Research Square

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A network examination of dynamic associations between momentary emotions and avoidant/restrictive eating behaviors

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Research Article

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Abstract

Background

Emotion regulation plays an important role in primary restrictive eating disorders, and preliminary evidence suggests that individuals with avoidant/restrictive food intake disorder (ARFID) exhibit deficits in emotion regulation. However, this research is exclusively cross-sectional and has not tested the time-directed associations between discrete emotions and ARFID behaviors, or if there are specific emotions that prospectively predict engagement in ARFID behaviors. The current study used ecological momentary assessment data and network analysis to test hypotheses that negative emotions would predict engagement in ARFID behaviors, and that emotion-behavior associations would vary according to ARFID profile.

Methods

Participants (N = 20; M_{age}=26.2) completed the Positive/Negative Affective Schedule and behavior constructs (i.e., Pica, ARFID, and Rumination Disorder Interview) eight times a day for 12 days (mean EMA compliance = 80%).

Results

Group-level networks showed that feeling *ashamed* was a core emotion (i.e., had the highest number of outgoing connections with other symptoms), which predicted ARFID behaviors at the next timepoint (e.g., *missing a meal, not finishing a meal*; *p*s<.05). Further, engagement in ARFID behaviors predicted reductions in negative emotions (e.g., feeling *nervous*) at the next timepoint. Individual networks demonstrated unique emotion-behavior associations according to ARFID profile—anxiety predicted fear-driven food avoidance, while shame predicted low appetite-driven food restriction.

Conclusions

Results suggest that negative emotions play a central and directed role in maladaptive behaviors in the daily lives of adults with ARFID, and that these behaviors may be negatively reinforcing. Further, these temporal processes differed according to ARFID profile, findings that may guide future longitudinal research and ultimately inform treatment development.

Plain English Summary

We explored the time-directed associations between emotions and behaviors in avoidant/restrictive food intake disorder (ARFID), as they occur in an individual's natural environment. We visualized these data using network analysis, which models associations between variables while accounting for all other

variables in the system. We found that specific negative emotions, including feeling *ashamed*, exhibited a high number of statistically significant, time-directed connections to ARFID behaviors. We also found that engagement in certain ARFID behaviors predicted reductions in negative emotions at the next timepoint, in line with emotion regulation models of eating disorders. Our findings support the role of emotions in maintaining ARFID symptoms, generating hypotheses that can guide additional longitudinal research in this area and contribute to intervention efforts.

Introduction

Avoidant/restrictive food intake disorder (ARFID) is a feeding and eating disorder that was reformulated in the fifth edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-5*) [1]. Unlike feeding disorder of infancy or early childhood, which previously described youth avoidant/restrictive eating, ARFID can occur across the lifespan. ARFID is characterized by limited food intake that is not driven by body image disturbances, leading to persistent failure to meet adequate nutritional and/or energy needs. Prevalence among adults is estimated to be between 0.3% [2] to 4.8% [3] and, like all eating disorders, ARFID is associated with adverse medical [4, 5] and psychiatric [6, 7] sequelae. Identified and commonly overlapping reasons for dietary insufficiency among individuals with ARFID include: 1) fears of aversive consequences of eating, including choking and vomiting; 2) avoidance due to sensory features of food; and 3) lack of interest in food/eating [8, 9].

Emotions are important maintenance factors underlying other primary restrictive eating disorders—i.e., anorexia nervosa (AN)—yet little research has explored the role emotions may play in maintaining ARFID symptoms. Additionally, there may be specific emotions that relate to specific behaviors. For example, studies using ecological momentary assessment (EMA) methods have implicated anxiety as an antecedent to dietary restriction and self-induced vomiting among those with AN [10].

Individuals with ARFID demonstrate greater difficulty across domains of emotion regulation (e.g., nonacceptance of negative emotions) compared to non-clinical participants [11], and researchers have theorized a role of disgust and anxiety in triggering ARFID behaviors [12, 13]. Taken together, individual emotions are important for understanding eating behaviors in the other primary restrictive eating disorder (i.e., AN) and certain emotions may also predict ARFID behaviors. However, the empirical literature base has yet to test the time-directed associations between discrete emotions and ARFID behaviors, including *which* emotions and/or behaviors may be most likely to maintain these interrelations and if specific ARFID profiles (i.e., fear of aversive consequences; sensory sensitivity; lack of interest in eating) show distinct emotion-behavior associations.

Over the last decade, there has been burgeoning interest in network theory, which aims to understand psychopathology as a web of dynamic, mutually reinforcing patterns of associations among symptoms (i.e., “nodes”) [14]. Network models estimate unique variance between symptoms and, when integrated with longitudinal data, model temporal—i.e. time-directed—processes [15, 16]. Network analysis has been leveraged in eating disorders research, lending information on key illness pathways and potential

intervention targets [17, 18]. However, among those with ARFID, in the absence of maladaptive behaviors driven by mechanisms previously studied in network research (e.g., overvaluation of weight/shape), there may be heterogeneous motivations for inadequate food intake (in volume/variety), and these motivations may be uniquely linked to discrete emotions. For example, anxiety may drive food restriction in individuals with *ARFID-fear of aversive consequences* [19], while disgust may play a prominent role in food avoidance among those with *ARFID-sensory sensitivity* [12, 20]. An approach that integrates longitudinal data with network analysis is uniquely suited to explore symptom maintenance in relation to emotion-behavior associations in ARFID by providing an illustration of how symptoms are interconnected over time [21, 22]. This approach also provides information on the relative influence of a given node which, in this context, may help to identify unique emotions that exert the highest magnitude of time-directed effects at nomothetic (i.e., group) and idiographic (i.e., individual) levels, thus contributing to the development of personalized, hypothesis-driven interventions [23].

The Present Study

To our knowledge, the present study is the first to integrate network methods with naturalistic, time-series data collected from individuals with ARFID (i.e., via EMA), addressing a clear gap in the symptom maintenance ARFID literature. The primary aims of this study are as follows:

Aim 1 (group-level networks): Measure the temporal associations between discrete emotions and behaviors in real-world contexts of adults with ARFID.

Aim 2 (individual networks): Explore how emotion-behavior dynamics vary according to primary ARFID profile.

We expected negative emotions to represent key drivers of ARFID behaviors at subsequent timepoints. We hypothesized that ARFID behaviors would predict reductions in some negative emotions at subsequent timepoints, and that emotion-behavior associations would differ according to ARFID profile.

Methods

Design

We drew participants for our analyses from a larger study funded by the National Institute of Mental Health examining the neurobiological underpinnings of emotional functioning in adults with ARFID (K23MH125143) that took place between February 2021 and December 2025. The Mass General Brigham Institutional Review Board approved all study procedures. We enrolled males and females aged 18–45 years old who met current diagnostic criteria for ARFID, as determined by the Pica, ARFID, and Rumination Disorder Interview (PARDI) [24]. As this study represents a sub-analysis of a sample collected for the larger study on the neurobiology of ARFID, we determined inclusion and exclusion criteria for interpretability of neurobiological data as well as safety for neuroimaging and blood draws

(**Table S1** includes full details on inclusion/exclusion criteria). Relevant to the aims of this study, we excluded participants who endorsed clinically significant weight or shape concerns, defined by: a global score > 4 on the Eating Disorder Examination-Questionnaire (EDE-Q) [25], current engagement with any binge eating/purging behavior, and/or a lifetime history of another eating disorder because research has already established that weight/shape-based eating disorders impact emotion functioning [10]. We also excluded individuals who reported a history of psychosis or mania, a current substance use disorder, or active suicidal or homicidal ideation.

