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Using Best-Worst Scaling to explore the perceived addictiveness of foods by processing level: a cross-sectional study among higher education students in Belgium

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Abstract

Background Higher education students increasingly consume ultra-processed foods (UPFs) because they are affordable, convenient, and heavily marketed, and this pattern has been linked to adverse health outcomes. Beyond health risks, emerging evidence suggests UPFs may elicit addictive-like eating behaviors. To better understand which foods are perceived as most addictive, we applied a Best–Worst Scaling (BWS) approach—a stated-preference method—to quantify the relative perceived addictiveness of foods varying in level of processing.

Methods A cross-sectional online survey was conducted between May 10 and July 5, 2024, among 609 higher education students in the province of Liège, Belgium. Food addiction was measured using the modified Yale Food Addiction Scale version 2.0 (mYFAS 2.0). To identify which foods were perceived as most and least addictive, we used a BWS choice experiment. Participants evaluated 15 sets of 5 foods (randomly selected from 30) and, in each set, identified the food that would trigger the most and the least addictive-like problems as defined by the mYFAS 2.0 criteria.

From these repeated choices, we calculated a Relative Importance Score (RIS) for each food, based on the standardized difference between its best and worst selections. The RIS provides a continuous measure of each food's perceived addictiveness relative to all others. Foods were categorized using the NOVA classification.

Results The prevalence of food addiction was 24.0% in the sample (5.4% mild, 6.4% moderate, and 12.2% severe). BWS results showed clear differences in perceived addictiveness across foods. Ultra-processed foods consistently ranked as the most problematic, with salted potato chips (RIS = 7.662; 95% CI 7.458–7.866), chocolate brownies (RIS = 7.579; 95% CI 7.357–7.802), sugary sweets (RIS = 7.462; 95% CI 7.234–7.689), and sugary soft drinks (RIS = 7.227; 95% CI 6.971–7.482). These foods did not differ significantly from one another but were distinctly more problematic than minimally processed or processed foods.

Conclusion Addictive-like eating behaviors were highly prevalent among higher education students. The application of a BWS design provided a nuanced, quantitative ranking of foods based on perceived addictiveness, highlighting

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the predominance of ultra-processed items. These findings underscore the need for targeted public health interventions addressing the role of UPFs in problematic eating behaviors.

Keywords Food addiction, Ultra-processed foods, Best-worst scaling, Students

Text box 1. Contributions to the literature

- In a context characterized by the rising prevalence of ultra-processed foods in modern diets, this study identifies higher education students as a population at risk of addictive-like eating behaviors, supporting the need for targeted public health interventions.
- The findings underscore the policy relevance of reducing the marketing and availability of ultra-processed foods, while promoting healthier alternatives in environments frequently accessed by students.
- By identifying specific foods commonly perceived as most problematic (e.g., chips, sweets, soft drinks), this study provides concrete targets for developing more focused and effective public health nutrition strategies and prevention campaigns.
- This study also demonstrates the value of Best–Worst Scaling as an innovative methodological approach to assess perceived food-related health risks at the population level, enabling more precise prioritization of intervention targets.

Background

The period of higher education represents a key transitional stage from adolescence to adulthood, particularly with respect to diet. During this transition, young adults gain autonomy, develop their own food choices and cooking skills, and lay the foundation for lifelong dietary behaviors [1]. At the same time, students face major changes - including increased independence, financial constraints, and academic demands - that can challenge and disrupt their eating behaviors [1, 2]. This period is frequently associated with a deterioration in dietary habits, including more frequent snacking and meals consumed outside the home [3–5], within a food environment characterized by abundant convenience and ready-to-eat products [6, 7]. Ultra-processed foods (UPFs) account for approximately 30% of total energy intake among Belgian adults [8, 9]. They are particularly appealing to young adults due to their affordability, accessibility, and convenience [10], contributing to rising consumption in this population.

The concept of UPFs was first introduced in 2009 by researchers at the University of São Paulo [11]. Although no universal definition exists, the most widely adopted is that of Monteiro (2016) [12]. UPFs are described as "formulations of several ingredients that, besides salt, sugar, oils, and fats, include substances not commonly used in culinary preparations—particularly flavorings, colorings, sweeteners, emulsifiers, and other additives—used to imitate the sensory qualities of minimally processed foods or to mask undesirable qualities of the final product" [10]. Monteiro et al. also proposed the NOVA classification, which categorizes foods into four groups based on processing level : unprocessed or minimally processed foods, processed culinary ingredients, processed foods, and UPFs [13, 14]. High consumption of UPFs is associated with an increased risk of cardiovascular diseases, cerebrovascular disorders, and depression, as well as a higher risk of overweight and obesity [15, 16].

Beyond health risks, emerging evidence suggests UPFs may elicit addictive-like eating behaviors [17]. The concept of food addiction was first proposed by Randolph in 1956 and has since gained increasing attention in the scientific literature, particularly with the development of models describing addictive-like eating behaviors [18, 19]. Although debated, several studies have highlighted strong similarities between food addiction and substance use disorders [20–22]. However, no clear consensus has been reached regarding its definition and conceptualization, particularly due to overlaps with certain eating disorders such as binge eating disorder and bulimia nervosa [23–25]. The Yale Food Addiction Scale (YFAS) is the most widely used instrument used instrument to assess these behaviors, although its ability to distinguish between clinical entities remains debated [25–27]. The modified Yale Food Addiction Scale version 2.0 (mYFAS 2.0), based on Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) diagnostic criteria, nevertheless provides a standardized tool to assess addictive-like eating behaviors [27–30]. Despite advances in the concept of food addiction, few studies have examined which specific foods or food attributes are most closely associated with problematic food consumption. Some evidence suggests a link between food addiction symptoms and the consumption of foods high in added fats and refined carbohydrates [22], as well as highly processed, hyper-palatable, and high-glycemic index foods [31]. These foods may promote addictive-like eating behaviors due to their enhanced palatability and energy density [22, 31, 32], as well as industrial processing techniques that increase the concentration and rapid absorption of rewarding nutrients. For example, the refinement of carbohydrates and the disruption of the natural food matrix may increase caloric availability and accelerate nutrient delivery, potentially enhancing food reward [33]. These characteristics may elicit neurobiological responses similar to those observed with addictive substances [22, 31]. However, most studies focus only on processed or ultra-processed products. Schulte et al. broadened the analysis by including unprocessed foods, showing, for instance, that nuts could be perceived as more addictive than certain processed cereal bars [34].

These findings underscore the need for further investigation into the relationship between food processing and perceived addictive potential.

