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Dynamic interplay between food addiction, psychological and behavioral factors, and weight-related measures: A longitudinal network analysis in developing youth

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FULL-LENGTH REPORT

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ABSTRACT

Background and aims: Food addiction (FA) likely contributes to obesity within a complex system of psychological, behavioral, and physiological factors. However, interactions among these factors remain incompletely understood. This study used a network approach to identify interrelationships among FA, eating motives, lifestyle habits, and weight indicators in a developmental youth cohort. *Methods:* A longitudinal panel study was conducted in Eastern China. Youth aged >8 years (mean ages 13–14 years) completed survey and anthropometric measurements. The Chinese version of the dimensional Yale Food Addiction Scale for Children 2.0 (dYFAS-C 2.0), Kids Palatable Food Eating Motive Scale (K-PEMS) and Mindful Eating Scale for Children (MEQ-C) were used to measure addictive eating motives and behaviors. Semi-quantitative food intake, physical activity and sleep duration were assessed, and height and weight were measured by trained researchers to calculate a Body Mass Index Z score (BMIZ). Body composition measurement utilized bioelectrical impedance for detecting subcutaneous fat content (FC) and a visceral fat level (VFL). Network analysis, including cross-sectional network estimation at each time point, longitudinal network comparison, and cross-lagged panel network (CLPN) modeling, was used to examine the centrality, connectivity, and temporal relationships among FA and key variables. *Results:* Among the 2680 participants enrolled, 2054 completed both waves of surveys (retention rate: 76.7%; 49.5% girls). In the baseline (T1) cross-sectional network, FA showed the highest closeness and betweenness and was linked to the weight-related subnetwork (BMIZ, FC, and VFL) primarily through VFL. The follow-up (T2) cross-sectional network showed a broadly similar overall pattern. Longitudinal comparison suggested generally stable centrality patterns across time, with lifestyle-related factors showing relatively greater prominence at T2. In the CLPN, the strongest directional paths primarily extended from FA to later eating motives, whereas direct longitudinal paths from FA to weight indicators were not observed. FA and mindful eating exhibited bidirectional relationships, and mindful eating was also negatively associated with subsequent reward-based eating motives. *Conclusion:* FA may represent an important intervention target within the broader obesity-related psychobehavioral system in youth, particularly in relation to eating motives and reward-driven eating processes. Interventions that address FA together with mindful eating and modifiable lifestyle factors may offer a more comprehensive approach to youth weight-related health.

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KEYWORDS

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INTRODUCTION

Childhood and adolescent obesity represent critical public health challenges with profound long-term health consequences ((NCD-RisC), 2020). Conventional approaches focusing primarily on dietary restriction and exercise have demonstrated limited long-term efficacy, with weight regain rates exceeding 80% within five years (Ells et al., 2018; Wang, Zhao, Gao, Pan, & Xue, 2021), suggesting complex etiologies for obesity extending beyond simple energy imbalance to include psychological factors in dynamic ways.

Food addiction (FA), a relatively new concept, may provide new insight into childhood obesity, especially in environments in which highly processed foods (HPFs) are widely available (LaFata & Gearhardt, 2022; Smith, Khalil, Li, & Mason, 2025). HPFs may be addictive, and behaviors reflecting addictive eating may resemble those reflecting addictive substance use (Gearhardt, Corbin, & Brownell, 2009). Despite debates regarding FA (Gearhardt & Schulte, 2021), FA may provide valuable insights into obesity's underlying mechanisms and difficulties in achieving sustained weight loss. Viewing FA and related patterns of food consumption within the context of other psychological and physiological factors may advance understanding, prevention and treatment of obesity (O'Brien et al., 2020).

The validation of the Yale Food Addiction Scale for Children (YFAS-C 2.0) has enabled operationalization of FA in youth populations through assessment of characteristic symptoms including: (1) persistent desire or unsuccessful efforts to reduce consumption; (2) considerable time spent obtaining or consuming specific foods; (3) intense cravings; (4) continued use despite negative consequences; (5) tolerance; (6) withdrawal; and (7) functional impairment. The consideration of FA as a clinically relevant construct provides the foundation for examining its role within a broader network of factors contributing to obesity (Gearhardt, Corbin, & Brownell, 2016).

Motives may drive addictive behaviors. One framework suggests that specific motives may trigger addictive behaviors (Koob & Volkow, 2016). Within this framework, specific eating motives, particularly those related to coping with emotional problems and seeking rewards (Bellitti, Rohde, & Fazzino, 2023), may represent central mechanisms in the development and maintenance of FA.

Complementing this addiction model, mindful eating represents a promising intervention approach rooted in mindfulness-based addiction models and self-regulation theories (Kaya Cebioğlu et al., 2022). Theoretical frameworks suggest that mindful eating counteracts addictive eating through multiple neurocognitive mechanisms: (1) enhancing interoceptive awareness of hunger and satiety cues; (2) reducing automaticity of eating behaviors; (3) decreasing cue reactivity and craving; and (4) strengthening cognitive control over urges (Katy Tapper, 2022). Despite this strong theoretical foundation, empirical research examining mindful eating within the context of FA, particularly in youth populations, remains limited. Biopsychosocial models further propose a multifactorial nature of weight regulation, incorporating physiological, psychological, behavioral, and environmental factors that interact in complex ways (Avena, Gearhardt, Gold, Wang, & Potenza, 2012).

A discussion of obesity is incomplete without addressing the role of modifiable lifestyle factors, such as sleep duration, physical activity, and dietary composition, which alongside addictive eating, likely contribute to obesity risk (Wittleder & Jay, 2022). Recent clinical guidelines emphasize that obesity should be defined by body composition (Rubino et al., 2025), rather than weight alone, as fat distribution (especially visceral fat) may more accurately predict metabolic risk than body mass index (BMI) (Lee, Choi, Jung, Goo, & Yoon, 2023). Our previous findings further revealed that FA exhibits a dose-response relationship with central adiposity indicators like waist to hip ratio (WtHR), but not with BMI z score (BMIZ) (Wang, Huang, et al., 2022), highlighting the importance of incorporating body composition measures. This study therefore examines FA within an integrated network encompassing eating motives, mindful eating, lifestyle factors, and adiposity indicators to identify key measures and pathways influencing obesity development.

Despite advances, significant research gaps remain. Current research primarily explores bivariate relationships between FA and weight-related measures, with few studies examining complex relationships between FA, eating motives, lifestyle factors, and body composition measures. Most existing research relies on cross-sectional data, limiting understanding of how these relationships evolve over time, particularly during critical developmental periods in youth populations (Wang et al., 2023).

Network theory provides a novel conceptual framework for addressing these limitations by conceptualizing obesity-related factors as a system of directly interacting psychological, behavioral, and physiological elements (Borsboom et al., 2021). To capture the temporal dynamics and directional relationships among these elements, we applied cross-lagged panel network (CLPN) modeling, which extends traditional network approaches by incorporating longitudinal data to examine directional relationships over time (Williams, Liu, Martin, & Rast, 2023). Given the exploratory nature of network analysis, the present study was designed to address broader research aims rather than test several predefined hypotheses. This study aimed 1) to examine the cross-sectional and longitudinal interrelationships among FA, eating motives, mindful eating, lifestyle behaviors, and adiposity-related measures using network analysis, with particular attention to the role of FA within these networks; and 2) to identify the most central and influential nodes within the cross-sectional and longitudinal networks.

