Shapley interaction patterns suggested that impulsivity primarily amplified the effect of emotional eating rather than acting as an isolated predictor of elevated psychosomatic risk.

Body mass index exhibited a nonlinear relationship with predicted risk. The lowest model contributions were generally observed among participants with body mass index values between approximately 22 and 25 kg/m². Predicted risk increased progressively at values above 28 kg/m² and became more pronounced above 32 kg/m². A smaller increase in predicted risk was also observed at body mass index values below approximately 19 kg/m². This shallow U-shaped pattern indicated that both relatively low and relatively high body mass index could contribute to elevated risk, although the effect was substantially stronger at higher values. Body mass index had the greatest predictive influence when combined with emotional eating and disordered interoceptive awareness. High body mass index in the absence of psychological risk factors generally produced only a modest increase in predicted probability, whereas high body mass index accompanied by elevated emotional eating and interoceptive deficits produced substantially higher predicted risk.

Local explanation analyses further demonstrated that elevated psychosomatic risk was generally produced by combinations of predictors rather than by a single extreme score. For example, participants with moderately elevated emotional eating, moderate interoceptive deficits, and high non-planning impulsivity were frequently assigned high-risk probabilities even when their body mass index was within the normal or overweight range. Conversely, some participants with obesity were assigned relatively low predicted probabilities when emotional eating, interoceptive deficits, and impulsivity were low. These findings indicated that body mass index did not function as a deterministic marker and that psychological characteristics substantially altered its predictive meaning.

Supplementary regression analyses using the continuous psychosomatic-risk index supported the classification findings. The final multimodal model produced a mean absolute error of 0.39 standardized units, a root mean squared error of 0.52, and an explained variance of 61.8% in the independent test dataset. The psychometric-only model explained 59.4% of the variance, whereas the body mass index-only model explained 11.7%. The complete model therefore retained its advantage when psychosomatic risk was represented continuously rather than dichotomously. Emotional eating and interoceptive deficits remained the two most influential predictors of continuous risk severity.

Sensitivity analyses also indicated that the principal findings were robust. Adding age and sex to the complete multimodal model resulted in only a small increase in ROC–AUC from .905 to .909 and did not materially change sensitivity, specificity, or the ranking of predictor importance. Excluding the 105 participants who reported current psychological, psychiatric, nutritional, or weight-management treatment produced an ROC–AUC of .899, sensitivity of .875, and specificity of .869. Repeating the analysis with class-balancing through synthetic

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oversampling within the training folds yielded an ROC–AUC of .901, but specificity declined slightly because the model generated more false-positive classifications. The class-weighted model was therefore retained as the primary approach.

Subgroup analyses showed generally comparable discrimination across demographic groups. The final model produced an ROC–AUC of .901 among women and .894 among men. Sensitivity was .889 among women and .867 among men, while specificity was .871 and .880, respectively. The model achieved ROC–AUC values of .897 among participants aged 18 to 24 years, .910 among those aged 25 to 34 years, and .889 among those aged 35 to 45 years. Performance also remained acceptable across recruitment sites, with ROC–AUC values ranging from .876 to .918. Calibration was slightly less precise in the smallest site-specific subgroup, but no systematic geographic pattern of overprediction or underprediction was observed. Across body mass index categories, discrimination was highest among participants with overweight or obesity and somewhat lower among underweight participants, although the underweight subgroup contained too few elevated-risk cases to support a definitive comparison.

Overall, the findings demonstrated that eating-related psychosomatic risk could be predicted with a high level of discrimination by integrating impulsivity, interoceptive deficits, emotional eating, and body mass index. The complete early-fusion multimodal model outperformed conventional regression and single-modality models, correctly identified 88.2% of elevated-risk participants, and generated well-calibrated probability estimates. Emotional eating and interoceptive deficits accounted for the largest proportion of predictive information, impulsivity improved identification of behaviorally vulnerable individuals, and body mass index contributed complementary anthropometric information. The consistency of the findings across classification, continuous-outcome, ablation, calibration, and subgroup analyses supported the stability of the final predictive framework.