The Best–Worst Scaling (BWS) method offers an innovative way to address this gap by providing a rigorous assessment of perceived problematic food consumption. Originally developed by Finn and Louviere [35–37] and subsequently widely applied in health economics, BWS requires respondents to make repeated, forced-choice evaluations in which they identify, within small sets of items, the option that would cause them the most problems and the one that would cause them the least [38–40]. In the context of food addiction, these judgments could explicitly refer to addictive-like problems as defined by the mYFAS 2.0 framework.

Unlike traditional rating scales, which are prone to ceiling effects and individual differences in scale use, BWS allows items to be compared on a common continuum. By aggregating these repeated choices, the method produces a continuous. Its methodological strengths—greater discriminative power and the ability to generate robust preference rankings [41]—make BWS particularly well suited to investigating perceptions of addictive-like eating, a domain where empirical evidence remains limited.

This study aimed to investigate the association between the degree of food processing, as defined by the NOVA classification, and addictive-like eating behaviors among higher education students in Belgium. More specifically, we applied BWS approach to identify which foods are perceived as most likely to trigger addictive-like problems and to assess how these perceptions correspond to their level of processing.

Methods

Participants

The study population consisted of higher education students from the province of Liège in Belgium, all aged over 18 years and fluent in French. Recruitment was voluntary and non-selective.

The required sample size for this cross-sectional study was calculated using the standard formula for estimating a population proportion in prevalence studies: $n = z^2p(1\text{-}p)/m^2$ [42, 43]. In this formula, z corresponds to the standard normal deviate associated with the desired confidence level, p represents the expected prevalence of the outcome of interest, and m corresponds to the desired absolute precision. A value of $z = 1.96$ was used for a 95% confidence level, $p = 0.177$ was based on the prevalence of food addiction reported among young adults by Pursey et al. [44], and $m = 0.05$ was selected as the desired absolute precision (margin of error) of 5% points. These assumptions yielded a minimum required sample size of 224 participants.

The data and the BWS experiment were collected through a self-administered online questionnaire. The online questionnaire and the BWS experiment were designed and programmed using Lighthouse Studio version 9.4 (Sawtooth Software, Inc., Provo, UT, USA) [45], which includes a dedicated MaxDiff module for BWS exercises. Participants accessed the survey through a secure web link. The questionnaire was disseminated through multiple channels, including posters and flyers displayed on campuses, social media, and institutional intranets. The survey was available between May 10 and July 5, 2024, and the data were hosted on the server of the Department of Public Health of the University of Liège.

Variables and measures

Food addiction assessment

Food addiction was measured using the French-validated modified Yale Food Addiction Scale 2.0 (mYFAS 2.0) [29, 30]. This instrument includes thirteen items measuring the 11 DSM-5 criteria for substance use disorders, along with clinically significant distress and impairment. Responses were recorded on an 8-point Likert scale. Two scoring approaches were used: a global score (0–11) corresponding to the number of criteria met, and a diagnostic method categorizing participants into four groups (no addiction, mild, moderate, or severe) [27, 29].

Best–Worst Scaling (BWS) task

The perceived addictiveness of foods was assessed using the BWS method. Thirty foods were chosen according to the dietary habits of Belgian young adults aged 18–21 years, as reported in the most recent national food consumption survey [46]. Foods were classified into three groups according to the NOVA classification: 10 unprocessed or minimally processed foods, 10 processed foods, and 10 ultra-processed foods [13, 14].

Each participant completed 15 choice sets, each containing 5 foods randomly generated using Sawtooth Software. For each set, participants selected the food that would cause them the most and the least addictive-like problems, explicitly as defined by the mYFAS 2.0 framework. Additional details regarding the BWS methodology, including the instructions provided to participants and an example of a BWS task, are available in the supplementary materials *(see Additional file 1)*.

Two complementary analytical approaches were used:

1. A counting analysis

   A relative score (ranging from − 1 to 1) was computed from the frequency with which each food was chosen as "best" or "worst," providing a simple index of relative perceived importance [39, 47].

2. A hierarchical Bayesian estimation

   A relative importance score (RIS) was generated for each food and each participant, with 95% confidence intervals. The sum of all RIS values for a given participant equals 100; if all foods were considered equally problematic, each would have a RIS of 3.334 (100 divided by 30 foods). Higher RIS values indicate foods perceived as more problematic, while lower values indicate foods perceived as less problematic [47–49]. Foods were ranked by mean RIS, and differences were assessed by overlap of confidence intervals [50].

Mean RIS scores were additionally calculated within each NOVA category (minimally processed, processed, and ultra-processed foods) by averaging the RIS of the 10 foods per group. These mean RIS values were used to identify the most problematic food category for each participant.

Sociodemographic and lifestyle variables

Participants reported sociodemographic, behavioral, and health-related characteristics. Gender was defined as woman, man, or other. Age was initially collected in single-year increments and subsequently grouped for analysis into three categories: 18–21 years, 22–25 years, and 26 years and over. Perceived financial resources were assessed via the following question: "In your opinion, do the financial resources you have allow you to meet your needs?" Response categories included very difficult, rather difficult, rather easy, or very easy. Dietary patterns were assessed using the question: "Do you follow a specific diet (e.g., vegetarian, lactose-free)?" (yes/no), followed by an open-ended specification when applicable. For analysis, dietary patterns were categorized into three groups: standard diet, vegetarian/vegan diet, and restrictive diet. Participants who did not report a specific diet were considered to follow a standard diet, while those reporting dietary restrictions such as lactose-free or gluten-free diets were classified as following a restrictive diet. Weight management status by asking participants whether they were trying to lose weight, maintain weight, gain weight, or not being concerned about weight. Snacking between meals was recorded as yes or no.

Addictive and substance-related behaviors were assessed over the past month. Perceived video game addiction was measured on a five-point scale ranging from never to very often. Cigarette and e-cigarette use were assessed separately and categorized as daily, occasional, or non-use. Use of other psychoactive substances (e.g., cannabis, cocaine, ecstasy) was assessed through self-report and categorized as non-use, occasional use, or regular use based on frequency.

Body mass index (BMI) was calculated as weight in kilograms divided by height in meters squared (kg/m²) and categorized according to World Health Organization (WHO) thresholds as underweight (< 18.5), normal weight (18.5–24.9), overweight (≥ 25), or obesity (≥ 30) [51, 52]. Finally, self-rated health was measured on a 1–10 scale.

These variables were selected because they have been shown in scientific literature to influence the consumption of ultra-processed foods or vulnerability to addictive eating patterns, and were therefore deemed relevant for inclusion in the statistical analyses [31, 53–62].

Statistical analysis

Data from Sawtooth Software were exported into Excel format. Quantitative variables were assessed for normality using comparisons of means and medians, histograms, quantile-quantile plots, and the Shapiro–Wilk test. As variables were not normally distributed, quantitative data were summarized using medians (P50) and interquartile ranges (P25–P75), while qualitative variables were reported as absolute and relative frequencies.