Participants

Participants recruited with ARFID for the larger study were *N* = 58 and from these, 20 participants (6 male and 14 female) provided extended EMA data. Original data collection for the larger study included an EMA protocol for 9 days (2 practice days followed by 7 data collection days; 56 timepoints per individual). In order to reach recommended data thresholds for individual network estimations of at least 75 timepoints per individual [26], we extended the EMA collection in the 4th year of the study to be 14 days (2 practice days followed by 12 days of data collection; 96 timepoints per individual) for the final 20 participants in the study.

Procedure

After initial screening to determine eligibility and completion of baseline surveys, participants completed the EMA protocol which asked about emotions, eating behaviors, and eating situations throughout the day. We used the Real Time Assessment in the Natural Environment (see ReTAINE.org) to collect EMA data. Participants received 8 signal-contingent prompts (i.e., reports in response to a signal) each day at times that were aligned with their personal sleep-wake schedules. We determined these times according to roughly equivalent anchor points throughout the day, around which the prompts were randomly distributed, with a mean of 0 minutes and a standard deviation of 30 minutes [27]. At each prompt, participants were instructed to select which (if any) ARFID behaviors they had engaged in since the last prompt and to rate their emotional states. We considered prompts completed within 60 minutes of delivery to be valid.

Measures

Demographics

All participants self-reported their age, sex assigned at birth, gender identity, race, and ethnicity.

Pica, ARFID, and Rumination Disorder Interview

We used the PARDI [24] to confirm ARFID diagnosis. Trained research assistants administered the PARDI to determine an overall ARFID severity score as well as a severity score for each ARFID phenotype (range = 0–6). To determine which ARFID profiles participants met criteria for, validated subscale cutoffs were applied: 0.5 for fear of aversive consequences [28], 0.6 for sensory sensitivity [29], and 1.1 for lack of interest [29].

Signal-Contingent EMA Items

Affective states. We used an abbreviated version of the Positive and Negative Affect Schedule (PANAS) [30] to assess emotions, consistent with prior EMA research in eating disorders [31]. The PANAS is a self-report measure that asks about different emotional states that are categorized as either positive or negative. Participants rated each item based on the extent to which they felt that emotion in the moment (1 = *very slightly or not at all*, 5 = e*xtremely*). In our study, the following emotions were assessed: upset, hostile, alert, ashamed, inspired, nervous, determined, attentive, afraid, active, disgusted, guilty, sad, happy, and proud.

Eating behaviors. Eating behaviors included those which map on to commonly endorsed ARFID symptoms. We created unique EMA items to assess these behaviors based on validated questions from the PARDI. Avoidant behaviors included: refusing to eat with others, eating preferred foods, declining new foods, and eating the same foods. Restrictive behaviors included: refusing preferred foods, eating slowly, missing a meal, and not finishing a meal. Participants indicated if they had experienced any of the behaviors at each timepoint and how long ago the behavior occurred. A full description of the eating behaviors included in our EMA protocol and how they were asked as well as the instructions given to participants can be found in **Table S2**.

Data Analytic Procedure

Network Estimation and Visualization

Aim 1: Group-level Networks. Analysis code is available in the supplementary materials. We prepared our data in Stata and conducted our analyses in R, version 4.2.0 (R Core Team, 2020). We estimated group-level (nomothetic; N > 1) networks on the full sample (*N* = 20) using the multilevel vector autoregressive (*mlVAR)* package in R [32]. The *mlVAR* package applies autoregressive methods to time-series data, which allows for the visualization of both temporal (within-subject) associations between nodes (i.e., how symptoms predict one another from one timepoint to the next) as well as contemporaneous (within-subject) associations between nodes (i.e., how symptoms relate to one another within one timepoint, thought to represent “fast-acting” processes) [32]. To this end, the time-lagged regression of variables (i.e., associations between time-points *t* and *t* – 1) results in a vector of lagged regression coefficients, or fixed-effects coefficients, which represent the strength of predictive associations between variables [21, 33]. We used the “dayvar” argument to address the longer overnight lag that occurred between days (i.e., to avoid regressing the first survey of the day on the last survey of

the prior day). Since *mlVAR* models assume stationarity [34], we detrended variables with linear trends. To test for stationarity, we used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [35] in the *tseries* package in R [36], which indicated that the assumption was met for all variables. By default, *mlVAR* employs person-mean centering to estimate temporal models. In multilevel models, person-mean centering rescales values such that they are represented as deviations from the individual's mean, which helps to disaggregate within- and between-subjects effects.

Aim 2: Individual Networks. We estimated individual (idiographic; $N = 1$) networks using the *graphicalVAR* package in R [37] for three individuals in our sample, based on their PARDI profile scores (i.e., one for fear of aversive consequences, one for sensory sensitivity, and one for lack of interest). We identified participants who had at least 75 EMA observations, as recommended by Mansueto and colleagues to support more robust parameter estimations [26]. From this subset of participants, we used a semi-random approach to identify those who scored well above the established PARDI cutoff score for the ARFID profile being represented [29], relative to the other two profiles.

We used the least absolute shrinkage and selection operator (LASSO) [38] for regularization, which shrinks spurious correlations to be exactly zero. We chose a value of regularization hyperparameter $\gamma = 0.1$ to compromise between a value that errs on the side of caution (e.g., 0.5) and the minimum value that errs on the side of discovery (e.g., 0) [39]. The goal of these analyses is to showcase heterogeneity in temporal emotion-behavior associations according to distinct ARFID profiles.

We used the *qgraph* package in R [40] to visualize all networks. In network applications to psychopathology, symptoms (in this case, emotional states and ARFID behaviors) are represented by “nodes,” and the correlations between nodes are represented by “edges.” When interpreting these networks, thicker edges (or, in the case of directed networks, arrows) indicate a stronger association. In our networks, green edges denote positive associations (i.e., as variable 1 increases, variable 2 increases), whereas red edges denote negative associations (i.e., as variable 1 increases, variable 2 decreases). An examination of both group-level and individual contemporaneous and temporal associations lends information regarding inter- *and* intra-individual variation in how symptoms predict one another at the same timepoint, and how symptoms predict one another over time.

Item Selection

Our EMA protocol consisted of 15 emotional states and 8 ARFID eating behaviors at any given prompt. We based our item selection on prior work in eating disorders [41], statistical recommendations—i.e., relatively few items with high endorsement [26, 42], and the theoretical assumptions on which our study rested—i.e., that negative emotions are central to ARFID psychopathology. Thus, we included only negative emotions in our networks, in addition to ARFID behaviors. Below, we describe our item selection process for the group-level and individual networks in more detail.

Group-level Networks: Item Selection. We estimated a group-level network which included negative emotions and all eating behaviors, resulting in 15 items. This approach is in line with previously

published research in this area that used network models to examine real-time associations between cognitive-affective factors associated with suicidal ideation [43].