METHODS

Participants

This study adopted a longitudinal panel design in which a fixed cohort of students was followed across two waves of data collection to observe within-subject changes over time. Participants were recruited using a convenience sampling approach. Children and adolescents aged 8–18 years from four schools in an eastern Chinese town were enrolled. Schools were identified based on their geographic proximity and willingness to participate, following initial contact via local education authority collaboration. Specifically, students from grades 3, 4 and 5 of primary school, grades 7 and 8 in junior high school and grades 10 and 11 in high school were considered for enrollment. The inclusion of third grade and above was based on the educational context in China, where students at this level have typically developed adequate reading comprehension, enabling them to complete the questionnaire independently. Considering the potential impact of academic pressure, students in classes preparing for entrance examinations (grade 6 and grade 9) were excluded.

To be included, participants needed not to have physical disabilities that would prevent them from participating in body composition measurements and not have diagnosed acute or chronic physical health diseases such as congenital heart disease, kidney disease, thyroid disorders, or diabetes. Additionally, participants needed not to have undergone any surgeries or been on medications such as growth hormones, antibiotics, or antidepressants in the prior three months. Health-related information, medication use, and cognitive status were assessed through self-report. All participants were deemed of normal intelligence (not needing special education) and capable of understanding the purpose and content of the measurements and had not experienced significant life events such as bereavement or parental divorce in the past three months.

MEASUREMENTS

Food addiction and eating behavior measurements

FA was measured by the Chinese version of dimensional Yale Food Addiction Scale for Children 2.0 (dYFAS-C 2.0), which consists of 35 items, using a single dimension and a 5-point Likert scale ranging from "never" to "always" and scored from 0 to 4 (Wang, Huang, et al., 2022). Higher scores indicate more severe FA. In this study, statistical analysis was conducted using the average score, calculated as the total score divided by the number of items. An average total score greater than 0.7 indicates a high risk of FA (Wang, Huang, et al., 2022). To assess internal consistency of the scales used, Cronbach's alpha coefficients were calculated separately for T1 and T2. The Yale Food Addiction Scale for Children (YFAS-C) demonstrated excellent reliability, with $\alpha = 0.953$ at T1 and $\alpha = 0.972$ at T2.

Eating motives were measured by the Chinese version of the Kids Palatable Food Eating Motives Scale (K-PEMS), which contains 19 items across four dimensions (coping, reward, social, conformity), utilizing a 7-point Likert scale ranging from "never" to "always" scored from 1 to 7 (Williams et al., 2023). Higher scores in each dimension reflect stronger dietary motivations (Williams et al., 2023). Statistical analysis was performed using the average score. The Eating Motives Scale showed high internal consistency across its four subdimensions. At T1, Cronbach's alphas were 0.863 (Coping), 0.854 (Reward), 0.861 (Social), and 0.876 (Conformity); at T2, these were 0.895, 0.886, 0.897, and 0.919, respectively.

Mindful eating was measured by the sub-questionnaire "Mindless Eating Questionnaire" from the Chinese version of the Mindful Eating Questionnaire for Children (MEQ-C). The subscale includes 5 items, scored using a 5-point Likert scale (Wang, Hu, Zhou, Ye, & Fu, 2022). This questionnaire uses reverse scoring, where "never" to "always" is scored from 5 to 1, respectively (Wang, Hu, et al., 2022). Higher scores indicate more mindful eating. The average score was used to perform statistical analysis. The Mindful Eating scale showed acceptable to good reliability, with Cronbach's alpha values of 0.799 at T1 and 0.837 at T2.

Anthropometric measurement indicators. **Height and weight measurement.** Height and weight measurements were conducted using medical instruments. During height measurement, participants stood barefoot with their heels, buttocks, and the back of the head against the stadiometer column, feet positioned naturally apart, and arms hanging naturally at their sides. The researcher took two readings of the vertex measurement and recorded the average to a precision of 0.1 cm. For weight measurement, participants removed their outerwear and shoes. This also facilitated accurate body composition measurements. Height and weight data were used to calculate BMIZ scores (*https://www.who.int/tools/growth-reference-data-for-5to19-years/application-tools*).

BMIZ Calculation. BMIZ was calculated using WHO's Anthro software (ages 5–19 years), based on age and sex. According to WHO standards (BMIZ $\leq$1: normal/underweight; 1 < BMIZ $\leq$2: overweight; BMIZ >2: obese), overweight and obesity status was determined (*https://www.who.int/tools/growth-reference-data-for-5to19-years/indicators/bmi-for-age*).

Weight and Body Composition Measurement. Weight and body composition was measured using a portable bioelectrical impedance analysis (BIA) device. BIA is a non-invasive and quick method for measuring body composition, which can be completed rapidly. The application of BIA in body composition measurement has been increasingly refined, and although its accuracy is slightly lower compared to the gold standard dual-energy X-ray absorptiometry (DEXA), its advantages of being economical, portable, and non-invasive, along with validation from numerous studies, have made BIA-based body composition measurement widely used in hospitals and other health examination centers (Chandler, Sanders, Cintineo, Murray, & Arent, 2019; Eisenmann, Heelan, & Welk, 2012). Moreover, using the same BIA measurement tool and technique consistently for all participants and at different time points introduces a similar systematic error across all measurements. This consistency ensures that the data remain comparable and suitable for statistical analysis. The BIA device used in this study features eight contact electrodes. Participants were required to remove shoes and socks before measurement. The researcher corrected each participant's posture before beginning the measurement, reading and recording data including weight (kg), body fat percentage (fat content; FC) (%), and visceral fat level (VFL).

Collection of lifestyle information. **Semi-quantitative assessment of food intake and dietary patterns.** A semi-quantitative dietary intake questionnaire, adapted from a previously validated food frequency questionnaire (Wang et al., 2016), was used to assess habitual dietary behaviors. Participants were first asked to report their weekly frequency of breakfast, lunch, dinner, and late-night meals—these items were treated as ordinal variables reflecting meal regularity.

Subsequently, intake across 13 major food categories was assessed (Figure S1):

> ① Staple foods, ② Meat and poultry, ③ Eggs, ④ Soy products, ⑤ Seafood, ⑥ Dairy, ⑦ Vegetables, ⑧ Tubers and roots, ⑨ Fungi and algae, ⑩ Whole grains and coarse cereals, ⑪ Nuts, ⑫ Fruits, and ⑬ Highly processed foods.

For each category, participants reported:

1. Whether they had consumed the food,
2. If yes, the frequency of consumption (per day/week/month/year), and
3. The portion size per consumption, estimated via standardized visual reference images.

To facilitate dimensionality reduction and enable more streamlined downstream analyses, the 13 food categories were first grouped into two broader types: "regular" (not highly processed) foods and highly processed foods. For each participant, the average daily intake (in portions/day) of both food types was computed based on reported frequency and reference portion sizes. These two continuous variables, along with the reported frequency of breakfast, lunch, dinner, and late-night meals, were standardized and subjected to principal component analysis (PCA).