Differences in mean RIS across NOVA categories were assessed using the Kruskal-Wallis test. To further explore the respective roles of food processing and nutrient composition, additional analyses were conducted using nutritional data for the 30 foods included in the Best–Worst Scaling task. Nutritional information was retrieved from the French CIQUAL database (ANSES) [63], including sugar content (g/100 g), fat content (g/100 g), sodium content (mg/100 g), and energy density (kcal/100 g).

As the distributions of the variables deviated from normality, non-parametric Spearman rank correlation analyses were performed to assess associations between the mean Relative Importance Score (SIR) and each nutritional variable.

To identify participant characteristics associated with the perceived addictive potential of UPFs, simple and multiple linear regression analyses were conducted using the mean RIS associated with UPFs as the dependent variable. Higher RIS values indicated a greater perceived problematic nature of UPFs. To satisfy the assumptions of multiple linear regression, particularly the normality and homoscedasticity of residuals, a cube transformation was applied to the dependent variable. Commonly used alternative transformations, including logarithmic and square transformations, did not adequately meet these assumptions. Significant variables ($p < 0.05$) in simple regression were included in multiple regression model. Results were reported using regression coefficients (β) and standard errors (SE) and adjusted coefficient of determination (adjusted R^2).

Statistical significance was set at $p < 0.05$. All statistical analyses were carried out with R software version 4.2.1.

Quality control and sensitivity analyses

Quality control was integrated into the BWS task: the software prevented duplicate responses by restricting the selection to one "best" and one "worst" attribute per task. Outliers were checked using scatterplots and descriptive statistics but were retained in the analyses as they remained plausible values. Analyses were conducted on 609 participants, except for BMI, which was available for 608 subjects. Internal consistency of responses was assessed using Sawtooth Software's fit statistic, with values above the recommended threshold of 0.269 were considered satisfactory [64].

Two sensitivity analyses tested the robustness of the BWS findings. First, given the under-representation of men in the study sample, BWS analyses were replicated in gender-specific subgroups to determine whether the relative ranking of foods differed between women and men. Second, as participants completed the mYFAS 2.0 prior to the BWS task, additional analyses were conducted restricting the sample to those meeting the criteria for food addiction, in order to evaluate whether perceptions of problematic food differed by addiction status. Results from these sensitivity analyses were compared with those obtained in the full sample.

Results

A total of 1,449 individuals accessed the questionnaire. After excluding responses with an unvalidated introduction, missing identification, or incomplete data, the final analytical sample consisted of 609 participants (see Fig. 1).

Sociodemographic, lifestyle, and health-related characteristics of the participants are summarized in Table 1. Most were women (73.4%) and aged 18–21 years (48.8%). Over half reported having relatively easy financial resources. A large majority followed a standard diet (84.7%), and 43.0% were trying to lose weight. More than half reported snacking between meals (57.5%). Most participants did not feel addicted to video games (69.1%) and were non-smokers (87.5%). Similarly, the vast majority did not use e-cigarettes (87.4%) or psychoactive substances (94.4%). Based on BMI, 70.2% were of normal weight. The median self-rated health score was 7.0 (IQR: 6.0–8.0).

Assessment of food addiction: mYFAS 2.0 results

The prevalence of food addiction in the sample was 24.0%, comprising 5.4% with mild food addiction, 6.4% with moderate food addiction, and 12.2% with severe food addiction. The results are presented in Table 1. The

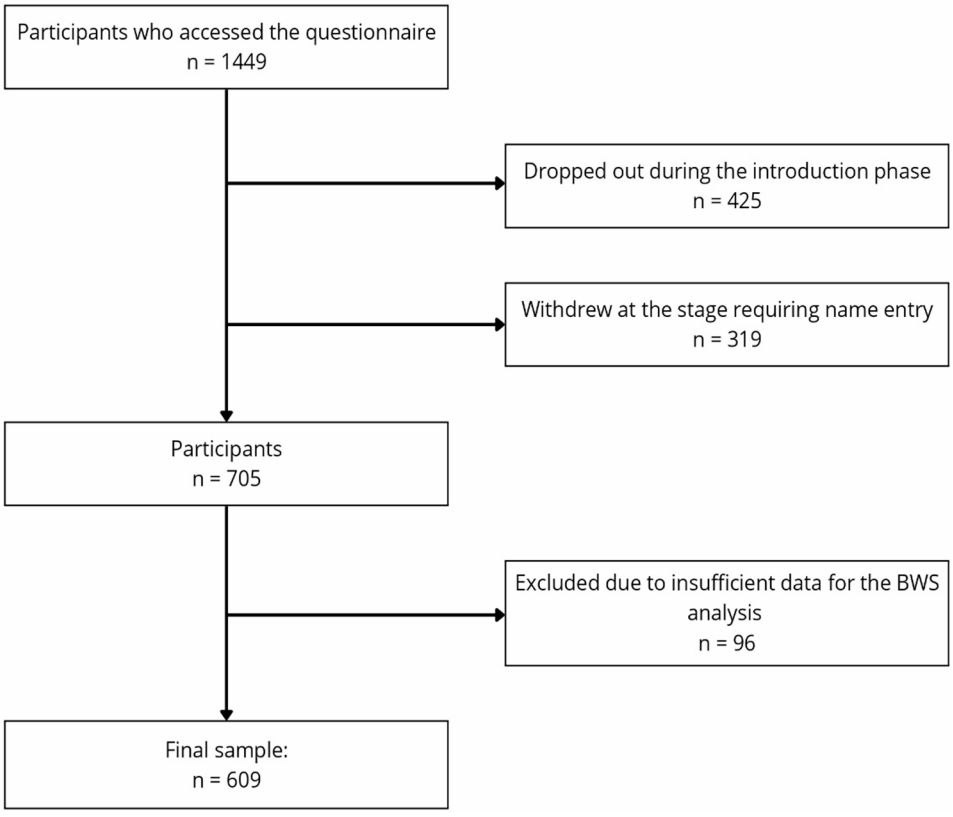

Fig. 1 Flow chart of recruitment and selection of higher education students participating in a cross-sectional study on food addiction and food processing in Liège, Belgium, May–July 2024. Flow diagram illustrating participant recruitment, exclusions, and selection for the final analytical sample ($n = 609$)

Table 1 Sociodemographic, lifestyle and health characteristics of higher education students participating in a cross-sectional study on food addiction and food processing in Liège, Belgium, May–July 2024