Individual Networks: Item Selection. In line with previous research, we selected items for our individual network models according to negative emotions and behaviors with the highest means for each exemplar case [41], as well as theoretical knowledge of each profile type, given that potential mechanisms underlying avoidant/restrictive eating may differ across profile types [8]. For example, because anxiety may be a central prompting emotion among those with *ARFID-fear of aversive consequences* [29], this emotion was included in the corresponding exemplar model. On the other hand, because disgust may be a central prompting emotion among those with *ARFID-sensory sensitivity* [12], this emotion was included in the corresponding exemplar model. The full list of selected items for individual network models can be found in **Table S3**.

Centrality Measures

We used the *centrality* function in the R package *qgraph* to assess the relative influence of each node in our networks. Namely, we chose to calculate strength centrality, defined as the sum of the absolute weights of all edges directly connected to a node [44], which is the most widely used centrality metric in network research as it is shown to be more stable than other metrics [22]. For our contemporaneous networks, we identified nodes with the highest strength centrality, meaning the highest degree of connectedness within the network [45]. In temporal networks, strength centrality is further divided into OutStrength and InStrength, which represent the number of outgoing and incoming edges from a node, respectively [44]. Clinically, OutStrength centrality values may be particularly meaningful: a node that is high in this index represents a potential source of “activation” in the network, and therefore a target on which to intervene [44, 46].

Sample Size Rationale

At present, there remains limited guidance for determining adequate sample size for temporal network analysis. Factors that contribute to the statistical power of these networks include the number of timepoints and the number of parameters. For example, Epskamp and colleagues [47] recommend that, for group-level networks, all participants have at least 20 EMA observations. For individual networks, Mansueto and colleagues [26] recommend that participants have at least 75 observations. Participants in our group-level and individual networks met these criteria.

Our decision to include 15 items in our group-level network was made to balance model comprehensiveness and statistical power [43], though we acknowledge that empirical guidance to support this decision remains limited, and expand on relevant future directions in the Discussion section. For individual networks, simulation studies suggest that limiting the number of nodes is important [26]. There is also research to show that, at the individual-level, with approximately 90 timepoints per individual and approximately six nodes (similar to the individual networks reported herein), VAR models can reliably identify bidirectional associations between variables [48].

Results

Participant Characteristics

Participants were 70% female, had a mean age of 26.2 (SD = 5.57) and a range of ARFID presentation types (see Table 1 for participant characteristics including ARFID presentations). The mean EMA compliance rate of the sample was 80% (SD = 17%), meaning that, across the 20 participants who completed the 14-day EMA protocol, individuals responded to, on average, 77 out of 96 total prompts. This is in line with the average compliance rate of 78% across 42 EMA studies [49], and compliance rates of 87% [50] and 76% [51] reported in similar EMA research within eating disorder samples. Across participants, the ARFID behavior with the most frequent endorsement was *eating preferred foods* (80% of participants engaged in this behavior at least once per day of the 14-day EMA protocol), followed by *missing a meal* (63% of participants engaged in this behavior at least once per day of the 14-day EMA protocol). The negative emotion with the highest endorsement was feeling *nervous* (*M* = 1.37; *SD* = 0.48), followed by feeling *ashamed* (*M* = 1.21; *SD* = 0.3).

Aim 1: Group-level Networks

Contemporaneous Association *s*

In the contemporaneous model of all participants (Fig. 1a), we did not observe any significant associations between negative emotions and ARFID behaviors. However, we did observe significant, positive associations between negative emotions, indicating that these items were connected when measured during the same assessment window. The contemporaneous network revealed that feeling *upset* (strength = 0.86) was the most central node, within subjects and within timepoints (Fig. 1b). Detailed information on the strength of associations in our contemporaneous network can be found in **Table S4**.

Temporal Associations

In line with our hypotheses, we found multiple significant, time-directed associations between negative emotions and ARFID behaviors. Results from our temporal, group-level network (Fig. 2a) revealed that the symptom with the highest OutStrength centrality (i.e., highest number of outgoing connections to other symptoms) was feeling *ashamed* (OutStrength = 0.74) (Fig. 2b). Feeling *ashamed* significantly predicted *missing a meal* at the next timepoint (fixed effects coefficient = 0.12, *p* = 0.02) and *not finishing a meal* at the next timepoint (fixed effects coefficient = 0.12, *p* = 0.01). Feeling *nervous* significantly predicted *declining new foods* at the next timepoint (fixed effects coefficient = 0.21, *p* = 0.03). We also observed that engagement in ARFID behaviors predicted reductions in some negative emotions at the next timepoint. Namely, *not finishing a meal* significantly predicted feeling less *guilty* (fixed effects coefficient = -0.07, *p* = 0.01); *eating the same foods* predicted feeling less *nervous* (fixed effects coefficient = -0.03, *p* = 0.04); and *declining new foods* predicted feeling less *upset* (fixed effects coefficient = -0.04, *p* = 0.02), *ashamed* (fixed effects coefficient = -0.06, *p* = 0.02), and *nervous* (fixed effects coefficient = -0.05, *p* = 0.01), all at the next timepoint. In other words, declining new foods at one

timepoint predicted lower levels of upset, shame, and nervousness at the next timepoint, consistent with expectations that ARFID behaviors reduce subsequent negative emotions.

Aim 2: Individual Networks

Participant A

Participant A met criteria for a primary profile of *ARFID-fear of aversive consequences* (PARDI Overall Severity score: 3.0; PARDI FC score: 4.8; EMA compliance rate = 85%). Despite testing revealing no known allergies, she avoided foods due to fear that she would be intolerant to them. In participant A's contemporaneous network (Fig. 3a), feeling *sad* had the highest strength centrality. As demonstrated by her temporal network (Fig. 3b), *feeling nervous* predicted *declining new foods* at the next timepoint. The symptom with the highest OutStrength centrality in participant A's temporal network was *refusing to eat with others* (OutStrength = 1.05), meaning that this item had the highest magnitude of time-directed effects on other items in the network.

Participant B

Participant B met criteria for a primary profile of *ARFID-sensory sensitivity* (PARDI Overall Severity score: 2.7; PARDI SS score: 2.2; EMA compliance rate = 100%). He reported avoidance of foods based on their smell and texture, such as foods that are "mushy, slimy, wet, or stringy." He also indicated that he preferred to eat alone, leading to avoidance of social events. In participant B's contemporaneous network (Fig. 4a**)** feeling *sad* had the highest strength centrality. As demonstrated by participant B's temporal network (Fig. 4b), *missing a meal* predicted feeling *disgusted* at the next timepoint. Additionally, *missing a meal* predicted *eating the same foods* at the next timepoint, suggesting a directed relationship between ARFID behaviors. The symptom with the highest OutStrength centrality in participant B's temporal network was *missing a meal* (OutStrength = 0.67), meaning that this item had the highest magnitude of time-directed effects on other items in the network.

Participant C

Participant C met criteria for a primary profile of *ARFID-lack of interest* (PARDI Overall Severity score: 3.2; PARDI LOI score: 3.3; EMA compliance rate = 88%). On the PARDI, she reported she reported reduced hunger cues and a lack of enjoyment from eating, even when eating her preferred foods. In participant C's contemporaneous network (Fig. 5a) feeling *sad* had the highest strength centrality. As demonstrated by participant C's temporal network (Fig. 5b), feeling *ashamed* predicted *missing a meal* at the next timepoint. Additionally, *eating preferred foods* predicted feeling *ashamed*. The symptom with the highest OutStrength centrality in participant C's temporal network was feeling *ashamed* (OutStrength = 0.96), meaning that this item had the highest magnitude of time-directed effects on other items in the network.