Two interpretable components were extracted:

- Balanced Regular Diet (BRD): characterized by frequent consumption of structured meals and diverse regular foods (e.g., vegetables, dairy, fruits, soy); and,
- Highly Processed Night Eating Diet (HND): characterized by elevated intake of processed snacks and frequent late-night eating.

Individual scores for each participant on the BRD and HND dietary patterns were computed based on PCA-derived factor weights. These scores served as continuous variables in all subsequent statistical analyses.

Detailed statistical procedures are provided in Supplementary Material. (**Dimensionality Reduction of Dietary Data,** Table S1 **and** Table S2).

Sleep duration. Participants reported their usual bedtime, wake-up time, and sleep latency separately for weekdays (5 days) and weekends (2 days). Daily sleep duration was calculated as the difference between bedtime and wake-up time minus latency. The weighted average across the week was then computed using the formula: $[(\text{Weekday sleep} \times 5) + (\text{Weekend sleep} \times 2)] \div 7$. The final sleep duration variable (in hours) was treated as continuous.

Semi-Quantitative Assessment of Physical Activity. Physical activity was assessed using the "Physical Activity Level Assessment Questionnaire for Chinese Children and Adolescents Aged 7–18 Years," a semi-quantitative instrument validated in a 2018 nationwide sample of 4,269 participants across six administrative regions in China (Cao, 2020). The questionnaire captures common physical activities among youth, documenting their frequency, average duration, and intensity. For each activity, total time was calculated as: activity time = frequency × average duration per session. Activity intensity was determined based on a validated reference table. Time spent in low-, moderate-, and high-intensity activities was summed accordingly. Moderate to vigorous physical activity (MVPA) was computed as the sum of time spent in moderate- and high-intensity activities and expressed as average daily duration (in minutes), which was treated as a continuous variable in analysis.

Data collection procedure

Data collection was conducted from November 2021 to May 2022 with intervals of 3–6 months. The 3–6-month interval was selected based on both empirical and practical considerations (Anusic & Schimmack, 2016). This timeframe aligns with the 5–6-month academic semester structure in China, allowing for complete follow-up assessments and data validation during the academic year to help ensure data quality and feasibility.

To promote temporal comparability, identical instruments were used at both waves. Lifestyle behaviors (diet, physical activity, and sleep) and psychological features were assessed based on the past 3 months. Timeframes were explicitly stated as "in the past 3 months" in the questionnaire.

Researchers assigned each student a unique numerical code to help ensure participants' privacy. After recording the code, information such as the student's school, grade, class, and student number was documented for future verification and information backtracking.

During the assessment process, researchers prepared a roster for each class, listing each student's code, student number, and name, along with measures of height, weight, body FC, and VFL; this information was recorded and backed up. After the measurements, the researchers transcribed and verified each person's information onto a card. The front of the card listed objective measures such as the participant's height, body FC, and VFL, along with a two-dimensional barcode (QR code) that could be scanned to access an online questionnaire. The back of the card included information about the school, grade, class, and the assigned numerical code to help ensure the card's ownership.

Cards containing measurement results and a QR code linking to the online questionnaire were distributed to participants on Friday afternoons, allowing them to complete the survey over the weekend. Informed consent was embedded at the start of the digital questionnaire: only students and their guardians who selected "Agree" could proceed. All students, including those who declined participation, received their measurement results.

Survey submissions were subsequently cross validated: objective measures (height, weight, FC, VFL) were checked against the original paper records. Inconsistent or erroneous entries were excluded to help ensure data quality. Participants received a brief individualized report on their physical development and a small gift as compensation.

Statistical methods

Data presentation and group comparisons. Participant characteristics were described using percentages, means (standard deviations), or medians (interquartile ranges). Differences between groups were assessed using independent two-sample *t*-tests or Mann-Whitney *U* tests, depending on the normality of the distribution and homogeneity of variance. For categorical data, associations between variables were analyzed using Chi-square tests. Pearson correlation analyses were additionally conducted separately for T1 and T2 to characterize the bivariate relationships among all variables included in the network models.

Longitudinal changes assessment. To examine changes in key variables over the 3–6-month follow-up period, paired *t*-tests (or Wilcoxon signed-rank tests for non-normally distributed variables) were conducted for the entire sample. This analysis aimed to identify which variables showed significant changes over time, providing context for the subsequent network analyses.

Network analysis approach. **Cross-Sectional Network Modeling** Network analysis was employed to explore complex relationships between FA-related motives and behaviors, lifestyle habits, and weight status measures. To characterize theses relationships at each measurement point, separate cross-sectional networks were estimated for T1 and T2. Each network comprising key variables including FA, eating motives (coping, reward, social, conformity), mindful eating, dietary patterns (BRD and HND), sleep duration, MVPA, and weight status measures (BMIZ, FC, VFL) was constructed.

To help ensure accurate estimation of network parameters while preventing overfitting, the Extended Bayesian Information Criterion Graphical Lasso (EBICglasso) method was implemented (Foygel & Drton, 2010). This approach combines the least absolute shrinkage and selection operator (LASSO) with regularization through the extended Bayesian information criterion, which optimizes the balance between network complexity and accuracy.

Centrality and Bridge Centrality Analysis Centrality indices, including strength (the sum of absolute connection weights), closeness (the inverse of the average shortest path to other nodes), betweenness (the number of times a node lies on the shortest path between other nodes), and expected influence (the sum of connection weights retaining their sign), were calculated to identify the most influential variables within the network, as these metrics help pinpoint variables that occupy central positions and potentially exert disproportionate influence on other network components (McNally, 2021). Additionally, to identify variables that connect different conceptual domains (e.g., weight status, addictive eating behaviors, and life habits), we computed bridge centrality indices, including bridge strength and bridge expected influence, which specifically quantify the importance of nodes in linking otherwise segregated network communities.

Network Stability and Accuracy The stability and accuracy of the network were assessed using non-parametric bootstrap methods with 1,500 iterations. Edge weight accuracy was evaluated through bootstrap confidence intervals, while the stability of centrality indices was assessed using case-dropping subset bootstrap techniques. The correlation stability coefficient (CS-coefficient) was calculated to determine the maximum proportion of cases that could be dropped while maintaining a correlation of at least 0.7 with the original centrality indices (Mengcheng Wang, 2023). Following established guidelines, CS-coefficients above 0.5 indicate strong stability, while values above 0.25 are acceptable for interpreting centrality order (Epskamp, Borsboom, & Fried, 2016).

Longitudinal Network Comparison Following the cross-sectional network estimation, we conducted a longitudinal network comparison to assess the stability of the network structure between baseline and follow-up assessments (Borkulo et al., 2023). To this end, a network comparison test (NCT) was employed. The NCT is a permutation-based method that evaluates whether two networks differ significantly in terms of global strength, individual edge weights, and overall network structure, while rigorously controlling for multiple comparisons.