			Population (*n* = 609) *
Gender			
	Woman		447 (73.4)
	Man		156 (25.6)
	Other		6 (1.0)
Age			
	18–21 years		297 (48.8)
	22–25 years		240 (39.4)
	26 years and over		72 (11.8)
Financial resources			
	Very difficult		12 (2.0)
	Rather difficult		75 (12.3)
	Rather easy		318 (52.2)
	Very easy		204 (33.5)
Dietary pattern			
	Standard diet		516 (84.7)
	Vegetarian/Vegan		54 (8.9)
	Restrictive diet		39 (6.4)
Weight management status			
	Trying to lose weight		262 (43.0)
	Trying to maintain weight		178 (29.2)
	Trying to gain weight		33 (5.4)
	Not concerned about weight		136 (22.3)
Snacking between meals			
	Yes		350 (57.5)
	No		259 (42.5)
Feeling of addiction to video games			
	Never		421 (69.1)
	Rarely		84 (13.8)
	Sometimes		69 (11.3)
	Often		26 (4.3)
	Very often		9 (1.5)
Cigarette consumption			
	Non-smoker		533 (87.5)
	Occasional smoker		71 (11.7)
	Regular smoker		5 (0.8)
E-cigarette use			
	Non-user		532 (87.4)
	Occasional user		61 (10.0)
	Regular user		16 (2.6)
Use of psychoactive substances			
	Non-user		575 (94.4)
	Occasional user		30 (4.9)
	Regular user		4 (0.7)
BMI classification			
	Underweight		44 (7.2)
	Normal weight		427 (70.2)
	Overweight		94 (15.5)
	Obesity		43 (7.1)
Self-rated health (1–10)			7.0 (6.0–8.0)
Food addiction threshold			
		No food addiction	463 (76.0)
		Mild food addiction	33 (5.4)

Table 1 (continued)

		Population (*n* = 609) *
	Moderate food addiction	39 (6.4)
	Severe food addiction	74 (12.2)

* Data are presented as n (%) except for self-rated health, which is presented as median (interquartile range)

BMI Body mass index

Table 2 Perceived addictive potential of foods ranked using Best–Worst Scaling among higher education students in Liège, Belgium, May–July 2024

Attributes	Hierarchical Bayesian Estimation			Counting Analysis	
	Rank	RIS	95% CI	Rank	(B-W)/*N*
#22 Salted chips	1	7.662	7.458–7.866	4	0.444
#25 Chocolate cake such as brownies	2	7.579	7.357–7.802	3	0.477
#29 Sweet candies (chewing candies)	3	7.462	7.234–7.689	2	0.482
#21 Sugar-sweetened soft drinks (sodas, colas, etc.)	4	7.227	6.971–7.482	1	0.486
#30 Hamburger	5	6.453	6.210–6.696	5	0.313
#24 Chocolate- or honey-flavored breakfast cereals	6	6.213	5.965–6.461	6	0.294
#26 Chicken nuggets	7	6.074	5.837–6.311	7	0.259
#23 Processed meats, except ham (salami, pâté, blood sausage, etc.)	8	5.588	5.338–5.839	8	0.234
#27 Pudding	9	4.812	4.606–5.018	9	0.145
#12 White bread	10	4.285	4.048–4.521	10	0.127
#15 Canned fruits in syrup	11	4.113	3.904–4.322	11	0.088
#1 Pasta	12	3.669	3.402–3.936	12	0.077
#28 Packaged vegetable soup	13	3.490	3.261–3.720	13	0.044
#11 Hard cheese (Gouda, Gruyère, Parmesan, etc.)	14	3.136	2.893–3.379	14	0.034
#20 Canned tuna in oil	15	2.395	2.199–2.590	16	-0.038
#13 Ham	16	2.242	2.080–2.404	15	-0.032
#14 Green olives (in olive oil)	17	2.005	1.847–2.163	17	-0.048
#9 Plain tea or coffee	18	1.769	1.540–1.997	22	-0.203
#19 Smoked salmon	19	1.748	1.586–1.910	18	-0.085
#8 Unsalted dried fruits (hazelnuts, walnuts, pistachios, etc.)	20	1.621	1.411–1.832	24	-0.229
#16 Fruit compote	21	1.568	1.419–1.717	19	-0.111
#18 Pickles (sweet and sour, in jar)	22	1.547	1.390–1.704	20	-0.123
#7 Beef or chicken fillet	23	1.408	1.239–1.578	21	-0.176
#17 Canned vegetables (peas, carrots, etc.)	24	1.103	0.957–1.249	23	-0.217
#3 Rice	25	1.052	0.912–1.193	25	-0.235
#6 Eggs	26	0.990	0.853–1.127	26	-0.279
#4 Fish (salmon, tuna, sole, etc.)	27	0.831	0.701–0.961	27	-0.306
#2 Fruits (banana, apple, kiwi, melon, etc.)	28	0.675	0.535–0.815	29	-0.498
#10 Vegetables (carrots, zucchini, peppers, etc.)	29	0.645	0.504–0.786	30	-0.581
#5 Plain yogurt	30	0.637	0.529–0.744	28	-0.337

Foods were ranked according to their perceived addictive potential based on hierarchical Bayesian estimation and counting analysis. Relative Importance Scores (RIS) represent the relative perceived addictiveness of each food compared with all other foods included in the experiment; higher values indicate greater perceived addictive potential

CI Confidence interval, *B* Number of times a food was selected as most problematic, *W* Number of times a food was selected as least problematic, *N* Number of times a food appeared in a choice set

median food addiction score was 2 (0–4). Full details of the food addiction assessment are provided in the supplementary materials *(see Additional file 2)*.

Association between level of processing and food addiction: BWS results

Table 2 shows the results of both the counting analysis and the hierarchical Bayesian estimation. RIS indicates the relative importance score, with higher values representing foods perceived as more problematic. According to the hierarchical Bayesian estimates, the most problematic food was salted chips (RIS = 7.662; 95% CI 7.458–7.866), followed by chocolate cake such as brownies (RIS = 7.579; 95% CI 7.357–7.802) and sweet candies (chewing candies) (RIS = 7.462; 95% CI 7.234–7.689), with sugar-sweetened soft drinks (sodas, colas, etc.) ranking next (RIS = 7.227; 95% CI 6.971–7.482). Overall, 9 of the 10 foods ranked highest for perceived

addictiveness were classified as ultra-processed foods, whereas none of the 10 lowest-ranked foods were classified as ultra-processed foods. Instead, these foods were mainly unprocessed or minimally processed.

The results from both methods were generally similar: the four most addictive foods were identical, although their ranking differed depending on the method used. However, as noted previously, the confidence intervals for these four items largely overlap, indicating no significant difference in their perceived problematic nature. Detailed calculations from the counting analysis are provided in the Supplementary Material *(see Additional file 3)*. Subsequent analyses were conducted using the RIS.