Discussion

The present study integrated ecological momentary assessment (EMA) data with network analysis to provide the first empirical network examination of the temporal associations between emotions and behaviors among adults with ARFID. Consistent with our hypotheses, we found that distinct negative emotions predicted ARFID behaviors both at the group- and individual-level, and unique emotion-behavior associations emerged according to ARFID profile type (i.e., fear of aversive consequences of eating; sensory sensitivity; lack of interest in eating). Further, we found that engagement in ARFID behaviors predicted small reductions in certain negative emotions at the next timepoint, suggesting that ARFID behaviors may be negatively reinforcing.

Aim 1: Group-level Networks

We estimated both temporal and contemporaneous associations between negative emotions and ARFID behaviors across the entire sample. Temporal models provide information on processes happening from one point in time to the next, whereas contemporaneous models demonstrate “fast-acting” associations within the same measurement window [52]. While our contemporaneous networks did not demonstrate significant associations between negative emotions and ARFID behaviors, they did demonstrate a clustering of negative emotions. These ‘null’ findings may be illustrative of the inherent temporal, dynamic nature of emotions and disordered eating behaviors that is posited by theoretical models (i.e., negative emotions *preceding* disordered eating, and disordered serving to down-regulate negative emotions) [53, 54]. Indeed, such findings provide evidence that emotions may be poorly regulated in the context of ARFID [11], while highlighting the importance of estimating emotion-behavior dynamics through methods that can capture fluctuations in these constructs over time.

In line with our expectations, our temporal, group-level network revealed time-directed associations between negative emotions and ARFID behaviors. Feeling *ashamed* emerged with the highest OutStrength centrality (i.e., a source of “activation” in the network) and significantly predicted several ARFID behaviors at the next timepoint, including *missing a meal* and *not finishing a meal*. This finding is consistent with prior qualitative research on AN, the other primary restrictive eating disorder, which suggests that shame (specifically body shame) may closely relate to core mechanisms of AN pathology —i.e., perfectionism [55, 56]. However, our study is the first to demonstrate a *time-directed* role of shame in triggering ARFID behaviors, specifically those conceptualized as restricting amount eaten. Although those with ARFID, in the absence of weight/shape concerns, may not experience facets of shame that have been studied in AN [57], these individuals may experience shame or embarrassment related to their limited food intake and/or food preferences [58], which may motivate decisions around eating.

We also found that feeling *nervous* significantly predicted *declining new foods* at the next timepoint. This is in line with theory that anxiety (e.g., food neophobia) prompts food avoidance in ARFID [13], because reliance on safe foods may be negatively reinforcing via reductions from high arousal negative emotions like nervousness [11, 59]. This finding also aligns with research identifying distinct daily patterns of anxiety that are associated with eating disorder behavior occurrence and timing among those with AN [10], though diverges from this research in demonstrating a downstream presence of food avoidance,

rather than food restriction. Taken together, these findings highlight specific negative emotions—i.e., shame and nervousness—which appear to be particularly salient in prompting ARFID behaviors, suggesting mechanistic processes that may contribute to psychopathology across individuals, pending experimental research.

Aim 2: Individual Networks

To assess emotion-behavior dynamics at the individual level, we constructed three exemplar models according to primary ARFID profile type. In line with our expectations and theoretical research in this area, different negative emotions predicted different ARFID behaviors in the three networks we explored. For example, our exemplar model of fear of aversive consequences (participant A) revealed a directed path between feeling *nervous* and *declining new foods*, while *refusing to eat with others* emerged with the highest OutStrength centrality. This may suggest that, while negative emotions are prompting food restriction for this individual, behavior associated with social isolation (i.e., eating alone) is propagating to symptoms overall in the network. On the other hand, our exemplar model of sensory sensitivity (participant B) demonstrated a central role of *missing a meal*, and suggested that this ARFID behavior predicted subsequent emotional states, which have been previously conceptualized among those with sensory aversions to food (i.e., disgust) [12]. Finally, our exemplar model of lack of interest in eating (participant C) identified feeling *ashamed* as the most influential node in the network, and suggested that shame shared bidirectional associations with avoidant and restrictive behaviors (i.e., *eating preferred foods* and *missing a meal*). Interestingly, across our individual network models, engagement in ARFID behaviors sometimes predicted increases, rather than decreases, in negative emotions. While ARFID behaviors may sometimes function to regulate negative emotion (as is the case with other eating disorders), they may not regulate *all* emotions related to ARFID. This suggestion is in line with previous research in other eating disorders, such as studies reporting that, while anxiety decreases following binge-purge episodes, depression increases [60, 61], and emerging evidence to suggest that eating-disorder behaviors may indeed function to increase/maintain negative affect [62].

The finding that feeling *ashamed* emerged with high OutStrength centrality and as a predictor of ARFID behaviors in our group-level network, and that shame demonstrated strong contemporaneous and temporal connections in our exemplar lack of interest network, suggests that this emotional state may play a key role in ARFID psychopathology and represent a potentially promising treatment target [45]. As such, intervention research may explore ways to target shame, possibly via adjunct approaches that promote self-compassion [63]. Additionally, future research should consider environments/circumstances that may elicit feelings of shame and/or negative thoughts about eating (e.g., social eating situations) among individuals with ARFID, as it may be that avoidance of these environments contributes to other maladaptive psychological processes. This proposition is strengthened by findings from our individual networks representing fear of aversive consequences and sensory sensitivity profiles, which suggested a reinforcing role of certain ARFID behaviors—i.e., *refusing to eat with others* and *missing meals*. Findings also lend support for techniques used in cognitive-

behavioral therapy for ARFID (CBT-AR) [59], such as regularizing eating (i.e., three meals and two snacks).

By leveraging the granular assessment of within-person variability that is provided by EMA data and integrating these data with network models, our study advances beyond cross-sectional methodologies to lend information regarding temporal precedence of discrete emotions and disordered eating behaviors in adults with ARFID. These findings inform how symptoms vary at the inter- and intra-individual level and may be used to generate hypotheses to guide future longitudinal research which, together, may help to inform and eventually personalize treatment development.

Strengths, Limitations, & Future Directions

Our study has several strengths, as well as limitations that may guide future directions. Our study benefits from the use of EMA, which helps to minimize recall bias by focusing on a participant's current state and natural context [64]. Further, our integration of EMA with the analytical frameworks of network analysis allowed for a fine-tuned examination of temporal interrelations between symptoms. This approach is in line with cognitive-behavioral theories of eating disorders, including ARFID, which posit that real-time cognitions, behaviors, and affect are dynamically related to maintain psychopathology [53, 59].