4. Discussion and Conclusion

The present study developed and evaluated multimodal machine-learning models for predicting eating-related psychosomatic risk from impulsivity, interoceptive deficits, emotional eating, and body mass index among 812 Mexican adults. Elevated risk, defined by the co-occurrence of clinically relevant disordered eating attitudes and moderate or greater somatic symptom burden, was identified in 21.3% of the sample. All four predictor domains were positively associated with the continuous psychosomatic-risk index, although emotional eating and interoceptive deficits demonstrated the strongest correlations. The early-fusion multimodal neural network achieved the best overall performance in the independent test sample, with an area under the receiver operating characteristic curve of .905, a precision–recall area of .742, sensitivity of .882, specificity of .875, and a Brier score of .098. This model outperformed conventional logistic regression and produced slightly better discrimination and calibration than the remaining machine-learning approaches. Ablation analyses showed that emotional eating made the largest unique contribution to prediction, followed by interoceptive deficits, impulsivity, and body mass index. Although body mass index alone had limited predictive performance, its inclusion modestly improved the complete model. The findings therefore indicate that eating-related psychosomatic risk is most accurately understood as a multidimensional pattern arising from the interaction of emotional, interoceptive, behavioral, and anthropometric characteristics rather than as a direct consequence of body mass alone.

The prevalence of elevated combined risk indicates that a substantial subgroup of adults in the community may experience eating-related psychological difficulties together with clinically meaningful physical symptom burden, even without being selected from a specialized eating-disorder service. This result is compatible with evidence that eating styles form heterogeneous profiles associated with different levels of psychological well-being rather than falling into a simple healthy-versus-disordered distinction (Serier et al., 2026). Eating-disorder vulnerability is also known to arise from multiple interacting risk domains, including emotional, cognitive, behavioral, interpersonal, and biological factors (Aouad et al., 2023). The present findings extend this multidimensional perspective by demonstrating that the simultaneous consideration of eating attitudes and somatic complaints can identify a clinically relevant risk group within a nonclinical adult population. This combined outcome may be particularly valuable because physical complaints can become the most visible manifestation of distress, while the eating-related and emotional processes underlying them remain unrecognized. Functional difficulties reported among adults with eating pathology further suggest that these symptoms may interfere with social and occupational adjustment well before or beyond formal diagnosis (Iida et al., 2023). Moreover, long-term

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outcomes in eating disorders depend on a broad configuration of clinical, personality, and psychopathological factors, reinforcing the importance of identifying risk at a multidimensional level (Amianto et al., 2022).

Emotional eating emerged as the strongest predictor of eating-related psychosomatic risk. It had the largest correlation with the continuous risk index, the highest global Shapley importance, and the greatest impact on model performance when removed. Excluding emotional eating reduced the test-set area under the receiver operating characteristic curve from .905 to .858 and generated a marked decline in sensitivity and calibration. This pattern suggests that eating in response to negative affect is a central pathway through which emotional distress becomes linked to problematic eating attitudes and bodily symptoms. Emotional states influence food valuation, appetite, attention, and decision-making, thereby affecting both whether an individual eats and the type and quantity of food selected (Ha & Lim, 2023). When food repeatedly serves as a rapid means of reducing sadness, anxiety, anger, loneliness, or boredom, the temporary relief associated with eating may reinforce the behavior and gradually weaken reliance on internal hunger and satiety signals. The systematic evidence that emotions can be experienced as or mistaken for hunger provides a particularly relevant explanation for the present findings (Marano et al., 2026). Participants with high emotional-eating scores may have interpreted emotional activation as a need to eat, while simultaneously experiencing the physical consequences of stress, overconsumption, guilt, or weight concern as somatic distress.