Sensitivity analyses showed that the overall ranking of foods derived from the BWS remained largely consistent across gender-specific analyses and when the sample was restricted to participants with food addiction. Given the high consistency of findings, results are presented for the full sample irrespective of gender or food addiction status. Detailed results from sensitivity analyses are provided in the Supplementary Material *(see Additional file 4)*.

Figure 2 presents the ranking of attributes according to their RIS, with 95% confidence intervals.

For each participant, the mean RIS was calculated for each NOVA category, and the category with the highest mean RIS was considered the most problematic. Using this approach, most participants (91.0%) identified ultra-processed foods as most problematic, followed by processed foods (4.8%) and unprocessed or minimally processed foods (4.3%).

The distribution of mean RIS differed significantly according to the level of food processing ($p < 0.0001$, Kruskal–Wallis test). Ultra-processed foods exhibited the highest median RIS (6.72; interquartile range (IQR): 5.45–7.45), followed by processed foods (2.26; IQR: 1.88–2.79) and unprocessed foods (0.93; IQR: 0.40–2.01). These findings indicate a greater perceived difficulty associated with ultra-processed items compared to less processed food categories.

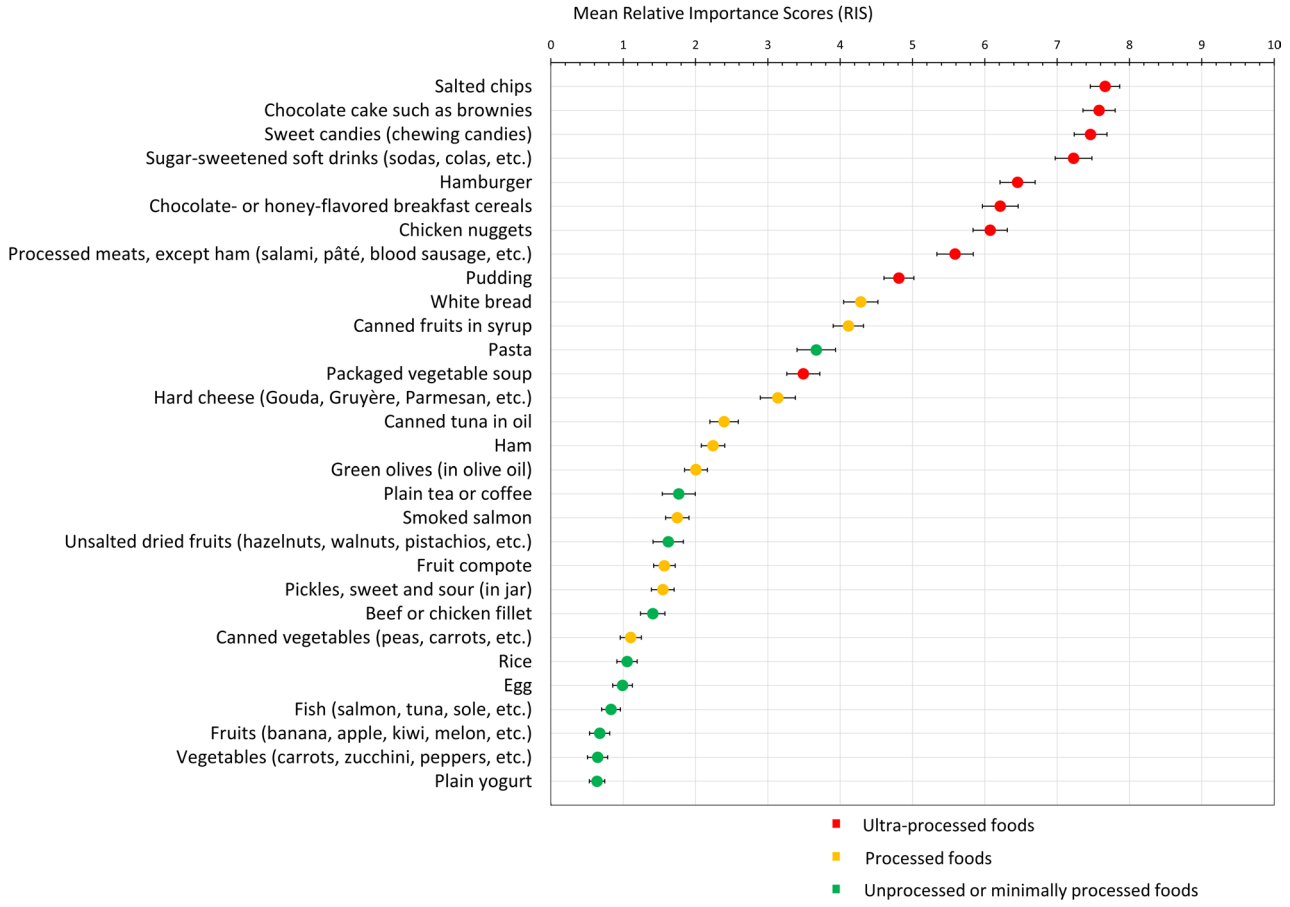

Fig. 2 Perceived addictive potential of foods according to degree of processing among higher education students in Liège, Belgium, May–July 2024. Foods are ranked according to their mean Relative Importance Score (RIS) derived from the Best–Worst Scaling experiment. Points represent mean RIS values and horizontal bars represent 95% confidence intervals. Higher RIS values indicate greater perceived addictive potential as defined by the modified Yale Food Addiction Scale version 2.0 (mYFAS 2.0). Food items are colour-coded according to the NOVA classification as ultra-processed, processed, or unprocessed/minimally processed foods. RIS = Relative Importance Score

Additional analyses examining nutritional characteristics of the foods included in the Best–Worst Scaling task showed that SIR was positively associated with sugar content ($\rho = 0.375$, $p = 0.041$) and energy density ($\rho = 0.505$, $p = 0.005$). No significant associations were observed with fat content ($\rho = 0.236$, $p = 0.209$) or sodium content ($\rho = 0.317$, $p = 0.088$).

Association of participant characteristics on the RIS associated with UPFs

Subsequent analyses were conducted using the RIS associated with UPFs. Higher RIS values for UPFs indicate a greater perceived problematic nature of these foods. Table 3 presents the results of the univariate and multivariate analyses. The adjusted R^2 was 0.039, indicating that 3.9% of the variability in the mean RIS for UPFs could be explained by gender, dietary pattern, psychoactive substance use, and BMI.