Despite the strengths of the present study, there are several limitations which may guide future research. Our sample size of 20 participants is small—though we had high levels of data per participant which allowed for individual-network analyses. However, the small sample size reduces the generalizability of findings, and our inclusion of 15 nodes in our group-level networks may have reduced statistical power. Additionally, our sample comprised mostly females, leading to unbalanced sex representation. Future research should consider replicating our findings in a larger and more sociodemographically diverse sample. Additionally, while our individual networks characterize emotion-behavior associations according to "primary" ARFID profile, these participants also endorsed features of other ARFID profiles, which may obscure the detection of meaningful heterogeneity in symptom dynamics. Nonetheless, it is common for ARFID profiles to overlap, and many individuals with ARFID present with features of multiple profiles (with one typically being primary) [8, 65]. Thus, our individual networks may also be well-suited to illustrate diagnostic presentations that are commonly observed in clinical settings; nonetheless, future research should explore these networks in individuals exhibiting only one ARFID profile and should do so with more severe clinical samples (e.g., an inpatient sample). Another consideration is the specific selection of items estimated in each individual network and that these items differed across the three exemplar networks, which may have overlooked symptoms that meaningfully contribute to psychopathological processes. Our individual networks should be interpreted as preliminary and with caution: one cannot infer that the temporal associations observed in our individual-sensory sensitivity network, for example, would generalize to another individual with a similar clinical presentation. Future research should test patterns of convergence and divergence across other profile-specific networks in ARFID, though our findings provide preliminary evidence that psychological emotion-behavior maintenance patterns may differ by ARFID profile. Finally, to ensure adequate variance of these data,

idiographic methods suggest that EMA indices be measured across a wide range [66], and thus our measurement scale may have been too narrow. Future research should replicate our analyses using data from EMA prompts asked on a wider numerical range and examine meaningful change in emotion-behavior symptom dynamics over the course of psychological intervention.

Conclusions

The present study provides the first empirical examination of the dynamic, mutually reinforcing associations between discrete emotions and eating disorder behaviors in adults with ARFID. Our findings revealed that negative emotions play a central, directed role in prompting ARFID behaviors, and that ARFID behaviors may function in a negatively reinforcing manner to impact downstream emotions. Individual networks demonstrated heterogeneity in these dynamics across ARFID profiles. Together, these findings advance our understanding of potential mechanisms underlying ARFID, which may inform future longitudinal research examining emotion-behavior trajectories, as well as guide the development of personalized, hypothesis-driven ARFID interventions.

Abbreviations

AN	Anorexia nervosa
APA	American Psychological Association
ARFID	Avoidant/restrictive food intake disorder
BMI	Body mass index
CBT-AR	Cognitive-Behavioral Therapy for Avoidant/Restrictive Food Intake Disorder
DSM-5	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
DSM-5-TR	Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition, Text Revision
EDE-Q	Eating Disorder Examination-Questionnaire
EMA	Ecological momentary assessment
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
LASSO	Least absolute shrinkage and selection operator
mlVAR	Multilevel vector autoregressive
MRI	Magnetic resonance imaging
PANAS	Positive and Negative Affect Schedule
PARDI	Pica, ARFID, and Rumination Disorder Interview
FC	Fear of aversive consequences (PARDI subscale)
SS	Sensory sensitivity (PARDI subscale)
LOI	Lack of interest (PARDI subscale)
PARDI-AR-Q	Pica, ARFID, and Rumination Disorder Interview
SCID-5	Structured Clinical Interview for DSM-5
SD	Standard deviation

Declarations

Ethics approval and consent to participate

The Mass General Brigham Institutional Review Board approved all study procedures (Protocol # 2020P002413). All participants were informed about the purpose and procedures of the study, and consent was obtained prior to participation. Participation was voluntary, and confidentiality and anonymity were ensured throughout the study.

Consent for publication

Written informed consent for publication was obtained from all individual participants included in the study.

Availability of data and materials

The data are not publicly available due to privacy or ethical restrictions. Analytic code is available in the supplementary materials.

Competing interests

Drs. Becker, Eddy, and Thomas receive royalties for their books on avoidant/restrictive food intake disorder from Cambridge University Press. Drs. Eddy and Thomas receive royalties for their book on anorexia nervosa from Routledge. Drs. Burton-Murray and Thomas receive royalties from Oxford University press for their book on rumination disorder. Dr. Burton-Murray receives royalties from Cambridge University Press for her forthcoming book on functional bowel disorders. Drs. Thomas, Eddy, and Kambanis receive consulting fees from Equip Health. Dr. Breithaupt serves as a consultant for Otsuka Pharamecuticals and HealthiVibe. Dr. Lawson receives grant support and research study drug from Tonix Pharmaceuticals and receives royalties from UpToDate. Dr. Lawson and/or immediate family member holds stock in Thermo Fisher Scientific, Zoetis, Danaher Corporation, Intuitive Surgical, Merck, West Pharmaceutical Services, Gilead Sciences, and Illumina. Dr. Lawson is an inventor on US provisional patent applications no. 63/467,980 (Oxytocin-based therapeutics to improve cognitive control in individuals with attention deficit hyperactivity disorder).

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Authors' contributions

K.P., writing – original draft, writing – review and editing, conceptualization, formal analysis, visualization; **A.D.,** writing – review and editing, project administration; **W.R.B.,** writing – review and editing; **S.G.E.,** writing – review and editing, methodology; **S.A.W.,** writing – review and editing, methodology; **L.A.L.,** writing – review and editing; **S.L.Y.,** writing – review and editing, methodology; **H.G.,** writing – review and editing, project administration; **S.B.W.,** writing – review and editing, methodology; **A.C.R.,** writing – review and editing; **K.A.,** writing – review and editing; **B.M.,** writing – review and editing; **E.K.,** writing – review and editing; **L.B.,** writing – review and editing; **H.M.,** writing – review and editing; **D.L.F**., writing – review and editing; **K.T.E**., writing – review and editing; **E.A.L.,** writing – review and editing; **L.M.H.,** writing – review and editing; **J.J.T.,** writing – review and editing, supervision; **K.R.B**., supervision, writing – review and editing, funding acquisition, project administration

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Table

Table 1.*Demographic and clinical characteristics of the study sample (N=20).*

Sex, n (%)	
Male	6 (30)
Female	14 (70)
Age (years), mean (SD)	26.2 (5.57)
Gender Identity, n (%)	
Female	10 (50)
Male	6 (30)
Transgender	0 (0)
Genderqueer	1 (5)
Nonbinary	3 (15)
Unsure	0 (0)
Another Identity	0 (0)
Race, n (%)	
Caucasian	20 (100)
Non-Caucasian	0 (0)
Ethnicity, n (%)	
Hispanic	1 (5)
Non-Hispanic	19 (95)
BMI, mean (SD)	25.1 (5.98)
PARDI scores, mean (SD)	
Total Severity	2.53 (0.67)
Fear of Aversive Consequences	1.19 (1.52)
Lack of Interest in Eating of Food	2.20 (1.14)
Sensory Sensitivity	2.26 (0.82)
ARFID presentation(s), n (%)	
Sensory sensitivity only	3 (15)
Lack of interest only	0 (0)
Fear of aversive consequences only	1 (5)
Sensory sensitivity + Lack of interest	9 (45)
Sensory sensitivity + Fear of aversive consequences	2 (10)

Lack of interest + Fear of aversive consequences	1 (5)
All 3 presentations	4 (20)
Current comorbid psychiatric diagnoses, n (%)	
Attention-deficit hyperactivity disorder	10 (50)
Social anxiety disorder	8 (40)
Major depressive disorder	8 (40)
Generalized anxiety disorder	7 (35)
Obsessive-compulsive disorder	6 (30)
Post traumatic stress disorder	5 (25)
Panic disorder	4 (20)
Agoraphobia	3 (15)
Specific phobia	3 (15)
Autism spectrum disorder	3 (15)
No comorbid diagnoses	3 (15)
Other specified trauma- and stressor-related disorder	1 (5)
Other specific anxiety disorder	1 (5)
Body dysmorphic disorder	1 (5)
EDE-Q Global, mean (SD)	0.34 (0.35)