Cross-Lagged Panel Network (CLPN) To further investigate the temporal dynamics and potential directional influences among variables, a CLPN analysis was performed. This model allowed us to disentangle within-timepoint (contemporaneous) associations from cross-lagged (potentially predictive) relationships between timepoints using regularized regression with LASSO penalty (Williams et al., 2023). Centrality indices specific to longitudinal networks were derived, including out-strength (representing the total influence a node exerts on others at the next timepoint), in-strength (reflecting the total influence a node receives from others), out-expected influence, and in-expected influence, which retain the sign of connections to capture the direction of relationships.

Statistical analyses were conducted using SPSS 23.0 for descriptive and conventional inferential statistics, while network estimation, comparison, and CLPN analysis were performed in R (version 4.4.1) using specialized packages including qgraph, igraph, bootnet, NetworkComparisonTest, and glmnet. A two-sided $p < 0.05$ was considered statistically significant.

Ethics

This study was approved by the ethics committee of the hospital and the participating schools, with an ethics code of 2021-IRB-235.

RESULTS

Demographic and descriptive information of participants

A total of 3,507 students were initially contacted for participation. Among them, 364 students were excluded based on predefined eligibility criteria (e.g., health conditions, medication use, cognitive capacity). Of the remaining 3,143 students who agreed to participate and completed baseline assessments, 463 were further excluded following data quality checks, such as logical inconsistencies and discrepancies between self-reported and measured anthropometric values. This resulted in 2,680 participants with valid baseline data. Among these, 2,054 participants completed both baseline and follow-up assessments and were included in the final longitudinal analytic sample.

The information from participants at each time point is listed in Table 1. The participants were aged from 8.39 to 17.99 years, with a mean age of 13.52 years at the initial time, and the proportions of boys and girls were similar. In Table 1, the two T1 columns represent different participant counts at the same time point: the first T1 column ($N = 2680$) includes the initial number of participants, while the second T1 column ($N = 2054$) includes participants who remained at the first time point after attrition. Compared with participants who completed the study, those who dropped out had higher proportions of males and individuals with high FA risk. They also showed higher conformity motive scores, consumed fewer dairy products, vegetables, tubers and root vegetables, and whole grains, had a higher total number of food categories consumed (excluding HPFs), reported less frequent breakfast intake, and had more night snacks (Table S3). In addition, the Pearson correlation matrices for all study variables at T1 and T2 are presented in Table S4 and Table S5.

Participants were categorized into high- and low-FA-risk groups based on dYFAS-C 2.0 scores, with scores above 0.7 indicating high FA risk. The low-FA-risk group had lower BMIZ (0.57 vs. 0.83, $t = 4.993$, $p < 0.001$), FC (27.4% vs. 30.3%, $t = 7.578$, $p < 0.001$) and VFL (5 vs. 7, $Z = 10.440$, $p < 0.001$). There were no differences in the proportions of individuals at high risk for FA between boys and girls (27.3% vs. 28.6%, $\chi 2 = 0.553$, $p = 0.457$). However, educational differences were evident, with primary level at 19.8%, junior high at 20.9%, and high school at 45.7% ($\chi 2 = 178.894$, $p < 0.001$). Additionally, FA risk varied between participants from downtown areas (23%) and the countryside (33.8%) ($\chi 2 = 38.432$, $p < 0.001$).

Longitudinal changes in key variables

Paired-samples t-tests revealed significant changes over the 3- to 6-month period in several variables. Specifically, FC, VFL, and MVPA decreased over time, whereas FA, conformity eating motives, mindful eating, and sleep duration increased (all $p < 0.05$). In contrast, no significant changes were observed in BMIZ, coping, reward, or social eating motives, nor in BRD or HND scores (all $p > 0.05$), see Table 2.

Centrality of food addiction in the cross-sectional network at T1 and T2

At T1, FA was positively connected with coping, reward, conformity, HND, and VFL and negatively connected with mindful eating and BRD (Fig. 1, left panel). FA was linked to the weight-related subnetwork primarily through VFL, which connected FA with BMIZ, FC, and VFL. In addition, mindful eating showed negative associations with reward-based eating motivation and HND. The FA–mindful eating edge was among the most prominent connections in the T1 network.

In terms of centrality, FA and VFL occupied relatively important positions in the T1 network (Fig. 2; Table S6). FA showed the highest closeness and betweenness, whereas VFL showed the highest expected influence. Mindful eating showed the lowest expected influence. In the bridge centrality analysis, HND, BMIZ, and FA showed relatively high bridge strength, with HND showing the highest bridge strength and BMIZ the highest bridge expected influence (Fig. 2; Table S6).

At T2, the overall network structure remained interpretable, and FA continued to be located within the eating-related portion of the network (Fig. 1, right panel). In terms of centrality, VFL showed the highest strength, followed by Reward, Conformity, FA, and FC. FA remained relatively high in closeness and betweenness, whereas mindful eating again showed the lowest expected influence (Fig. 2; Table S7). In the bridge centrality analysis, Sleep showed the highest bridge strength, followed by VFL, BRD, BMIZ, and HND (Fig. 2; Table S7).

The stability and accuracy analyses are presented in Supplementary Figure S2–Figure S5. For the T1 network, the 95% confidence intervals for edge weights were relatively narrow, and the CS-coefficients for strength, closeness, betweenness, and expected influence were all 0.75 (Figure S2 and Figure S3). For the T2 network, the corresponding CS-coefficients were 0.75 for strength, 0.594 for closeness, 0.205 for betweenness, and 0.75 for expected influence, indicating that the betweenness results at T2 should be interpreted more cautiously (Figure S4 and Figure S5).