In the multivariate model, gender was significantly associated with RIS ($p = 0.005$). Men showed a significantly higher mean RIS compared with women ($\beta = 41.05 \pm 14.21$, $p = 0.004$). Dietary pattern was also associated with RIS ($p = 0.042$), although none of the pairwise comparisons remained statistically significant after adjustment. RIS differed significantly according to psychoactive substance use ($p = 0.017$). Regular users displayed a significantly lower mean RIS compared with non-users ($\beta = -215.68 \pm 75.88$, $p = 0.005$). BMI showed a non-significant overall association with RIS ($p = 0.059$). However, pairwise comparisons indicated that underweight participants had a significantly lower mean RIS than those with a normal BMI ($\beta = -54.74 \pm 23.87$, $p = 0.022$).

Discussion

In a food environment increasingly dominated by ultra-processed products, this study provided new insights on how the degree of food processing relates to addictive-like eating behaviors among higher education students. By coupling a validated measure of food addiction with an innovative preference-based approach, our findings move beyond global associations to pinpoint which foods are perceived as most likely to trigger addictive-like problems. This approach advances current knowledge by demonstrating that perceptions of problematic eating are not uniformly distributed across foods but strongly concentrated in items with higher levels of processing.

The use of Best–Worst Scaling represents a major methodological contribution. Unlike traditional rating scales, which are vulnerable to bias and limited discrimination, BWS captures participants' judgments through repeated trade-offs. This method not only clarifies relative perceptions that are difficult to obtain through conventional tools, but also generates a robust hierarchy of foods based on perceived addictiveness—an aspect rarely explored in nutrition research to date.

The results show that UPFs dominate the top of the ranking, particularly salted chips, chocolate cakes, sugary candies, and soft drinks. This finding is consistent with previous studies. Pursey et al. found that higher food addiction scores in young adults were associated with greater intake of energy-dense, nutrient-poor processed foods [65]. Schulte et al. found that ultra-processed, high-fat, and refined-carbohydrate foods were most often linked to addictive eating, though nuts—a minimally processed food—also showed unexpectedly high addictive potential, contrasting with the present study. Malika et al., using a qualitative approach, found that only UPFs high in added sugar and/or fat were identified as potentially addictive [66]. The most problematic foods identified in this present study also correspond to the most frequently consumed foods among young Belgian adults, suggesting a heightened risk of food addiction [46].

Additional analyses conducted on the nutritional characteristics of the foods included in the BWS task further suggest that certain nutritional characteristics, particularly those related to energy density and sugar content, may contribute to the perceived addictive-like properties of foods. Although these associations were of moderate magnitude, these findings highlight the persistent uncertainty regarding the respective roles of nutrient composition and food processing. While highly rewarding nutrients—such as refined carbohydrates and energy-dense foods—are known to contribute to addictive-like eating behaviors [34, 67], ultra-processed foods also possess structural and sensory properties that may further enhance their appeal [32, 57]. Taken together, our results support an integrative perspective in which both nutrient composition and degree of processing contribute to perceived addictiveness. These dimensions are closely intertwined in many foods, making their independent effects difficult to disentangle. Further research combining detailed nutritional profiling with processing classifications is needed to better understand these mechanisms.

In the multiple regression model, gender, certain dietary patterns, and psychoactive substance use were significantly associated with higher perceived difficulty in consuming UPFs, as reflected by the RIS.

Dietary pattern was associated with RIS in the present study. Although participants following restrictive diets tended to report higher RIS values than those following ordinary diets, these differences did not reach statistical significance in pairwise comparisons after adjustment. Given the heterogeneity of restrictive dietary practices and the limited number of participants in some categories, these findings should be interpreted cautiously. One possible explanation is that individuals adhering to restrictive diets may be more attentive to their

Table 3 Participant characteristics associated with perceived addictive potential of ultra-processed foods among higher education students in Liège, Belgium, May–July 2024

		Mean RIS associated with UPFs	Simple regressions		Multiple regression	
		M (P25 – P75)	β ± SE	*p**	β ± SE	*p**
Gender				**0.011**		**0.005**
	Woman	6.67 (5.37–7.35)	--	--	--	--
	Man	6.93 (5.79–7.65)	36.10 ± 14.14	**0.011**	41.05 ± 14.21	**0.004**
	Others	5.25 (4.84–6.663)	-92.33 ± 62.49	0.140	-85.51 ± 62.22	0.170
Age				0.959		
	18–21 years	6.74 (5.45–7.50)	--	--		
	22–25 years	6.71 (5.46–7.41)	-3.16 ± 13.30	0.812		
	26 years and more	6.76 (5.41–7.48)	-4.61 ± 20.12	0.819		
Financial resources				0.181		
	Rather easily	6.89 (5.67–7.54)	--	--		
	Very difficultly	6.84 (6.21–7.08)	-8.60 ± 44.91	0.848		
	Rather difficultly	6.58 (5.34–7.24)	-26.11 ± 19.60	0.183		
	Very easily	6.61 (5.21–7.38)	-28.21 ± 13.70	**0.040**		
Dietary pattern				**0.029**		**0.042**
	Ordinary diet	6.74 (5.44–7.50)	--	--	--	--
	Vegetarian/Vegan	6.38 (5.03–6.98)	-45.09 ± 21.79	**0.039**	-39.59 ± 21.78	0.070
	Restrictive diet	6.99 (6.29–7.56)	38.22 ± 25.29	0.131	39.90 ± 25.26	0.115
Weight management status				0.694		
	Trying to lose weight	6.79 (5.68–7.39)	--	--		
	Trying to maintain weight	6.72 (5.17–7.50)	-10.06 ± 14.88	0.499		
	Trying to gain weight	6.84 (5.67–7.65)	6.56 ± 28.29	0.817		
	Not concerned about weight	6.62 (5.33–7.42)	-17.03 ± 16.19	0.293		
Snacking between meals				0.823		
	Yes	6.74 (5.47–7.47)	--	--		
	No	6.72 (5.37–7.43)	-2.81 ± 12.55	0.823		
Feeling of addiction to video games				0.853		
	Never	6.69 (5.46–7.43)	--	--		
	Rarely	6.76 (5.45–7.43)	0.02 ± 18.32	0.999		
	Sometimes	6.99 (5.79–7.51)	19.90 ± 19.91	0.318		
	Often	6.48 (4.64–7.78)	-0.09 ± 30.98	0.998		
	Very often	5.96 (5.36–7.35)	-26.85 ± 51.64	0.603		
Cigarette consumption				0.417		
	Non-smoker	6.77 (5.46–7.49)	--	--		
	Occasional smoker	6.57 (5.23–7.11)	-23.27 ± 19.33	0.229		
	Regular smoker	5.42 (5.36–6.85)	-40.66 ± 68.74	0.554		
E-cigarette use				0.432		
	Non-user	6.72 (5.45–7.46)	--	--		
	Occasional user	6.83 (5.50–7.49)	13.93 ± 20.68	0.501		
	Regular user	6.23 (5.31–7.14)	-41.49 ± 38.82	0.286		
Use of psychoactive substances				**0.019**		**0.017**
	Non-user	6.72 (5.46–7.46)	--	**--**	**--**	**--**
	Occasional user	6.93 (5.31–7.32)	3.21 ± 28.51	0.910	8.27 ± 28.35	0.771
	Regular user	3.89 (2.93–4.66)	-215.17 ± 76.37	**0.005**	-215.68 ± 75.88	**0.005**
Body Mass Index				**0.030**		0.059
	Normal weight	6.75 (5.46–7.49)	--	--	**--**	**--**
	Underweight	6.00 (4.42–7.22)	-58.39 ± 24.12	**0.016**	-54.74 ± 23.87	**0.022**
	Overweight	6.96 (5.89–7.50)	22.57 ± 17.35	0.194	18.37 ± 17.22	0.287
	Obesity	6.59 (5.35–7.18)	-17.12 ± 24.37	0.483	-15.07 ± 24.20	0.534
Food addiction threshold				0.569		
	No food addiction	6.72 (5.43–7.47)	--	--		
	Mild food addiction	6.99 (5.86–7.22)	4.37 ± 27.58	0.874		