Note: BMI = body mass index; PARDI = Pica, ARFID, and Rumination Disorder Interview; EDE-Q = Eating Disorder Examination Questionnaire; SD = standard deviation

Figures

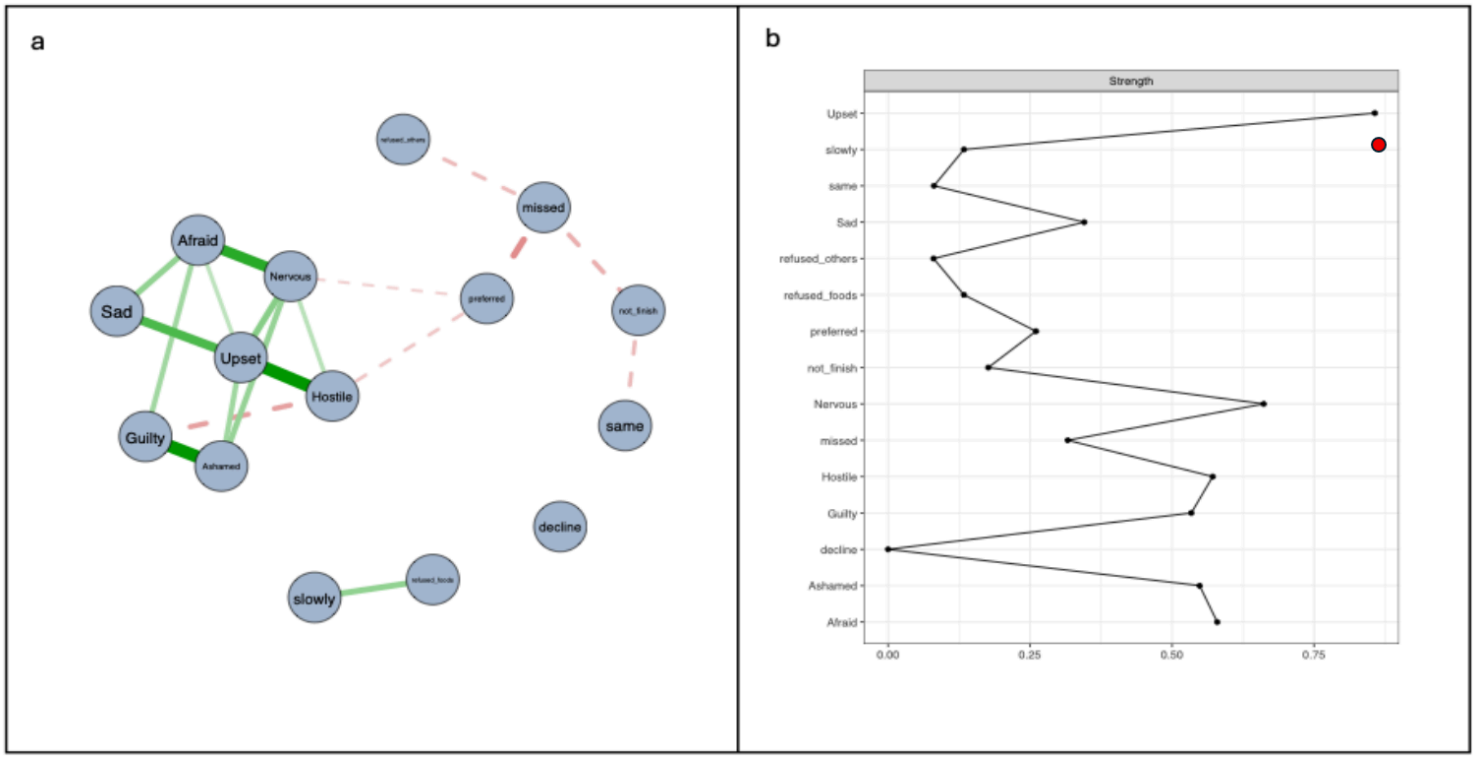

Figure 1

*Group-level contemporaneous network **(a)** and strength centrality metrics **(b)** of emotion-behavior associations in ARFID.*

Note: “Slowly” = “ate very slowly”; “same” = “ate the same food(s) as your previous meal”; “refused_others = “refused to eat with others”; “refused_foods”= “refused to eat foods you would normally eat”; “preferred” = “only ate preferred foods”; “not_finish” = “did not finish a meal”; “missed” = “missed a meal”; “decline” = “declined to eat a new food”. In (a) thicker edges between nodes indicate stronger associations; curved edges represent autoregressive effects (i.e., a variable predicting itself); green and red edges denote positive and negative associations, respectively. In (b) red dots indicate items with the highest centrality.