Table 1. Demographic and baseline information of participants

	T1 (N = 2680)	T1 (N = 2054)	T2 (N = 2054)
Age, years	13.52 ± 2.56	13.39 ± 2.52	13.66 ± 2.54
Sex			
Male	1353 (50.5%)	1012 (49.3%)	1014 (49.4%)
Female	1327 (49.5%)	1042 (50.7%)	1040 (50.6%)
Education			
Primary	839 (31.3%)	673 (32.8%)	673 (32.8%)
Junior High	1038 (38.7%)	803 (39.1%)	803 (39.1%)
High	803 (30%)	578 (28.1%)	578 (28.1%)
Type of Living Location			
Downtown (City)	1443 (53.8%)	1033 (55.2%)	1197 (58.3%)
Countryside	1237 (46.2%)	921 (44.8%)	857 (41.7%)
Weight Measures			
BMIZ	0.57 (−0.20, 1.47)	0.59 (−0.18–1.5)	0.56 (−0.17, 1.48)
Overweight and obesity (BMIZ >1)	982 (36.6%)	765 (37.2%)	742 (36.1%)
Subcutaneous Fat Content	28.19 ± 8.67	28.30 ± 8.59	27.28 ± 8.69
Visceral Fat Level	5 (4, 9)	5 (4, 9)	5 (3, 9)
Eating Motives			
Coping	1.5 (1, 2.5)	1.5 (1, 2.5)	1.5 (1, 2.5)
Reward	1.8 (1.2, 2.6)	1.8 (1.2, 2.6)	1.8 (1.2, 2.6)
Social	1.8 (1.2, 2.6)	1.8 (1.2, 2.6)	2 (1.2, 2.8)
Conformity	1.2 (1, 1.8)	1.2 (1, 1.8)	1.2 (1, 2)
Eating Approach			
FA	0.37 (0.14, 0.76)	0.37 (0.14, 0.74)	0.33 (0.09, 0.83)
High FA Risk (FA > 0.7)	750 (28.0%)	569 (27.7%)	609 (29.7%)
Mindful Eating	4.07 ± 0.74	4.07 ± 0.74	4.13 ± 0.75
Food Intake			
Staple Foods	2 (1, 3)	2 (1, 3)	2 (1, 3)
Poultry & Meat	0.5 (0.21, 1)	0.5 (0.21, 1)	0.5 (0.21, 1)
Eggs	1 (0.29, 1)	1 (0.29, 1)	1 (0.14, 1)
Soy products	0.07 (0, 0.43)	0.07 (0, 0.43)	0.03 (0, 0.43)
Seafood	0 (0, 0.14)	0 (0, 0.14)	0 (0, 0.14)
Dairy products	0.5 (0, 1)	0.57 (0, 1)	0.5 (0, 1)
Vegetables	1 (0.29, 2)	1 (0.29, 2)	0.86 (0.21, 2)
Tubers & Root Vegetables	0.43 (0.14, 1)	0.43 (0.21, 1)	0.43 (0.14, 0.86)
Fungi & algae	0.04 (0, 0.21)	0.04 (0, 0.21)	0 (0, 0.14)
Whole grains	0.11 (0, 0.43)	0.14 (0, 0.43)	0 (0, 0.29)
Nuts	0 (0, 0.29)	0 (0, 0.29)	0 (0, 0.14)
Fruits	0.43 (0.14, 1)	0.5 (0.14, 1)	0.43 (0.04, 1)
HPFs	0.14 (0, 0.5)	0.14 (0, 0.5)	0.07 (0, 0.43)
Food Number (Except HPFs)	8.38 ± 2.94	8.49 ± 2.85	7.76 ± 3.16
Breakfast	6.24 ± 1.52	6.27 ± 1.49	6.20 ± 1.53
Lunch	6.72 ± 0.95	6.73 ± 0.90	6.66 ± 1.07
Dinner	6.46 ± 1.23	6.46 ± 1.24	6.39 ± 1.39
Midnight Snack	0 (0, 1)	0 (0, 1)	0 (0, 1)
Exercise and Sleep			
MVPA	36.72 (15.71, 72.86)	37.14 (17.14, 72.86)	27.14 (9.8, 60.47)
Sleep Duration	7.42 ± 1.05	7.45 ± 1.06	9.08 ± 1.12

Note: BMIZ: body mass index z score; HPFs: highly processed foods; MVPA: Moderate-to-vigorous physical activity. Continuous variables are presented as means ± standard deviations (SDs); categorical variables as numbers (%); and non-normally distributed variables as medians (P_{25}, P_{75}).

Dynamic changes in global strength, edge weights, and centrality between T1 and T2

The overall network strength of the FA motivation-behavior-weight-lifestyle habits network showed significant differences over time (Fig. 1). The overall network strength at T1 was 4.79, while at T2 it increased to 5.81, with a network strength comparison of $p < 0.001$. In the network estimation, out of 168 relevant estimates, 18 showed significant differences in edge weight permutation tests: BMIZ-Reward ($p = 0.02$), FA-Social ($p = 0.03$), BMIZ-Conformity ($p = 0.01$), VFL-Conformity ($p = 0.03$), Coping-Conformity ($p = 0.02$), BMIZ-Sleep ($p = 0.02$), FC-Sleep ($p < 0.001$), VFL-Sleep ($p < 0.001$), Conformity-Sleep ($p < 0.001$),

Table 2. Paired samples *t*-tests and descriptive statistics for pre–post changes in variables

T1 & T2	Test–retest r	Mean	SD	95%CI Lower	95%CI Upper	*t*	*P*	Cohen's d
BMIZ	0.888	0.02	0.58	−0.01	0.04	1.466	0.143	0.03
Fat Content	0.885	1.02	4.14	0.84	1.20	11.205	<0.001	0.25
Visceral Fat Level	0.911	0.15	1.67	0.08	0.22	4.083	<0.001	0.09
Food Addiction	0.546	−0.03	0.51	−0.05	0.00	−2.295	0.022	−0.05
EM_Coping	0.461	−0.04	1.03	−0.08	0.00	−1.747	0.081	−0.04
EM_Reward	0.456	−0.05	1.08	−0.09	0.00	−1.908	0.056	−0.04
EM_Social	0.454	−0.05	1.08	−0.09	0.00	−1.952	0.051	−0.04
EM_Conformity	0.425	−0.13	0.88	−0.17	−0.09	−6.675	<0.001	−0.15
Mindful Eating	0.538	−0.06	0.71	−0.09	−0.03	−3.841	<0.001	−0.08
Sleep	0.232	−1.63	1.35	−1.68	−1.57	−54.419	<0.001	−1.20
MVPA	0.407	10.06	58.20	7.54	12.58	7.835	<0.001	0.17
BRD	0.481	<0.001	1.23	−0.05	0.05	−0.002	0.999	<0.001
HND	0.351	<0.001	1.20	−0.05	0.05	<0.001	0.999	<0.001

Note: df = 2053; Mean represents the mean paired difference between T1 and T2 (T1 − T2). Test–retest correlations are Pearson correlations between the same variable measured at T1 and T2; all were statistically significant at $p < 0.001$. BMIZ: Body Mass Index z-score; EM: Eating Motivation; MVPA: Moderate-to-Vigorous Physical Activity Time; BRD: Balanced Regular Diet; HND: Highly Processed Night Eating Diet. 95%CI: 95% confidence interval.