Table 3 (continued)

	Mean RIS associated with UPFs	Simple regressions		Multiple regression	
	M (P25 – P75)	β ± SE	*p**	β ± SE	*p**
Moderate food addiction	7.15 (5.91–7.67)	31.60 ± 25.52	0.216		
Severe food addiction	6.44 (5.33–7.27)	-10.62 ± 19.16	0.580		
Self-rated health (1–10)			0.367		
		3.48 ± 3.85	0.367		

Results of simple and multiple linear regression analyses examining associations between participant characteristics and Relative Importance Scores (RIS) attributed to ultra-processed foods among 609 higher education students in the province of Liège, Belgium. Higher RIS values indicate greater perceived addictive potential of ultra-processed foods. Results are presented as regression coefficients (β), standard errors (SE), and p-values

UPFs Ultra-processed foods, *RIS* Relative Importance Score

*Significant p-values are in bold

eating behaviors or more aware of potentially problematic foods, which could influence their perception of addictive-like properties. However, further research is needed to clarify whether specific dietary patterns consistently shape perceptions of UPFs.

Previous studies have suggested that reward-related responses to food may not increase linearly with BMI. Some authors have proposed that alterations in reward processing emerge early during weight gain and may be attenuated as obesity develops [68–72]. However, the present findings do not support this hypothesis. Although participants with overweight showed descriptively higher mean RIS scores than those with obesity, no statistically significant differences were observed between BMI categories.

These findings are also consistent with previous research linking food addiction to substance use disorders [20–22]. For example, data from the *Baromètre Santé 2005* indicate that men are generally more likely to engage in risk behaviors associated with addictive consumption. These findings suggest that gender-related factors may contribute to the propensity for developing addictive behaviors, whether involving psychoactive substances or ultra-processed foods [73]. These behavioral patterns may reflect underlying neurobiological mechanisms that contribute to the development of addictive behaviors. The concept of food addiction is based on neurobiological similarities between food intake and other addictive behaviors. Certain foods activate the dopaminergic reward circuit, leading to increased dopamine release in the nucleus accumbens, a mechanism comparable to that observed in substance-related addictions [74]. Preclinical studies indicate that natural rewards (e.g., food) and addictive rewards (e.g., psychoactive substances) engage largely overlapping brain circuits [75]. However, repeated exposure to addictive substances induces more widespread activation, persistent synaptic plasticity, and increased functional modularity, which is often described as maladaptive [75]. These findings suggest that drugs may profoundly alter the reward circuitry normally involved in processing natural rewards [75].

In the present study, regular users of psychoactive substances reported lower perceived addiction to ultra-processed foods. This may reflect a decrease in the relative salience of these foods, potentially due to desensitization of the reward system or a recalibration of subjective standards of addiction in these individuals. In addition, the anorexigenic effects of some psychoactive substances could contribute to a reduction in appetite, which may partly explain the lower perceived addictive-like consumption of ultra-processed foods observed in these individuals [76–78].

Despite the statistically significant associations observed, the multivariate model explained only a limited proportion of the variability in perceived problematic consumption of ultra-processed foods (adjusted R^2 = 0.039). This relatively low explanatory power suggests that perceived food addictiveness is influenced by a broader set of factors not captured in the present study. Previous research has highlighted the role of psychological characteristics such as depressive symptoms, anxiety and eating disorders in food addiction [79, 80]. In addition, exposure to food marketing represents a potentially important determinant of food addiction. Studies have consistently shown that marketing for energy-dense and ultra-processed foods influences food preferences, purchase intentions and consumption patterns. These effects appear particularly pronounced among vulnerable populations and may operate through mechanisms like cue-induced craving observed in substance-use disorders [81, 82].

Furthermore, individual differences in reward sensitivity, emotional regulation, as well as social and environmental contexts, may also contribute to shaping perceptions of addictive-like eating. Such multidimensional influences are consistent with the broader literature indicating that eating behaviors result from complex and interacting determinants. However, it should be noted that the primary aim of this study was not to comprehensively model these determinants, but rather to explore perceived addictive-like responses to foods. As such, the limited explanatory power of the model does not detract from the main contribution of the study, but

instead highlights the need for future research specifically designed to integrate the broader range of factors influencing food addiction-related perceptions.

Beyond these findings, the interpretation of results should also be considered in light of ongoing debates surrounding the concept of food addiction. While the concept remains debated, notably due to overlaps between YFAS-defined food addiction and established eating disorders such as binge eating disorder and bulimia nervosa [23–25], this overlap has raised concerns regarding the specificity of the construct and the ability of current instruments to distinguish between these conditions. In this context, the use of the term "addictive-like eating behaviors" in the present study reflects a cautious and conceptually consistent approach. Rather than aiming to establish food addiction as a distinct clinical entity, our findings contribute to the broader understanding of how certain foods—particularly ultra-processed foods—may elicit behavioral responses that share characteristics with addictive processes.

The present findings could have implications for public health nutrition. The observed association between UPFs and food addiction, along with their frequent consumption in Belgium, suggests a potential role of the food environment in shaping addictive-like eating behaviors. Food addiction prevalence in this student population (24%) was higher than in some previous studies among young adults, possibly reflecting students' particular vulnerability to problematic eating behaviors [30, 44, 83, 84]. These results highlight the need to consider UPFs not only as nutritional risk factors but also as potential contributors to compulsive consumption patterns linked to overweight, obesity, and chronic diseases [65].