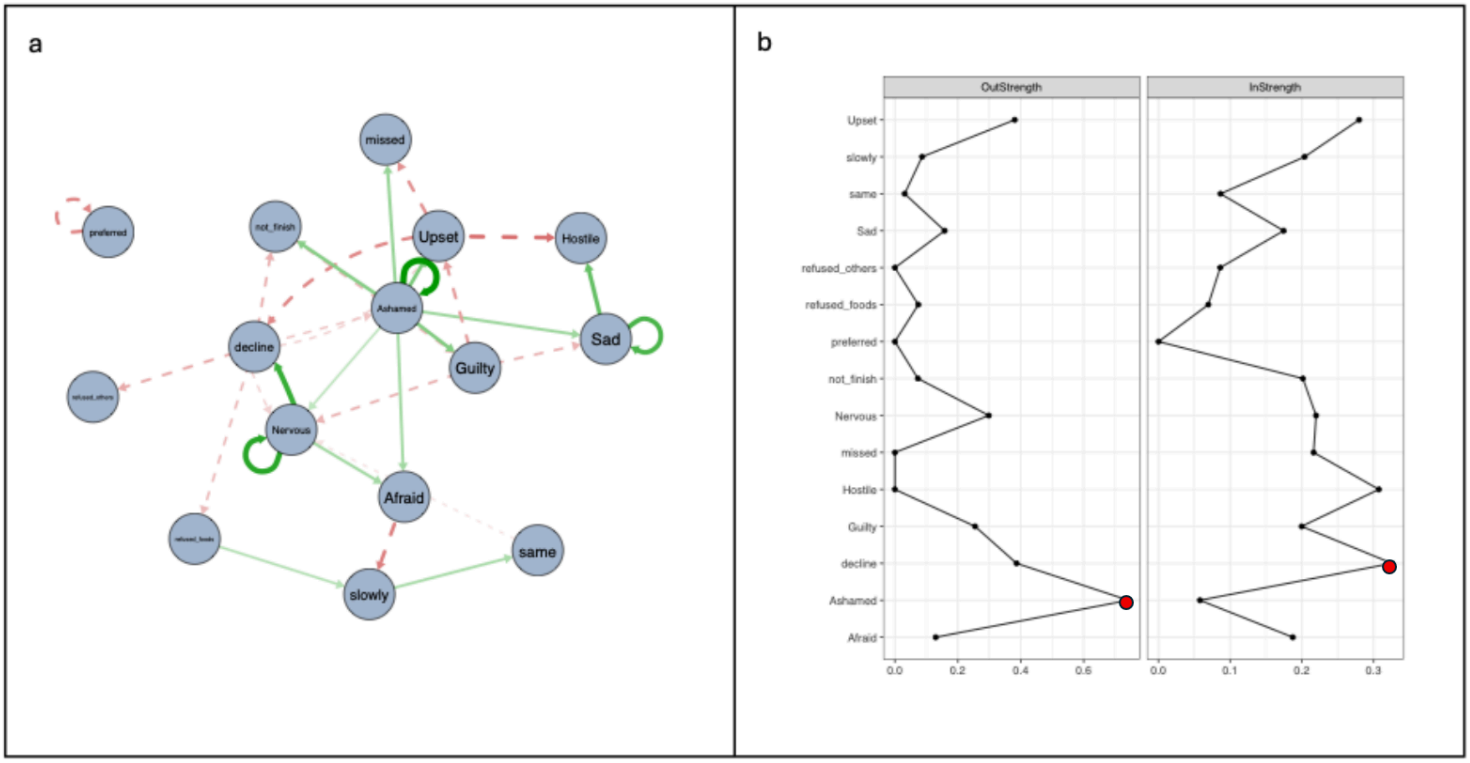

Figure 2

*Group-level temporal network **(a)** and strength centrality metrics **(b)** of emotion-behavior associations in ARFID.*

Note: "Slowly" = "ate very slowly"; "same" = "ate the same food(s) as your previous meal"; "refused_others = "refused to eat with others"; "refused_foods"= "refused to eat foods you would normally eat"; "preferred" = "only ate preferred foods"; "not_finish" = "did not finish a meal"; "missed" = "missed a meal"; "decline" = "declined to eat a new food". In (a) thicker edges between nodes indicate stronger associations; curved edges represent autoregressive effects (i.e., a variable predicting itself); green and red edges denote positive and negative associations, respectively. In (b) red dots indicate items with the highest centrality.

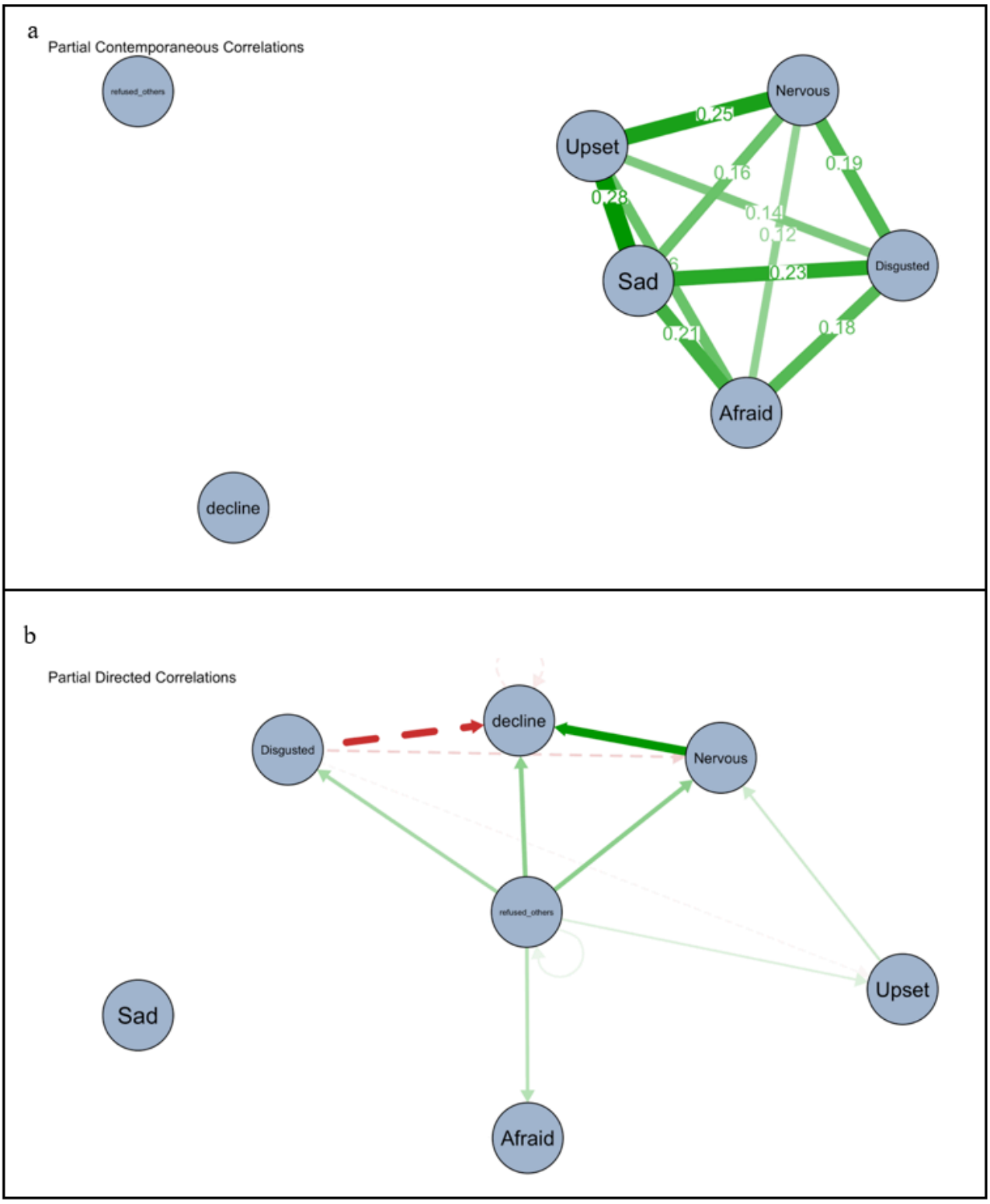

Figure 3

Individual networks for participant A depicting contemporaneous ***(a)*** *and temporal* ***(b)*** *emotion-behavior associations.*

Note: “Decline” = “declined to eat a new food”; “refused_others” = “refused to eat with others”. Thicker edges indicate stronger associations. Green and red edges denote positive and negative associations,

respectively.