The strong contribution of emotional eating also aligns with the view that stress-related eating reflects a learned coupling between negative affect and food consumption. Restoring a healthier relationship with food may require disruption of this connection rather than exclusive emphasis on calorie restriction or weight control (Warren & Frame, 2025). The nonlinear pattern identified in the Shapley analysis, in which predicted risk increased more sharply at higher emotional-eating scores, suggests that emotional eating may become particularly harmful after it develops into a frequent and generalized response across multiple negative emotional states. Evidence that brief mindfulness can reduce emotional eating through alleviation of negative affect supports the interpretation that emotion regulation is a modifiable mechanism underlying this relationship (Huang et al., 2025). Mindfulness interventions may also alter attention toward salient food stimuli and reduce automatic reactivity to food cues, although existing findings show variability across intervention types and populations (Duffy & Attuquayefio, 2025). In the current study, the importance of emotional eating remained substantial even when impulsivity, interoceptive deficits, and body mass index were simultaneously considered, indicating that its predictive value could not be reduced to general behavioral dysregulation or weight status.

Interoceptive deficits were the second most influential predictor domain. Their removal reduced the model's area under the receiver operating characteristic curve to .874 and increased the number of false-negative classifications. This finding indicates that difficulty detecting and interpreting internal bodily signals contributed information beyond emotional eating alone. Eating regulation depends on the recognition of hunger, gastric fullness, satiety, tension, autonomic arousal, and other internal cues. When these sensations are unclear or incorrectly interpreted, individuals may have difficulty determining whether the urge to eat reflects physiological need, emotional distress, habit, or responsiveness to external food cues. Research among individuals with obesity and bariatric surgery candidates has similarly shown that interoceptive sensibility is associated with intuitive and disordered eating behavior (Joshi et al., 2024). The present findings broaden this relationship by showing that interoceptive deficits also contribute to a combined eating-related and somatic risk outcome in a heterogeneous community sample.

The interaction between emotional eating and interoceptive deficits observed in the explanatory analyses is theoretically meaningful. Emotional eating was most strongly associated with high predicted risk when participants also reported substantial difficulty identifying internal sensations. This suggests that emotional activation may be especially likely to produce maladaptive eating when the individual cannot accurately distinguish emotional arousal from hunger or other bodily states. Previous work has examined whether the association between alexithymia and binge eating primarily reflects maladaptive emotion regulation or deficient interoception, concluding that both processes may be relevant and closely connected (Lyvers, Truncali, et al., 2022). Alexithymia, reward sensitivity, and excessive exercise have also been associated with severe binge-eating patterns, demonstrating that impaired emotional awareness may coexist with broader reward-driven and compensatory behaviors (Lyvers, Kelahroodi, et al., 2022). The present model supports an integrated

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explanation: interoceptive deficits may create uncertainty about bodily needs, emotional eating may provide an immediate behavioral response to that uncertainty, and psychosomatic symptoms may emerge from sustained attention to confusing or distressing physical sensations.

The predictive importance of interoception is also consistent with findings that impaired bodily awareness in eating disorders extends beyond hunger and satiety. Interoceptive awareness has been associated with the accuracy of subjective time evaluation, suggesting a broader disturbance in the integration of internal experience (Meneguzzo et al., 2022). An abnormal sense of agency has also been identified in individuals with eating disorders, indicating that some patients experience reduced ownership or control over bodily actions and behavioral outcomes (Colle et al., 2023). Such disturbances may help explain why eating is sometimes described as automatic, uncontrollable, or disconnected from conscious intention. Interoceptive impairment has additionally been associated with self-injury and suicidal ideation among adolescents with restrictive eating disorders and borderline personality disorder, showing that altered bodily awareness may be embedded within severe affective dysregulation (Riva et al., 2025). Borderline personality comorbidity has been linked to poorer or more complex treatment outcomes in anorexia nervosa, further emphasizing the clinical relevance of emotion regulation and bodily awareness (Voderholzer et al., 2021). Although the current sample was not restricted to clinical cases, these studies support the interpretation that interoceptive deficits represent a transdiagnostic vulnerability that may contribute to both eating-related disturbance and somatic distress.