From a public health perspective, these findings could support structural interventions to reduce exposure to the most problematic UPFs, such as targeted taxation of sugar-sweetened beverages, sweets, and salty snacks [85], restrictions in school and university cafeterias and vending machines [86], and limitations on marketing to young adults [87, 88]. Promoting less processed foods through education and awareness campaigns that emphasize their potentially lower addictive properties may also be effective. Multi-component strategies combining several approaches may be most effective for reducing UPF accessibility and improving student health.

These results also point to avenues for future research, including expanding to non-university populations and diverse socio-economic backgrounds, incorporating psychological measures (stress, anxiety, depression, eating disorders, addictions), and using qualitative approaches to explore students' perceptions of problematic food behaviors. Investigating these issues in children and adolescents may be important, as early eating habits can persist into adulthood and affect prevention strategies across the life course [89, 90].

Strengths and limitations

This study has several limitations. The non-probabilistic sampling method may have introduced selection bias, as voluntary participants may not be fully representative of the overall population. In addition, women were overrepresented in the study sample (73.4%), which may limit the generalizability of the findings to man higher education students. This imbalance partly reflects the composition of the Belgian higher education population; however, it may still have influenced the overall estimates of perceived food addictiveness [91]. Indeed, man participants showed significantly higher RIS values for UPFs in multivariate analyses, suggesting potential gender-related differences in perceptions of addictive-like eating behaviors. Although gender-specific sensitivity analyses yielded largely consistent food rankings, these analyses do not fully compensate for the underrepresentation of men. Future studies should aim for more balanced gender distributions to confirm the robustness of these findings across genders. Furthermore, although participants identifying as "Other" gender were retained in the analyses to avoid unnecessary exclusion, the very small sample size for this subgroup limited the robustness and interpretability of the corresponding estimates. This sample profile, characterized by a high educational and socio-economic level, could explain why BMI was not significantly associated with perceived addiction to UPFs [44, 92, 93].

Moreover, the concept of UPFs lacks a universal definition; the NOVA classification, recognized as reliable in nutrition and public health research, was used [94, 95]. In addition, the foods presented in the study may not have been described in sufficient detail—for example, a homemade chocolate cake could have been considered a processed food, whereas an industrial chocolate cake would be classified as an UPF. However, this limitation is mitigated by the fact that three of the four foods rated as most addictive—salted chips, sweet candies, and sugar-sweetened soft drinks—are clearly UPFs, which supports the validity of the observed results.

A major strength of this study lies in the innovative use of the BWS methodology to complement the assessment of food addiction. Food addiction has been conceptualized as sharing similarities with substance-related addictions [21, 22]. The Yale Food Addiction Scale (YFAS) captures addictive-like eating behaviors toward "certain foods," broadly defined as foods high in sugar, fat, and/or salt, sugar-sweetened beverages, and starchy foods [96].

In this context, the use of the BWS method provided important added value. The BWS tasks, based on the most frequently consumed foods from the

Belgian food consumption survey, anchor the assessment in the target population's real dietary habits. This approach enables the comparison of specific food items rather than broad food categories, by asking participants to make relative judgments through forced choices. By identifying both the most and least problematic foods, the BWS method provides a more discriminating assessment of perceived addictive foods and offers complementary insights to the YFAS within a public health nutrition perspective. To our knowledge, this is the first application of the BWS method in the field of food addiction, highlighting the originality and innovative contribution of this work. Furthermore, the robustness of these findings was supported by sensitivity analyses showing consistent BWS results across gender and food addiction status, despite minor subgroup-specific variations (*see Additional file 4*). Finally, the sample size ($n = 609$) far exceeds the minimum required ($n = 224$), thereby enhancing the study's statistical.

Conclusions

This study underscores the importance of examining food addiction in the context of ultra-processed food consumption among higher education students. Our findings reveal a notably high prevalence of addictive-like eating behaviors in this population and show that the foods perceived as most likely to trigger such problems are predominantly ultra-processed items—including soft drinks, confectionery, chocolate pastries, and chips—that are widely consumed in this population. By integrating a Best–Worst Scaling approach, the study also provides a nuanced and data-driven hierarchy of foods based on their perceived addictive potential.

These findings suggest that targeted public health interventions, including educational initiatives and policies, could contribute to limiting exposure to highly processed foods and increasing awareness of their potentially addictive potential. Moreover, additional research is needed to confirm these findings and inform potential prevention and intervention strategies for students and other at-risk populations, which could ultimately contribute to improved dietary behaviors and public health outcomes.

Abbreviations

BMI	Body Mass Index
BWS	Best–Worst Scaling
CI	Confidence interval
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
GI	Glycemic Index
IQR	Interquartile range
mYFAS 2.0	Modified Yale Food Addiction Scale version 2.0
R^2	Coefficient of determination
RIS	Relative Importance Score
SE	Standard Error
UPFs	Ultra–processed foods
WHO	World Health Organization

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13690-026-02006-x.

Additional file 1. Detailed description of the Best–Worst Scaling methodology: This supplementary file provides a detailed description of the Best–Worst Scaling (BWS) methodology used in the study, including the rationale for the selection of food items and experimental design, the counting and hierarchical Bayesian analyses used to derive Relative Importance Scores (RIS), the introductory instructions provided to participants, and an example of a BWS task displayed during the survey.

Additional file 2. Detailed results of food addiction assessment using the mYFAS 2.0: This supplementary file presents the detailed distribution of the mYFAS 2.0 diagnostic criteria in the study sample.

Additional file 3. Detailed results of the counting analysis: This supplementary file presents the detailed calculations of the Best–Worst Scaling (BWS) counting analysis, including the frequency with which each food item was selected as most and least problematic.

Additional file 4. Sensitivity analyses of Best–Worst Scaling results: This supplementary file presents the results of the hierarchical Bayesian estimation of the Best–Worst Scaling (BWS) analyses conducted in different subgroups (woman participants, man participants, and participants meeting the criteria for food addiction).

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Authors' contributions

EG conceived the study, collected the data, performed the analyses, interpreted the results, and wrote the manuscript. OE provided access to and expertise with Sawtooth Software for the BWS analysis, contributed to the execution of the analyses, and assisted in writing the BWS-related sections. ND assisted with statistical analyses and contributed to the interpretation of the statistical results. SP assisted with statistical analyses and contributed to the interpretation of the statistical results. AH provided support throughout the entire research process, including study conception, data interpretation, and supervision. All authors contributed to manuscript review and approved the final version.

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Data availability

The data and analysis code generated and/or analysed during the current study are available in the ULiège Open Data Repository (Dataverse): https://doi.org/10.58119/ULG/ADCEQD.

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of the University Hospital of Liège (approval number 2023/377). All participants provided informed consent prior to participation by entering their first name, last name, and date of birth before gaining access to the questionnaire. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. All participants were informed about the purpose of the study and assured of confidentiality. Participation was voluntary, and respondents could withdraw at any time without consequence.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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