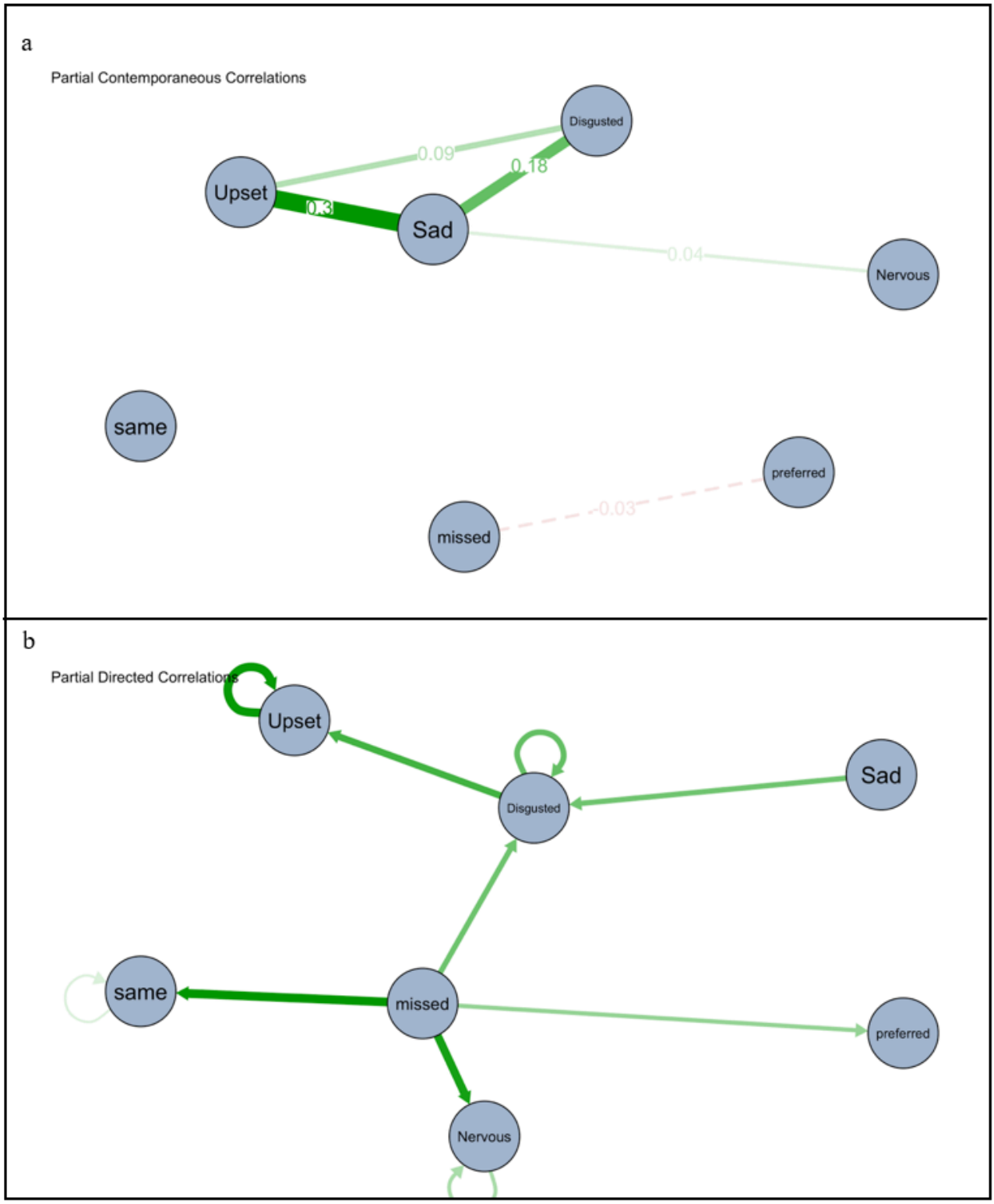

Figure 4

*Individual networks for participant B depicting contemporaneous **(a)** and temporal **(b)** emotion-behavior associations.*

Note: “Same” = “ate the same food(s) as your previous meal”; “missed” = “missed a meal”; “preferred” = “only ate preferred foods”. Thicker edges indicate stronger associations. Green and red edges denote positive and negative associations, respectively.

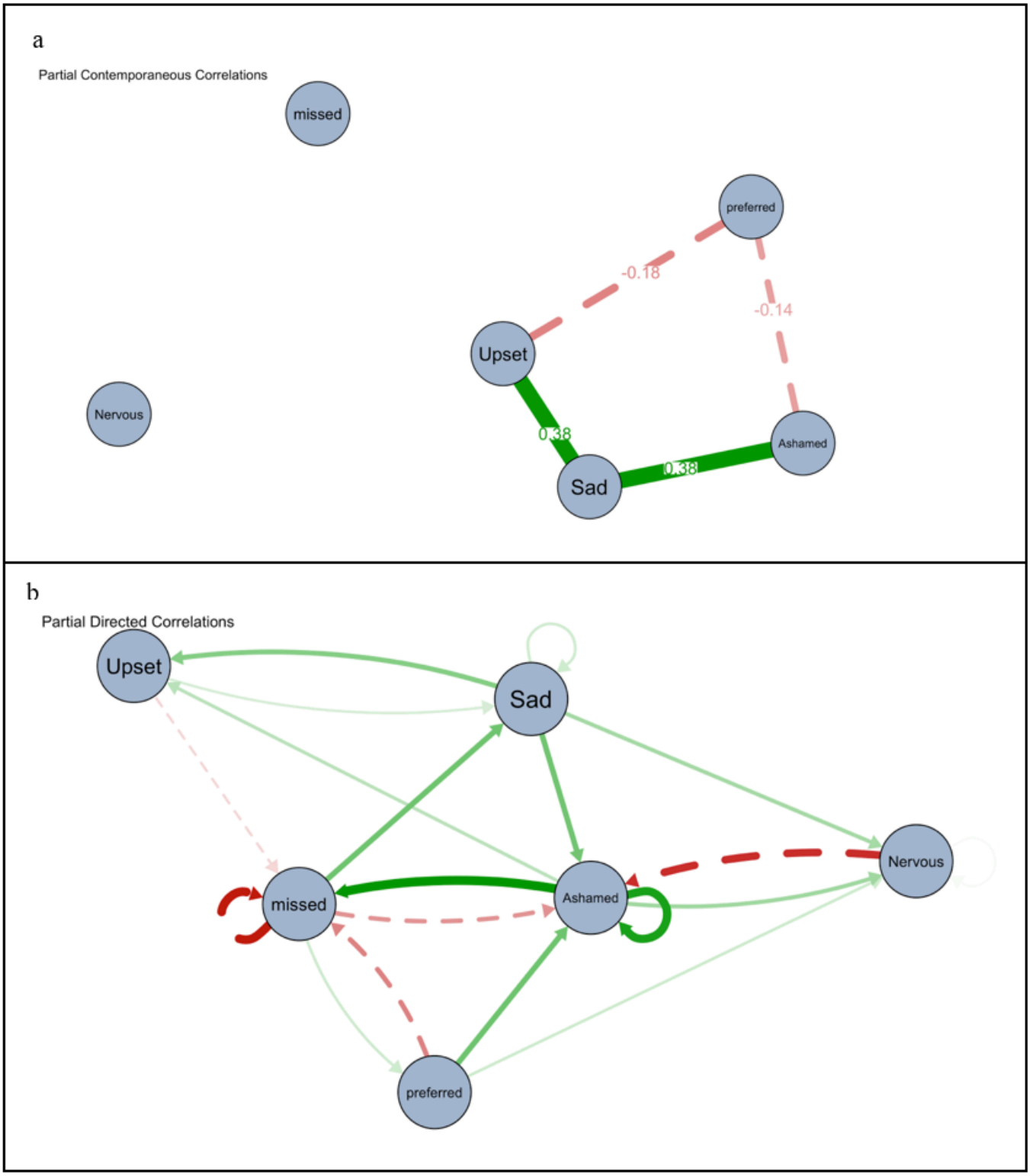

Figure 5

*Individual networks for participant C depicting contemporaneous **(a)** and temporal **(b)** emotion-behavior associations.*

Note: “Missed” = “missed a meal”; “preferred” = “only ate preferred foods”. Thicker edges indicate stronger associations. Green and red edges denote positive and negative associations, respectively.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Codefile.docx
- supplementary072926.docx