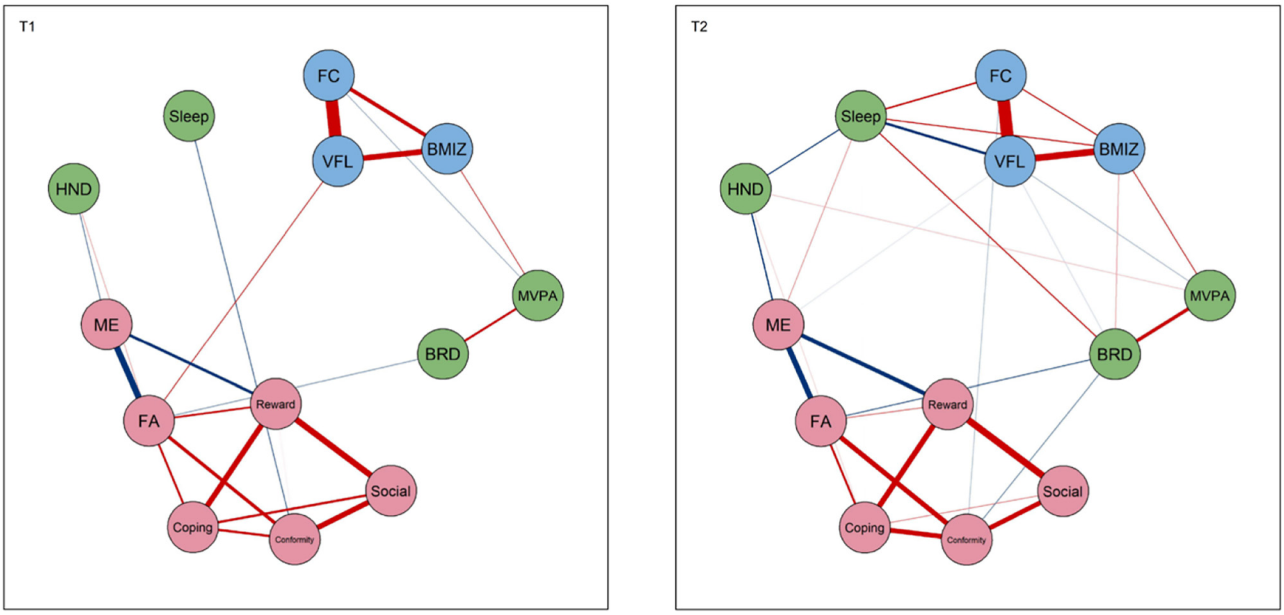

Fig. 1. Cross-sectional network structures of food addiction and related variables at T1 and T2
Note: FA: Food Addiction; Coping: Eating Motivation - Coping; Reward: Eating Motivation - Reward; Social: Eating Motivation - Social; Conformity: Eating Motivation - Conformity; ME: Mindful Eating Traits; Sleep: Sleep Duration; MVPA: Moderate-to-Vigorous Physical Activity Time; BRD: Balanced Regular Diet; HND: Highly Processed Night Eating Diet; BMIZ: Body Mass Index z-score; FC: Subcutaneous Fat Content; VFL: Visceral Fat Level. Red edges indicate positive correlations; blue edges indicate negative correlations. Edge thickness reflects the strength of the correlation.

ME-Sleep ($p < 0.001$), FC-MVPA ($p = 0.05$), Sleep-MVPA ($p < 0.001$), Sleep-BRD ($p = 0.02$), BMIZ-HND ($p = 0.05$), FA-HND ($p = 0.03$), Reward-HND ($p = 0.01$), Sleep-HND ($p = 0.05$), MVPA-HND ($p = 0.02$).

Analysis of changes in network centrality indices revealed that the centrality index for FA decreased over time, but this change was not statistically significant ($p > 0.05$). In contrast, the centrality indices for lifestyle habits showed significant increases over time ($p < 0.05$). Additionally, the influence strength of VFL and the betweenness centrality of reward-based eating motivation and mindful-eating tendencies showed an increasing trend over time, but these changes did not reach statistical significance ($p > 0.05$). Detailed results are presented in Fig. 1, Fig. 2 and Table S8.

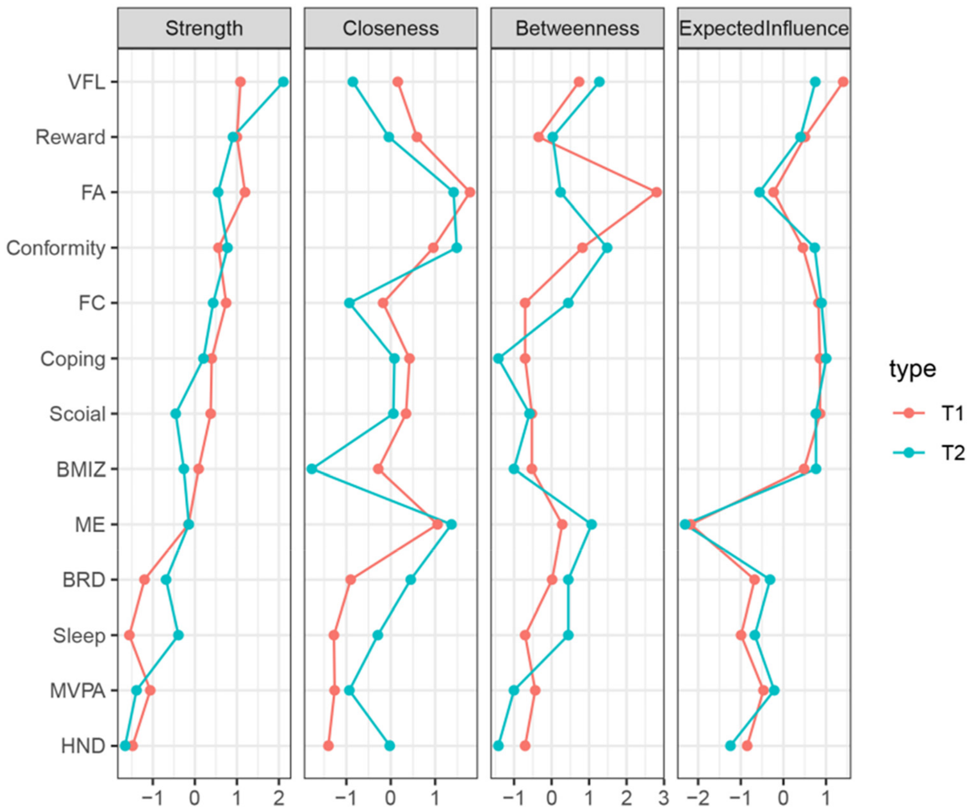

Fig. 2. The dynamics of centrality of network variables

Note: FA: Food Addiction; Coping: Eating Motivation - Coping; Reward: Eating Motivation - Reward; Social: Eating Motivation - Social; Conformity: Eating Motivation - Conformity; ME: Mindful Eating Tendencies; Sleep: Sleep Duration; MVPA: Moderate-to-Vigorous Physical Activity Time; BRD: Balanced Regular Diet; HND: Highly Processed Night Eating Diet; BMIZ: Body Mass Index z-score; FC: Subcutaneous Fat Content; VFL: Visceral Fat Level.

Centrality and connectivity in the cross-lagged panel network

The analysis revealed several cross-lagged pathways among variables, with the strongest connections primarily indicating directional paths from FA at T1 to eating-related variables at T2, particularly reward ($\beta = 0.19$), mindful eating ($\beta = -0.17$), conformity ($\beta = 0.17$), and coping ($\beta = 0.15$), rather than to adiposity-related measures (Fig. 3). In addition, a bidirectional relationship was observed between FA and mindful eating (FA→ME: $\beta = -0.17$; ME→FA: $\beta = -0.04$), indicating their mutual influence over time. Additionally, the findings suggested that mindful eating was negatively associated with subsequent reward motives (ME→Reward: $\beta = -0.04$). These findings are detailed in Table S9.

Regarding CLPN centrality, FA showed the highest out-strength (0.734), followed by mindful eating (0.245) and VFL (0.233). Sleep showed the highest in-strength (0.640), followed by reward (0.230), mindful eating (0.178), conformity (0.167), and coping (0.163). FA also showed the highest out-expected influence (0.368), whereas conformity showed the highest in-expected influence (0.167), followed by coping (0.163) and reward (0.142). These findings indicate that FA exerted the strongest outgoing influence in the network, whereas eating-motive variables were relatively more influenced by other variables. Detailed results are presented in Fig. 4 and Supplementary Table S10.