Impulsivity also made a meaningful, although smaller, contribution to prediction. Total impulsivity was moderately associated with psychosomatic risk, and non-planning impulsivity was more influential than attentional and motor impulsivity in the Shapley analysis. Removing impulsivity reduced sensitivity and decreased overall model discrimination, indicating that impulsive tendencies helped identify participants whose elevated risk was not fully explained by emotional eating or interoceptive deficits. Impulsivity has previously been associated with food intake, eating attitudes, and maladaptive eating behavior (EmİRoĞLu & IŞIk, 2022). Non-planning impulsivity may be particularly relevant because it reflects a preference for immediate outcomes and limited consideration of future consequences. Under emotional distress, individuals high in non-planning impulsivity may prioritize the immediate soothing or rewarding effects of food despite anticipated guilt, physical discomfort, or long-term weight concerns. Attentional impulsivity may further impair sustained monitoring of internal signals, while motor impulsivity may facilitate rapid and unplanned consumption.

The interaction pattern observed between impulsivity and emotional eating suggests that impulsivity may function primarily as an amplifier of emotion-driven food intake. High impulsivity in the absence of emotional-eating tendencies did not consistently produce high predicted risk, whereas elevated impulsivity combined with emotional eating substantially increased risk estimates. This finding is consistent with the neural literature showing that stress can affect inhibitory control, reward processing, and disinhibited eating (Giddens et al., 2023). During periods of stress, heightened food reward and reduced inhibitory capacity may make emotionally motivated eating more difficult to resist. Cognitive impulsivity has also been associated with eating and obsessive symptoms in anorexia nervosa, demonstrating that impulsivity is not limited to binge-type or obesity-related presentations (Bevione et al., 2024). The multidimensional assessment used in the present study therefore appears advantageous because it captures forms of impulsivity that may operate across restrictive, compulsive, and disinhibited eating patterns.

Body mass index demonstrated a positive but comparatively modest association with psychosomatic risk. The body mass index-only model showed limited discrimination, with an area under the receiver operating characteristic curve of .664, whereas the psychometric-only model achieved an area of .892. These results clearly indicate that weight status alone cannot adequately identify individuals experiencing the combination of problematic eating attitudes and somatic symptom burden. Nevertheless, including body mass index improved the full model's discrimination and calibration, suggesting that anthropometric information provided a small but meaningful complementary contribution. The nonlinear Shapley pattern indicated increased risk at higher body mass index values and a smaller elevation at relatively low values. This pattern is plausible because eating-related psychopathology and bodily distress may occur at both ends of the weight continuum, although higher body mass may increase exposure to weight stigma, physical discomfort, dieting attempts, and emotion-related overeating.

Differences in bodily sensations associated with snack consumption across body mass index groups support the idea that weight status may alter how food intake is physically

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experienced (Frederiksen et al., 2024). Interoception has also been implicated in age-related obesity, suggesting that body weight may partly reflect long-term interactions between bodily awareness and eating regulation (Young & Brennan, 2023). Among bariatric surgery candidates, disordered eating behaviors have been associated with mood-spectrum symptoms and impulsivity, confirming that high body mass index often coexists with substantial psychological heterogeneity (Carmassi et al., 2026). The present results similarly showed that participants with obesity were not uniformly classified as high risk. Some had low predicted probabilities when emotional eating, interoceptive deficits, and impulsivity were limited, whereas participants with normal or moderately elevated body mass index could be classified as high risk when psychological vulnerabilities were pronounced. This finding argues against using body mass index as a proxy for eating-related psychopathology and supports its use as one component within a broader multimodal assessment.

The superiority of the early-fusion multimodal neural network indicates that psychosomatic risk involves nonlinear and interactive relationships that may not be fully represented by conventional additive models. The neural network combined psychometric and anthropometric pathways before generating a final risk probability, allowing it to learn patterns involving emotional eating, interoceptive deficits, impulsivity dimensions, and nonlinear body mass index effects. Its advantage over conventional logistic regression was statistically significant, although its performance was only modestly better than extreme gradient boosting. This result suggests that flexible nonlinear algorithms are useful, but that multiple machine-learning approaches can produce strong prediction when preprocessing, validation, and class imbalance are handled appropriately. The interpretability analyses were essential because predictive performance alone does not clarify why a model classifies an individual as high risk. The Shapley findings showed that risk generally resulted from combinations of features rather than one isolated value, which is consistent with contemporary calls to understand the psychological constructs underlying self-report eating-behavior measures rather than treating scale totals as simple and independent traits (Dakin et al., 2025).