The CLPN centrality metrics for all variables are reported in Table S10. The case-dropping bootstrap analysis indicated good stability of all centrality indices, with maximum drop proportions of 0.517 for in-strength, out-strength, and in-expected influence, and 0.439 for out-expected influence, while maintaining a correlation of at least 0.7 in 95% of the samples. The corresponding plots are shown in Figure S6 and Figure S7.

DISCUSSION

This study used a network approach to position FA within an obesity-related psychobehavioral system in youth. FA emerged as a relatively central node in the network. Although FA was linked to the weight-related subnetwork primarily through VFL in the baseline cross-sectional network, this pattern was not further supported at follow-up or in the CLPN. Instead, the strongest directional paths in the CLPN extended from FA to later eating-related variables rather than to weight-related indicators. Mindful eating was

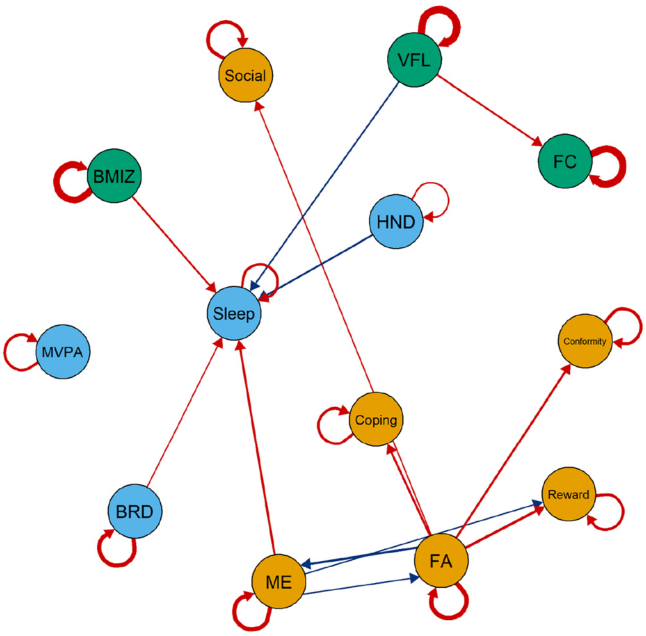

Fig. 3. Temporal dynamics and temporally directional pathways in addictive eating motives and behaviors, lifestyle habits and weight status network

Note: FA: Food Addiction; Coping: Eating Motivation - Coping; Reward: Eating Motivation - Reward; Social: Eating Motivation - Social; Conformity: Eating Motivation - Conformity; ME: Mindful Eating Traits; Sleep: Sleep Duration; MVPA: Moderate-to-Vigorous Physical Activity Time; BRD: Balanced Regular Diet; HND: Highly Processed Night Eating Diet; BMIZ: Body Mass Index z-score; FC: Subcutaneous Fat Content; VFL: Visceral Fat Level. Red edges indicate positive temporal influences; blue edges indicate negative temporal influences. Edge width represents the strength of the effect

also closely involved in this network, showing a bidirectional longitudinal relationship with FA and a negative association with subsequent reward-based eating motives. These findings point to the value of integrated interventions that target FA together with mindful eating and modifiable lifestyle factors.

The network analysis identified FA as a highly central element with the strongest closeness and betweenness centrality, indicating its role as a critical connector within the obesity-related network. In the T1 cross-sectional network, FA was linked to the weight-related subnetwork primarily through VFL, rather than through direct connections to BMIZ or FC. Although this pattern was not replicated in the T2 cross-sectional network or the CLPN, it is consistent with the physiological understanding that visceral adipose tissue functions as an active endocrine organ, secreting hormones and cytokines (e.g., leptin, adiponectin, IL-6) (Wedell-Neergaard et al., 2019) that influence appetite regulation and reward processing in the brain (Baak & Mariman, 2023). Overall, these findings suggest a possible cross-sectional link between FA and visceral adiposity, rather than a stable longitudinal pathway.

Longitudinally, the centrality of FA remained stable without significant change over the 3- to 6-month period, while the centrality of lifestyle-related nodes significantly increased from T1 to T2. The stability of FA suggests that it may function as a persistent trait-like driver rather than a transient state in an obesogenic network. In contrast, the increasing prominence of lifestyle factors such as sleep and physical activity suggests that these behaviors may serve as promising targets for intervention. The modifiable nature of these lifestyle elements suggests they may exert beneficial effects on both addictive eating and metabolic health (Baak & Mariman, 2023; Mehr, Mitchison, Bowrey, & James, 2021), providing opportunities for intervention even when FA itself remains stable.

The CLPN analysis indicated that FA was more strongly connected to later eating-related psychological variables than to obesity measures. This pattern suggests that FA may be more proximally involved in motivational and behavioral processes than in direct changes in weight-related indicators. Accordingly, interventions focused exclusively on weight management may overlook an important role for FA and its related eating processes, thereby limiting their effectiveness (FatemeGhafouri-Taleghani et al., 2024). Our findings support integrated interventions that simultaneously address FA-related processes and modify associated lifestyle factors. Additionally, the use of adiposity markers like FC and VFL, as opposed to BMIZ, may offer greater sensitivity for detecting early intervention effects (Naik, Allen, Eickhoff, & Carrel, 2020), reducing the risk of false negatives sometimes encountered in short-term obesity trials.

Unlike previous conceptualizations that primarily viewed motives as precursors to addictive behaviors (Koob & Volkow, 2016; Robinson & Berridge, 2025), our CLPN analysis suggests that FA prospectively influenced eating motives, rather than being primarily driven by them. This suggests that coping, reward, social, and conformity motives may function as behavioral manifestations of the underlying addictive process, particularly once FA is established. These findings may help to refine conventional addiction models by highlighting the dynamic interplay between FA and motivational factors, indicating that such motives may serve as indicators of FA vulnerability or progression in youth.

CLPN analysis revealed a bidirectional relationship between mindful eating and FA, suggesting a dynamic feedback loop: while addictive behaviors may erode mindfulness, mindful eating may help mitigate FA, consistent with a previous study in college students (Kaya Cebioğlu et al., 2022). Notably, mindful eating tendencies prospectively related to reductions in reward-based eating motives, providing mechanistic insight into how mindfulness-based interventions may reduce hedonic responsiveness to food cues. Given the central role of reward processing in sustaining addictive behaviors, these findings highlight mindful eating's potential to disrupt core reinforcement mechanisms in FA, supporting its integration into interventions targeting both addictive processes and their motivational underpinnings.

Clinical and public health implications

These findings suggest the importance of integrating FA assessment into routine screening for youth at risk of

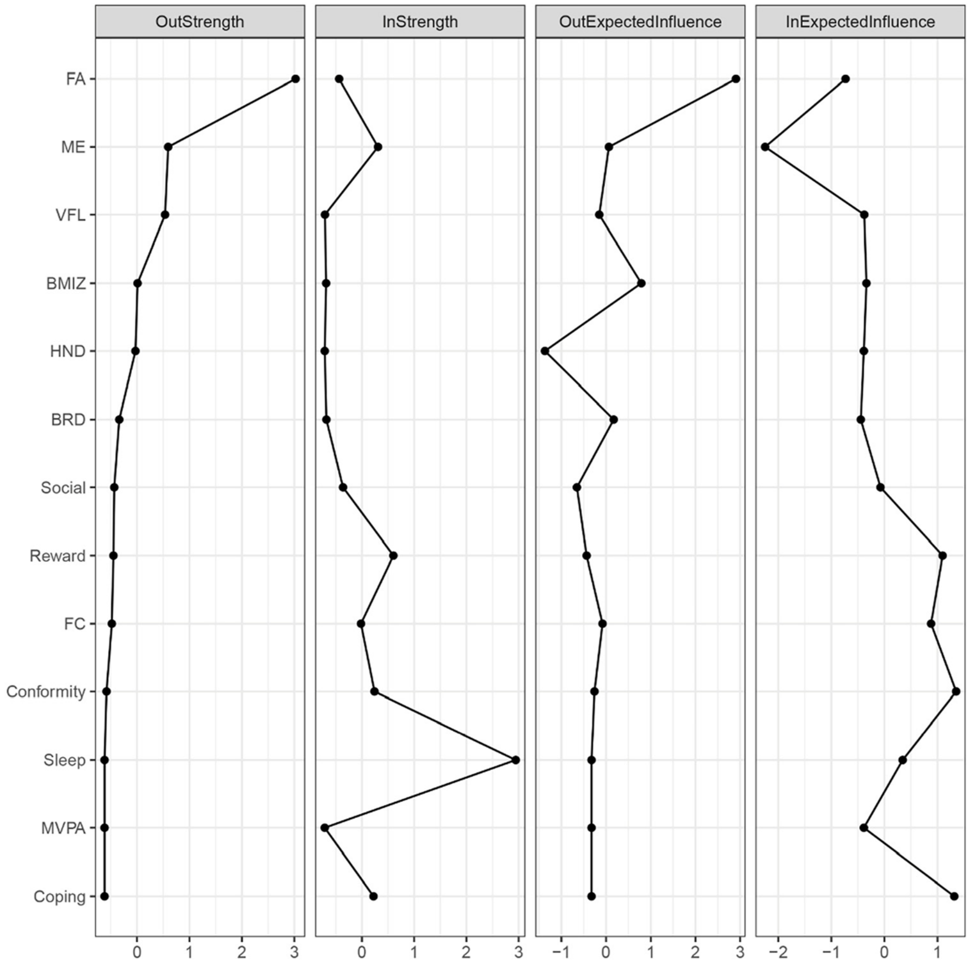

Fig. 4. Centrality metrics distribution in the cross-lagged panel network analysis
Note: FA: Food Addiction; Coping: Eating Motivation - Coping; Reward: Eating Motivation - Reward; Social: Eating Motivation - Social; Conformity: Eating Motivation - Conformity; ME: Mindful Eating Traits; Sleep: Sleep Duration; MVPA: Moderate-to-Vigorous Physical Activity Time; BRD: Balanced Regular Diet; HND: Highly Processed Night Eating Diet; BMIZ: Body Mass Index z-score; FC: Subcutaneous Fat Content; VFL: Visceral Fat Level

obesity, given its relatively central role within the obesity-related psychobehavioral network, particularly in relation to eating-related variables. In the present study, VFL served as the main cross-sectional link between FA and the weight-related subnetwork at T1, and VFL also occupied a prominent position in the network. This pattern highlights the potential relevance of body composition indicators, particularly visceral adiposity, in research on FA, eating-related behaviors, and obesity-related risk beyond BMI alone. Additionally, as mindful eating showed bidirectional relationships with FA and was negatively associated with subsequent reward-driven eating motives, its inclusion in weight management programs appears supported.

From a public health perspective, these results advocate for integrated obesity prevention strategies targeting both psychological (e.g., FA, reward sensitivity) and lifestyle factors (e.g., sleep, physical activity). School-based programs could incorporate psychoeducation on addictive eating and mindful eating techniques. These findings suggest the need for policies that regulate the marketing, availability, and use of HPFs among youth to reduce excessive consumption.

Limitations

This study has limitations. First, although DEXA is more accurate for body composition assessment, we used BIA due to school-based setting constraints. Though less precise, BIA provided consistent estimates across timepoints, enabling capture of relative changes.

Second, key behavioral variables, such as FA, sleep duration, and physical activity, were based on self-report, which may introduce recall or social desirability biases. Incorporating objective tools (e.g., actigraphy or wearable devices) in future studies could improve measurement validity.

Third, the sample was drawn from a single town, potentially limiting generalizability. However, as our study aimed to examine dynamic associations rather than estimate population prevalence, this limitation is less likely to compromise the internal validity of the findings.

Fourth, 23.4% of participants (626/2680) were lost to follow-up. Attrition analysis showed that those lost were more likely to be male and have high risk for FA (Table S3).

These patterns were reported and considered in analysis to reduce potential bias.

Fifth, the network models examined direct associations between core variables without adjusting for sociodemographic factors such as age and gender, as our primary aim was to explore the core interplay within the food addiction network. Future studies could address these influences by estimating separate networks for specific age and gender subgroups to control for potential confounding.

Finally, the observational study design and relatively short follow-up period (3–6 months) constrain the examination of long-term dynamics and potentially causal pathways. Longer-term longitudinal or quasi-experimental studies would be valuable to investigate further these directional relationships.

CONCLUSIONS

In summary, the data suggest that FA functions as a central and stable driver in obesity-related networks among youth, with its metabolic consequences likely mediated through visceral adiposity. The dynamic rise in lifestyle factors' centrality underscores their potential as effective intervention levers, with mindful eating emerging as a particularly promising target that demonstrates both bidirectional relationships with FA and significant negative effects on reward-based eating motives. Future strategies could integrate FA-specific interventions with lifestyle modifications that leverage mindful eating capacity to disrupt addictive reinforcement mechanisms and prioritize adiposity-based measures like VFL and FC to accurately capture treatment efficacy.

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Authors' contribution: Dan Wang contributed to the conceptualization and design of the study, participated in data collection, performed statistical analyses, and drafted the manuscript. Hui Zhou provided critical revision of the manuscript. Xuechun Chen was responsible for data cleaning and data management. Qi Long provided expertise in nutritional assessment and contributed to the evaluation of measurement tools. Yuzheng Hu supervised the study design and provided critical revision of the manuscript. Marc N. Potenza contributed to critical revision of the mansucript, assisted with manuscript submission, and provided guidance on responses to reviewers. Junfen Fu contributed to funding acquisition, participant recruitment, and overall study supervision.

Conflict of interests: Dr. Potenza discloses that he has consulted for and advised Neurofinity and Boehringer Ingelheim; been involved in a patent application with Yale University and Novartis; received research support from the Mohegan Sun Casino and the Connecticut Council on Problem Gambling; consulted for or advised legal, non-profit, healthcare and gambling entities on issues related to impulse control, internet use and addictive behaviors; performed grant reviews; edited journals/journal sections (including being an Associate Editor for the Journal of Behavioral Addictions); given academic lectures in grand rounds, CME events, and other clinical/scientific venues; and generated books or chapters for publishers of mental health texts. The other authors have no conflict of interest to disclose.

SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2025.00141.

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