The findings also have implications for embodied and awareness-based interventions. Educational programs designed to improve food consciousness may strengthen interoceptive sensitivity and awareness of external eating cues (Palazzo et al., 2021). Evidence that food-consciousness interventions can improve interoceptive sensitivity and the expression of exteroceptive experience supports the modifiability of processes identified by the current model (Palazzo et al., 2022). Body-oriented approaches, such as dance movement therapy, may also help individuals recognize, tolerate, and express bodily states rather than responding to them through restrictive or dysregulated eating (Bastoni et al., 2023). The association between trauma timing and distorted body image further indicates that bodily experience may be shaped by developmental adversity and should be assessed within a broader psychological context (Idini et al., 2024). Taken together, the results support a model in which emotional eating, interoceptive deficits, impulsivity, and body mass index contribute through partially distinct but interacting pathways to eating-related psychosomatic risk.

The findings should be interpreted in light of several limitations. The cross-sectional design prevented determination of temporal or causal relationships among impulsivity, interoceptive deficits, emotional eating, body mass index, and psychosomatic risk. The psychological predictors and outcomes were assessed primarily through self-report measures and may therefore have been influenced by recall bias, social desirability, limited introspective accuracy, and overlap among questionnaire constructs. Although the sample included participants from five major Mexican urban areas, it was not obtained through national probability sampling and may not represent rural populations, older adults, adolescents, Indigenous communities, or individuals with limited access to digital or health services. The combined outcome was intended as a risk indicator rather than a psychiatric diagnosis, and participants were not evaluated using structured clinical interviews. The independent test set strengthened internal validation, but it was relatively small and was drawn from the same overall recruitment process as the development sample. Consequently, the reported performance may not fully generalize to other regions, clinical settings, or cultural groups. Body mass index was the only anthropometric indicator included and did not capture body composition, metabolic status, weight history, or recent weight change.

Future studies should examine the temporal ordering of these variables through longitudinal designs that follow participants across periods of stress, weight change, treatment, and recovery. External validation should be conducted in independent Mexican samples and in other Latin American populations before the model is considered for broad clinical application. Research should incorporate

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structured diagnostic interviews, clinician-rated symptoms, ecological momentary assessment of affect and eating episodes, objective measures of food intake, physiological indicators of stress, and behavioral or physiological measures of interoception. Additional predictors such as trauma history, body-image disturbance, sleep, food insecurity, weight stigma, executive functioning, social support, and metabolic markers may improve prediction and clarify subgroup-specific pathways. Future models should also evaluate temporal prediction, fairness across demographic and socioeconomic groups, and the clinical consequences of false-positive and false-negative classifications. Prospective intervention studies could determine whether reductions in emotional eating or improvements in interoceptive awareness produce corresponding reductions in predicted psychosomatic risk.

In practice, eating-related psychosomatic risk should be assessed through an integrated evaluation rather than inferred from body weight alone. Health professionals working in primary care, nutrition, psychology, bariatric services, and university health settings should consider screening for emotional eating, difficulty recognizing hunger and satiety, impulsive decision-making, disordered eating attitudes, and recurrent physical symptoms. Individuals with high predicted risk should receive a comprehensive assessment that distinguishes physiological hunger from emotion-driven eating and examines the psychological meaning of somatic complaints. Interventions may benefit from combining emotion-regulation training, mindful awareness of internal sensations, impulse-management strategies, nutritional education, and non-stigmatizing discussion of body weight. Machine-learning predictions should support, rather than replace, clinical judgment, and risk scores should be communicated as probabilistic indicators requiring further evaluation rather than as diagnoses.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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